EFFECTS OF WOOD HARVESTING ON FOREST BIOMASS AND CARBON SEQUESTRATION IN WEST VIRGINIA

by

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List of Abbreviations/Symbols

AGB	aboveground biomass
AGBD	aboveground biomass density
AHC	Appalachian Hardwood Center
ANOVA	Analysis of Variance
AS	ash
BA	basal area
BAG	basal area growth
BAL	basal area large
BC	black cherry
BF	board-feet
C	carbon
CERW	cerulean warbler
CO	chestnut oak
CO_2	carbon dioxide
^oC	celsius
CFM	Carbon Forest Management
cft	cubic feet
cm	centimeter
DBH	diameter at breast height
eq	equivalence
FIA	Forest Inventory and Analysis Database
FSV	Forest Vegetation Simulator
g	grams
GDP	Gross Domestic Product
ha	hectare
HK	hickory

HM	hard maples
in	inch
kg	kilograms
LUC	land use change
m	meters
MBF	thousand board-feet
MIS	Management Indicator Species
MO	mixed oak
NADP	National Atmospheric Deposition Program
NEP	net ecosystem productivity
NIPF	non-industrial private forest landowner
NPP	net primary productivity
NWOS	National Woodland Ownership Survey
O	other species
PC	principal component
PPI	Producer Price Index
RIL	reduced impact logging
RO	red oak
SI	site index
SM	soft maples
SOC	soil organic carbon
SQL	standard query language
tg	teragram
USDA	United States Department of Agriculture
USFS	United States Forest Service
USFWS	United States Fish and Wildlife Service
USGCRP	United States Global Change Research Program
WO	white oak
WN	walnut
YP	yellow poplar

Abstract

EFFECTS OF WOOD HARVESTING ON FOREST BIOMASS AND CARBON SEQUESTRATION IN WEST VIRGINIA

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George Mason University, 2011

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The objective of this research is to evaluate the long-term effects of wood harvesting and sustainable forest timbering practices on forest biomass and carbon sequestration in West Virginia. Although several forest management and carbon models have been coupled for scenario analysis, this integrated modeling approach is novel as it predicts timbering events, disturbance events, and forest stand growth as endogenous processes operating at multiple scales (tree, stand, region, and state). This approach allowed for simulating a number of key micro-scale, cross-scale feedback mechanisms, including the long-term interaction between forest stand volume dynamics, growth, timbering event frequency, and disturbance event frequency at multiple scales. The results of the logistic regression analyses indicated that timber stand value density, tree prices, and plot ownership were key drivers in predicting timber stand and tree selection for commercial timber removal events. Beyond the direct effect of timbering events (i.e., removal of forest biomass), timbering events in West Virginia did not have a statistically significant indirect effect on net annual forest stand growth rates, landscape level disturbances, regeneration rates,

nor mortality rates. Overall, the integrated model estimated that the average net annual growth rate for West Virginia in 2000 for the validation dataset was 1.38% (1.33% was the 5 year average), which was within 1% of the observed rate of 1.40%. From 2000 to 2050, aboveground biomass and carbon stocks in West Virginia forests are projected to continue to increase, despite increased timbering activity, with nearly half of the state forest acreage being classified in an advanced stage of recovery from past timbering by 2050 (up from 28% in 2000). However, the rate of annual increase in forest carbon and biomass decelerates over time. This deceleration is due to a projected doubling of the timber removal rates toward mid-century (due to increases in timber prices and stand density), increases in landscape scale disturbances, and declining stand net annual growth, which are all due to increases in stand density. Forest stands with steeper slopes, lower annual average precipitation, and greater stand volume density were more likely to experience a landscape disturbance event, resulting in a net negative growth rate for the stand. Overall, these disturbance events are projected to increase in frequency by approximately 50% from 2000 to 2050, as forest stands increase in stand biomass density. Application of sustainable timbering techniques was found to significantly enhance long-term projections of biomass, carbon, net annual growth (50% higher than status quo), and system carrying capacity.

1. Introduction

The objective of this research is to evaluate the effects of wood harvesting and sustainable forest timbering practices on forest biomass and carbon sequestration at multiple scales using an integrated modeling approach. The principal novel aspect of this research is the synthesis of many areas of research (e.g., land use change, silviculture, socioeconomics, quantitative ecology, carbon sequestration, and public policy) using an integrated modeling approach to address the cumulative effect of timbering, market conditions, land use change, and key environmental processes on forest resources at multiple scales. Essentially, the integrated modeling approach will focus on evaluating alternative timbering scenarios using a positive modeling approach (Parker et al. 2002) to determine potential long-term changes in forest resources, forest management, sustainability, and carbon sequestration potential through management of a state-wide forest system.

There is a significant body of research that addresses the anthropogenic adverse effect of timbering, sustainable silviculture techniques, and land use change on forest resources. Much of this research focuses on a very specific aspect of forest management or ecological processes in order to address a discipline-specific research question and hypothesis. However, focusing on just one element of the system (e.g., the effect of timber removal on stand biomass) cannot be used to evaluate large-scale cumulative effects associated with the myriad of human and environmental interactions affecting the entire forest system, as well as the effect of new and unmeasured forces that may affect the forest system in the future (e.g., climate change or new policies). There are some examples of complex modeling projects that address the cumulative effects of human and environmental interactions, land use change, and related policy questions at different scales (e.g., Bousquet and Le Page 2004, Carpentier et al. 2000, Kerr et al. 2003, Lewis and Plantinga 2007, Mahapatra and Kant 2005, Mathevet et al. 2003, Muller and Zeller 2002, Sohngen and Brown 2006, Sohngen and Sedjo 2006, Verburg et al. 2002, Verburg and Veldkamp 2001, Walsh et al. 2006), including research funded by the National Science Foundation (NSF) in the area of Dynamics of Coupled Natural Human Systems (CNH) (NSF 2010). This body of human and environmental interaction modeling research; however, has not addressed the cumulative effect of timber markets, timbering events, forest ecosystem recovery, and carbon sequestration effects at multiple scales all within the same model, with market interactions modeled as a micro-scale, endogenous process. Furthermore, much of this human and environmental interaction modeling research focuses on smaller scale studies that only allow for qualitative assessment of policy issues at a larger regional scale. For this research, a multi-scale modeling approach will be tested that will simulate human and environmental interactions (e.g., decisions and effects for specific trees and plots, which impact state-level outcomes), which will enable a quantitative assessment of outcomes at both a micro-scale and large landscape scale. The effects will be influenced by many variables that operate at multiple scales, including regional climate, national and regional timber markets and prices, state policy, localized timber plot selection and transportation networks, plot-specific conditions, and tree-level variables (biomass, board-feet [BF], and market price) as further discussed in Section 3. Sensitivity analysis will also be applied to evaluate the relative effect of integrated model input variables on model outcomes. In this context, an integrated model is defined as a computer model that incorporates many sub-models (i.e., logistic regression models, multiple regression models, probability models) into one system in order to simulate processes and interactions over time.

Since the plots are based on a stratified random sampling design across West Virginia, it is possible then to extrapolate the micro-scale effects at the tree and plot-level to the regional level in order to inform state- and national-level policy development.

Below are four general questions to be addressed by this research effort:

1. *What are the factors affecting* ***timbering rates, timber stand selection, and tree selection*** *in West Virginia?*

2. *What is the cumulative effect of timbering and other key processes on* ***net annual forest growth*** *in West Virginia, including the indirect effect of timbering on forest growth, tree mortality, forest regeneration, and other disturbances?*

3. *What long-term effect will status quo and sustainable timbering scenarios, under varying timber market conditions, have on* ***forest ecosystem and timber resource indicator metrics*** *in West Virginia?*

4. *What long-term effect will status quo and sustainable timbering scenarios, under varying timber market conditions, have on* ***forest carbon sequestration*** *in West Virginia?*

For this research, the status quo scenario is defined as the continuation of the relationships between potential future forest market conditions and timber removal event activities that satisfy market demand. Sustainable timbering in this context is defined narrowly to be low impact timbering performed according to an array of site-specific restrictions (further defined in Section 2) to preserve forest resources for future generations, and for the production of ecological services at multiple scales.

Addressing questions 1 and 2 are necessary in order to understand current and future timbering and the long-term impact on forest resources under status quo timbering and most-likely timber market conditions. Question 1 focuses on understanding the underlying economic and site conditions that drive timber stand and tree selection, and removal rates. Question 2 focuses on understanding how timbering affects key growth processes that impact forest resources, as well as how the cumulative effect of these processes impact net annual growth of the forest system. Net annual growth of the forest includes the cumulative effect of annual biomass removals from timbering, incremental positive tree growth in a year, incremental negative tree growth in a year (i.e., partial loss of the tree in a given year), annual tree mortality rates, landscape scale disturbances (which impact mortality and growth rates), and annual tree regeneration rates. By accurately evaluating and modeling the cumulative effect of these processes on the forest system, it is then possible to address questions 3 and 4 by simulating long-term biomass and carbon effects under status quo conditions, as well as test other timbering and market scenarios (as further discussed in Sections 4 through 7).

The dissertation is organized around these four research questions, with each question explored in detail in Sections 4, 5, 6, and 7, respectively. The order of this presentation is important because the models and results presented in each section are used in the subsequent section to address the next research question, culminating with estimation of carbon impacts in Section 7. One or more of these four sections of the dissertation (Sections 4 through 7) may eventually form the basis of a separate publication(s) beyond this dissertation effort. To that end, Sections 4 through 7 are mainly written to be stand alone reports with introductions, methods, results, and discussions that pertain to each research question. This approach was also used because of the complexity of the topics and the need to discuss the detailed methods, results, and discussion in an integrated manner for each of the four research questions.

As an introduction to all of the research topics, Section 2 of this dissertation provides introductory discussion pertaining to all of the hypotheses being tested (which is largely reiterated and expanded upon in Sections 4 through 7). Section 3 also provides an overview of the technical approach, which includes a general discussion of the conceptual model (see Section 3.1) and a detailed description of Forest Inventory and Analysis (FIA) data management and filtering techniques that supports all aspects of this research (see Section 3.2). The detailed methods, results, and discussion that relate to each of the research questions and hypotheses being tested are presented in Sections 4 through 7. A summary of the dissertation results are provided in Section 8.

1.1 Significance of Research

In 2008, Senators Lieberman (Connecticut) and Warner (Virginia) co-sponsored the Climate Security Act, which would have created a carbon market and a series of policies directly and indirectly affecting land use in the United States, particularly forest conservation and afforestation/reforestation projects (e.g., creation of carbon credits, government sponsored habitat afforestation/reforestation projects, purchase of conservation easements and forest sustainability measures, and fund private/public conservation subsidies). Although the legislation was not passed by Congress, new climate change legislation is under development by the Obama administration, and eventually some form of a national climate change legislation may pass in the future. Although near-term climate policies under consideration could have a significant impact on land use and forest management, there was no detailed comprehensive study done for this specific piece of legislation that would address its impact or effectiveness related to forest system change and sequestration potential (according to Senator Warner's Senior Legislative Assistant [personal communication 2008]). Given the potential for more comprehensive legislation to pass in some form in the future, it is important to research carbon sequestration and related forest management issues.

Utilizing forest systems as carbon sinks has been put forward as one of many viable policy solutions for mitigating climate change and achieving carbon sequestration goals (United States Forest Service [USFS] 2006). Land use change (LUC) and forest systems have not been the principal means for creating carbon credits due to concerns over long-term management, monitoring, release of carbon in the future, and effectiveness (Stavins and Richards 2005). To address these concerns, certifiable carbon credits created through forest regeneration and afforestation projects require costly land use controls (e.g., purchase of long-term easements) and long-term management and monitoring, which reduces their cost effectiveness relative to alternative carbon credit methods (e.g., energy efficiency solutions) (Stavins and Richards 2005). These certifiable credits will also create easement controls and other restrictions that make them less attractive for large-scale adoption as compared to energy efficiency measures. On the other hand, management and natural recovery of large-scale forest systems could provide an alternative means for enhancing carbon sequestration and credits at a much lower cost than forestry-based certified carbon credits created through forest regeneration, easements, and afforestation projects. For example, by the end of the 20th century, land use changes, including natural recovery of forest systems and abandonment of agricultural lands, resulted in the creation of significant carbon sinks in the United States (Brown et al. 1997, Houghton et al. 1999, Houghton 2003, United States

Department of Agriculture [USDA] 2008). Although there has been small declines in the spatial extent of forestlands in West Virginia (Drummond and Loveland 2010, USFS 2008), the annual regrowth of forest biomass across West Virginia currently exceeds the losses due to timbering and land use conversion, which has created a large carbon sink (see Section 5 for further discussion). Even with continued timbering, it may be possible to implement forest management strategies that allow for accelerated recovery of forest ecosystems and increased carrying capacity for timbering, as well as additional net carbon sequestration benefits. Such improvements may increase ecosystem biodiversity and provide expanded habitat for flora and fauna supported by these systems. Given that most of the timber resources in the eastern U.S. occur on private lands, it is also important to carefully consider policy solutions that enhance carbon sequestration and forest recovery while still ensuring private property rights; thereby increasing the potential for policy acceptance and success.

In parallel to climate change legislation being considered by policy-makers, forest systems are simultaneously undergoing land use conversion, active forest management, natural and anthropogenic-related disturbances, as well as system-wide climate change. The cumulative effect of these forces can create synergistic and antagonistic effects, which can potentially eclipse the benefits gained through natural regeneration, as well as afforestation/reforestation projects and easements. For example, several recent research studies have shown that recovering forest systems with increasing biomass have become increasingly vulnerable to large-scale disturbance regimes that may eclipse expected carbon sequestration benefits of these recovering systems (United States Global Change Research Program [USGCRP] 2008). Although West Virginia is not a fire-prone area, large-scale disturbances may occur from local drought conditions, insect infestation, and disease (which have generated carbon sources in Canadian forests, which were once carbon sinks [USGCRP 2008]). As such, it is important that a more holistic systems approach be used to evaluate the net cumulative effect of all forest and carbon processes that occur in the entire system, including: natural regeneration and recovery of forest climax communities in the east, landscape scale disturbance regimes, forest sustainability policies that could conserve and potentially accelerate recovery on private and public lands, ongoing timbering, timber market fluctuations and trends, and timber product lifecycles. Given the complexity of such a task, this research focuses on developing a baseline forest model that will allow for testing status quo and forest management scenarios that may enhance forest ecosystem recovery and sustainability metrics (discussed further below) and carbon sequestration. The motivation is to identify approaches for improving forest system recovery, in consideration of current and future U.S. timber market demand for forest products from West Virginia.

2. Research Project Overview

This section outlines the specific hypotheses to be tested and their relationships to the basic research questions outlined in the introduction. The hypotheses are then related to the general methodology requirements (e.g., model elements), which are then discussed further in subsequent sections. The four subsections (2.1 through 2.4) essentially relate to the four major research questions, which are developed as separate major sections in this dissertation, as previously discussed. A portion of this discussion in Section 2 is reiterated and expanded upon in Sections 4 through 7 in order that the information pertinent to each research question is presented together, along with the methods, results, and discussion.

2.1 Timbering Drivers and Removal Rates

With respect to timbering effects in West Virginia, the first basic research question is: *What are the factors affecting* ***timbering rates, timber stand selection, and tree selection*** *in West Virginia?* For example, in any given year, why are certain timber stands selected for commercial timber removal (i.e., clear cuts, select cuts) and not others? To what extent do economic drivers impact stand selection and removal methods, including stand value density, stand volume density, stand accessibility, ownership, and/or proximity to a mill for processing? If timber firms operate in a system with full knowledge of the timber resources and full access to these resources, it was deduced that timber stand selection and removal methods would be based in large part on economic drivers in order to maximize the objectives of the firm. *Thus, it was hypothesized that timber stand and tree selection for commercial timbering operations are driven by underlying economic drivers.* Inferred relationships between specific economic drivers and timber stand selection for commercial timber removals are presented in Table 2-1 and are discussed further in Section 4. Given that these are only inferred relationships, the null hypothesis that timber stand and tree selection for commercial timbering are not driven by economic processes, with no emerging pattern, was also tested.

Table 2-1 Econometric Drivers of Timber Stand and Tree Selection for Commercial Timber Removals

Econometric Independent Variables	Effect
Stand/tree value	+
Stand/tree volume	+
Distance to mill	-
Slope	-
Private ownership	+
Public ownership (for profit timbering allowed)	-
Population density	+
Income	+
Elevation	-

Although these tests are sufficient for understanding the selection of forest stands and trees for timbering events in West Virginia, they do not necessarily test the underlying human motivation and preferences of timber firms. Testing this hypothesis would require the use of a survey instrument. For example, it would be theoretically possible for the null hypothesis discussed above to be accepted, even if timber firm decision-making were motivated foremost to increase economic profit, as imperfect knowledge of the resource and/or access restrictions may inhibit their actions, thereby masking their underlying motivation. On the other hand, if the null hypothesis is rejected for each economic variable, it does not necessarily mean that economic factors explain *all* stand and tree selection processes, as a portion of the variance may be explained by non-economic factors and decision-making processes that are not captured in this study. For example, firms may have imperfect knowledge of the resource and as a result cannot fully make optimal financial decisions; they may have limited access to the resource when private owners are unwilling to sell them timber resources that would be most profitable for them to harvest; there may be limited access to high value stands or trees; or firms may self impose forest management policies that are not solely driven by short-term profit. Other study methods and models would be required to delve deeper into these micro-scale processes, as further discussed in Section 4.

General Methods: To address the hypothesis for timber stand selection for commercial removals discussed above, it was necessary to build a model that relates the dependent variables (stand and tree selection) to economic independent variables (discussed in Table 2-1 and presented in detail in Section 4) using an available dataset that represents timber resources and removals across West Virginia. To that end, the FIA database (USFS 2009a, 2010a) for West Virginia was used to build multivariate models, including logistic regression models, to test hypotheses related to timber stand and tree selection, as further discussed in Sections 3 and 4.

2.2 Cumulative Effect of Timbering and Other Key Processes on Net Annual Forest Growth in West Virginia

The second research question is: *What is the combined effect of timbering and other key processes on* ***net annual forest growth*** *in West Virginia, including the indirect effect of timbering on forest growth, tree mortality, forest regeneration, and other disturbances?* In this context, net annual forest growth is defined as the net change in aboveground total tree volume per hectare (m^3/ha) of the live portion of poletimber trees (>5" and < 11" diameter at breast height [DBH]) and sawtimber trees (>11" DBH) between consecutive years, factoring in changes in live volume due to timbering, growth (positive and negative), mortality, and regeneration (see Section 7 for a discussion of how smaller trees and understory are evaluated). Using the FIA database, it was necessary to test these relationships based on changes in live growing stock tree volume because all of the field measured growth estimates stored in FIA used for model validation are based on volumetric measures. Furthermore, economic variables of stand and tree value were derived from stumpage prices per unit tree volume; therefore, measures of stand and tree volume were more relevant to the hypotheses being tested than measures of tree and stand biomass. For certain analyses, the net annual growth in commercial timber volume was also evaluated in the study. Commercial timber volume was defined in this context as the BF volume per hectare (m^3/ha) using the International ¼-inch rule (i.e., standard rule used by USFS for measuring board-feet in the sawlog portion of lumber, allowing for ¼ inch saw cut, ½ inch tapering per 4' of length, and shrinkage of boards following drying) in the sawlog portion of the central stem for hardwood trees with DBH greater than 11", the minimum DBH for hardwood commercial sawlog trees. Forest and BF volumes were estimated at the tree-, forest plot-, and state-level. These metrics were then simulated over time under different economic and silviculture scenarios and then integrated with other conversion regression models to assess near and long-term impacts of timbering practices on aboveground biomass density (AGBD) (g/m^2) and BF (see Section 6 for more details), as well as carbon sequestration (Section 7).

The primary factors that may significantly alter forest volume and BF metrics include: forest growth (both positive and negative), tree mortality rates, regeneration, and timbering rates and intensity. Timbering events have the potential to impact forest growth, mortality rates, other disturbances, and stand regeneration of saplings and poletimber on the plot; thereby impacting forest and BF volumes at the stand- and tree-level. For example, forest stands that have recently been timbered will have more open canopies, which may stimulate increased annual growth rates for the trees that remain, as compared to trees located on forest stands where the canopy is closed and undisturbed. Opening up the canopy may also provide opportunity for saplings to grow and regenerate at a higher rate, thereby increasing the survival and growth rates of saplings (DBH < 1”) and poletimber (DBH between 1” and 5”) leading to higher stand regeneration. Timbering event disturbances could also increase the mortality rates for the trees that remain on the plot due to direct injury, soil and surface water flow disturbances, and/or increased potential for natural disturbances (fire/pest infestations). On the other hand, timbering may lower potential mortality rates by reducing inter- and intra-species competition. In any event, if timbering affects tree-growth rates, mortality rates, disturbances, or regeneration rates, then it may have an indirect effect on the change in live tree volume estimates, beyond the direct effect of volume removals. As these are inferred relationships, the *null hypothesis was tested that timbering has no effect on growth rates, mortality rates, other disturbances, or regeneration rates*.

General Methods: Since timber events may have an indirect impact on forest growth, mortality, disturbances, and regeneration at a plot or tree-level, it was necessary to test these relationships and incorporate these findings into an integrated model for timbering effects. The logistic and multiple regression models developed in this portion of the study for evaluating disturbances, mortality, and regeneration, as well as regional tree growth models developed by the USFS (2010b,c), were utilized for simulating these processes in the integrated model. To address fine-scale tree-level silviculture impacts, an integrated model was developed that tracks the life history of approximately 60,000 trees across 1,500 forest plots in West Virginia. Tree- and plot-level dynamics were simulated using an integrated modeling approach to evaluate the cumulative impact of these processes on net annual growth rates, which were validated against field measured data. These results along with other models were then used to estimate other tree-, plot-, and state-level metrics to assess impacts to stand structure, BF, biomass, carbon dynamics, and other metrics, as further discussed in Sections 5, 6, and 7.

2.3 Long-Term Effects of Status Quo and Sustainable Timbering Scenarios and Timber Market Scenarios on Forest Biomass and Forest Resource Metrics using an Integrated, Multi-Scale Model

The third principal research question is: *What long-term effect will status quo and sustainable timbering scenarios, under varying timber market conditions, have on* ***forest ecosystem and timber resource indicator metrics*** *in West Virginia?* To address this question, specific forest ecosystem indicator metrics were defined and changes in these metrics were simulated to evaluate changes in forest resources over time. Forest ecosystem indicator metrics are defined and discussed in Section 6.2.4. These metrics were estimated for the status quo timbering scenario under varying timber market economic conditions in order to evaluate potential outcomes under status quo conditions, as discussed in Section 6.1.1. To address the sustainable forestry research question, sustainable forest management requirements (e.g., limiting removals to < 30% of forest stand biomass, 20 year rotation cycles, conservation of large trees [Buehler et al. 2007, Register and Islam 2008, Brown et al. 1997, U.S. Fish and Wildlife (USFWS) 2009, Wood et al. 2005]) were imposed on the system to evaluate potential impacts to selected metrics, as compared to the status quo timbering scenario. The analysis makes no prediction of specific policy outcomes, but only an assessment of theoretical maximum outcomes (i.e., long-term forest indicator metrics) that could be achieved by implementing sustainable forest management strategies across the state.

The development and testing of specific policy instruments (e.g., a regulation versus a subsidy) was beyond the scope of this research.

Addressing this research question at a state scale involved modeling the effect of timbering at the forest stand level across an array of plots that were statistically representative of the state. AGBD (g/m^2) (state and stand-level measures) and density of standing commercial timber (i.e., state and stand-level measures of net BF volume [International ¼-inch rule] in the sawlog portion of the central stem for hardwood trees with a DBH > 11") were estimated at the forest stand level and aggregated to the state level for evaluating the impact of timbering on biomass and timber resources. These metrics were then simulated over time under varying economic conditions to assess near and long-term impacts of timbering practices on AGBD. An overview of these elements, along with hypotheses to be tested and methodology requirements are discussed in Section 6.

2.3.1 Status Quo Timbering Scenario

Several status quo timbering scenarios were simulated to evaluate how, and the degree to which, forest ecosystem indicator metrics would change from 2000 to 2050. These metrics were estimated for the status quo scenario under different timber market economic scenarios in order to evaluate potential future outcomes. Due to the uncertainty associated with future timber market conditions, a range of market scenarios were tested including a most-likely market scenario (which is a 0.24% annual increase in timber prices as projected based on national economic modeling by USDA [2003]) and a high timber market scenario (1% annual increase in timber prices, which has occurred over the past 2 decades), as further discussed in Section 6.2.5.

USDA reported that natural growth and regeneration of forest stocks in West Virginia appear to have resulted in a net annual growth rate of about 0.5% per year of sequestered carbon and biomass in West Virginia from 1990 to 2005 (USDA 2008), which factors in the cumulative effect of timbering, growth (positive and negative), mortality, disturbances, and regeneration. Thus, the annual net growth of forest biomass in West Virginia is currently greater than the loss in biomass due to timbering. Based on these recent trends, *it was hypothesized that under most-likely timber market conditions forest ecosystem indicator metrics and forest stand recovery will continue to improve to 2050.* However, if timber prices continue to increase as they have in the past two decades (~1% per year), then *it is hypothesized that forest ecosystem indicator metrics and forest stand recovery will diminish relative to most-likely timber market conditions to 2050 (i.e., 0.24% annual price increases)*, assuming rising timber prices increase timber removal events as hypothesized previously. Table 2-2 presents inferred relationships between these scenarios and the indicator metrics, which are defined in Section 6.2.4. As these are inferred relationships, the null hypothesis that these market scenarios have no impact on forest ecosystem indicator metrics was also evaluated.

2.3.2 Sustainable Timbering Scenario

Currently, all timber removals are not conducted in a manner that would be considered sustainable. In some cases, forest plots may be over-harvested and become depleted. Also, removal of the largest and commercially valuable trees (e.g., diameter limited cuts) reduces stand structure and complexity, which are important for biodiversity. Implementing sustainable timbering measures would constrain the amount of biomass and short-term economic return that can be harvested from a forest stand, thereby conserving much of the trees for future growth and production of ecological services. Based on several sustainability research studies and metrics

Table 2-2 Hypothesized Long-term Annual Trends in Forest Ecosystem Indicator Metrics Over Time for the Status Quo Timber Scenario Under Most-Likely and High Timber Market Conditions

Forest Indicator Metrics	Most-Likely Timber Market Scenario Relative to Conditions in 2000	High Timber Market Scenario Relative to Most-Likely Conditions in 2050
State Forest AGB (teragrams [tg])	+	—
Average AGBD (g/m^2)	+	—
Average % of State Timber Harvest to Net Growth in AGB	—	+
State Commercial Timber Volume (10^6 m^3)	+	—
State Forest AGB (tg) of Black Cherry and Red Oak AGB (tg)	+	—
Average State Frequency of Low Intensity Timbering Events (< 30% AGBD removals)	+	+
Average State Frequency of Medium/High Intensity Timbering Events (> 30% AGBD removals)	+	+
% of Biomass in Large Trees (>70 cm)	+	—
% of Advanced Recovery Plots (AGBD > 15,000 g/m^2)	+	—
% of Old Growth Plots (AGBD > 25,000 g/m^2, 30% of AGBD in Large Trees > 70 cm)	+	—
"+" = Increase in the long-term average metric from previous years; "—" = decrease in average metric from previous years; "blank" = no major change in metric		

discussed further in Section 6, the following constraints were placed on timber removals to replicate a "sustainable forest management" approach to timber removals:

- No more than 30% of the AGBD can be removed from a plot;
- Timber rotations cannot be less than 20 years;
- The largest tree on a 0.1 hectare area grid must be preserved; and

- Trees larger than 70 cm in diameter must be preserved.

These measures will significantly constrain the amount of biomass and short-term economic return from a given forest stand that may have been timbered more extensively under status quo timbering conditions (as the average removal was over 60% under status quo timbering conditions, rather than under 30%). To make up for the loss in opportunity for removals from a given forest stand, timber firms may spread the removals across more acreage of land in order to meet annual market demand for timber. The end result may be that more area across the state is timbered in a given year in order to meet annual market demand for timber. As such, the cumulative effect of implementing sustainability practices at the state level will be addressed, including shifts in timber impacts (as further discussed in Section 6).

It was deduced that application of sustainable silviculture methods would enable forest stands to recover more quickly following timber removal events (e.g., retaining ample forest resources on the stand for regrowth and through increased rotation cycles) as compared to clear cuts and other higher intensity timbering events. Furthermore, sustainable timbering methods would help conserve the larger trees on the forest stand for enhancing stand structure. Table 2-3 presents inferred relationships between the sustainable timbering scenario and indicator metrics under status quo timber market conditions, which are further discussed in Section 6 (the high market scenario was not tested). Overall, *it was hypothesized that if sustainable silviculture practices are applied across West Virginia (while still achieving the same annual timber production as under status quo timber scenario), then forest ecosystem indicator metrics and forest stand recovery will be significantly enhanced.* As the relationships presented in Table 2-3 are inferred, the null hypothesis was also evaluated.

General Methods: Results of the modeling effort previously described in Sections 2.1 and 2.2 were used to evaluate the status quo timbering scenario. In order to conduct this analysis, forest removals were simulated not only at the state- and plot-level, but also at the individual tree-level in order to properly simulate tree removals and more accurately track forest ecosystem indicator metrics (which include measures of stand structure diversity and old growth metrics). To address the sustainable timbering scenario, forest removals were simulated with the sustainability rules previously discussed.

Table 2-3 Hypothesized Annual Trend in Forest Ecosystem Indicator Metrics Over Time for the Sustainability Scenario Under Most-Likely Economic Conditions Relative to Status Quo Timbering Scenario

Forest Indicator Metrics	Net Annual Change in Metric for the Sustainability Scenario Relative to Status Quo Timbering Scenario
State Forest AGB (tg)	+
Average AGBD (g/m^2)	+
Average % of State Timber Harvest to Net Growth in AGB	—
State Commercial Timber Volume (10^6 m^3)	+
State Forest AGB (tg) of Black Cherry and Red Oak AGB (tg)	+
Average State Frequency of Low Intensity Timbering Events (< 30% AGBD removals)	+
Average State Frequency of Medium/High Intensity Timbering Events (> 30% AGBD removals)	—
% of Biomass in Large Trees (>70 cm)	+
% of Advanced Recovery Plots (AGBD > 15,000 g/m^2)	+
% of Old Growth Plots (AGBD > 25,000 g/m^2, 30% of AGBD in Large Trees > 70 cm)	+
"+" = Increase in metric from the previous year; "—" = decrease in metric from the previous year; "blank" = no major change in metric	

2.4 Long-Term Effect of Status Quo and Sustainable Timbering Scenarios on Forest Carbon Sequestration

The fourth research question is: *What long-term effect will status quo and sustainable timbering scenarios, under varying timber market conditions, have on* ***forest carbon sequestration*** *in West Virginia?* To address this question, the same timbering and market scenarios previously discussed in Section 2.3 will be applied to the system in order to assess changes in carbon sequestration. Carbon sequestration includes not only the increase in AGBD, but also estimates of carbon fluxes in various pools of above- and belowground biomass to include carbon in soil, roots, litter, understory brush, saplings, standing deadwood, and down deadwood. Table 2-4 presents inferred relationships between the timbering scenarios and market conditions on carbon sequestration. Based on current carbon sequestration rates and market conditions, it was hypothesized that *West Virginia forests will continue to operate as a carbon sink through 2050, with a reduction in the carbon sink under the High Timber Market Scenario (1% annual increase in timber prices)*. It was further hypothesized that *sustainable timbering practices will increase carbon sequestration relative to status quo timbering practices under most-likely timber market conditions*. As these are inferred relationships, the null hypotheses that these scenarios have no impact on carbon sequestration were also evaluated.

General Methods: Carbon regression models developed by the USFS and USEPA (2009) and carbon data provided in FIA (USFS 2010a) were integrated with the timber removal and forest growth models discussed in Sections 2.2 and 2.3 to estimate carbon sequestration metrics. This fully integrated model simulates the change in carbon sequestration potential for the forest system. The carbon model estimated fluxes in various pools of above- and belowground biomass to include carbon live trees (roots, stump, central stem, tree tops), soil, litter, understory brush, saplings, standing deadwood, down deadwood, timber removals, and wood products. Forest carbon sequestration metrics included average net change in carbon sequestration over time and total carbon sequestration for the forest system at the stand and state level. The conceptual framework of the carbon model and methodology are further discussed in Sections 3, 4.1, and 7.

Table 2-4 Hypothesized Net Change in Carbon Sequestration for the West Virginia Over Time Under Timbering and Market Condition Scenarios

Timbering and Market Scenarios	Carbon Sequestration	
	Short-Term	Long-Term (2050)
Most-Likely Timber Market Conditions (projected 0.24% annual growth [USDA 2003]), using Status Quo Timbering Practices	+ Relative to 2000	+ Relative to 2000
High Timber Market Conditions (1% Annual Growth in Timber Prices), using Status Quo Timbering Practices	— Relative to Most-likely Market Conditions	— Relative to Most-likely Market Conditions
Sustainable Timbering Practices (using the Most-Likely Timber Market Conditions)	+ Relative to Status Quo Scenario	+ Relative to Status Quo Scenario

3. Technical Approach Overview

This section introduces the study framework and data compilation methods that are common to all four research questions introduced in Section 1. The specific technical approach and methods used for addressing each of the four research questions and hypotheses are detailed in the methods section of the last four major sections of this dissertation (i.e., Sections 4.2, 5.2, 6.2 and 7.2). The conceptual framework of the model is presented in Section 3.1. The technical approach to data compilation that pertains to all of the research questions is presented in Section 3.2.

3.1 Conceptual Modeling Framework and Coupling

The integrated model, referred to as the Carbon and Forest Management (CFM) Model, estimates forest system dynamics over time at multiple scales, including tree-, stand-, and state-level. CFM was developed using statistical modeling, probability analysis, and mathematical modeling techniques (Parker et al. 2002, 2003, 2008; Grimm 2007; Bousquet and LePage 2004) and programmed in a Visual Basic 2007 platform, using data from FIA (USFS 2010a, 2009a). Overall the Visual Basic model consists of over 2,300 lines of code, with over 30 graphic displays of model output. The modeling approach was based in part on methods and concepts presented in Parker et al. (2008) and a National Science Foundation Grant proposal (0414565). This grant proposed to develop a model for simulating timber markets and carbon in forest systems over time. The grant team consisted of Drs. Parker, Davis, Hessl, Peterjohn, and Thomas. The conceptual model of key system processes are presented in Figure 3-1, which includes three key components: forest carbon and biomass growth; forest management; and ecological services.

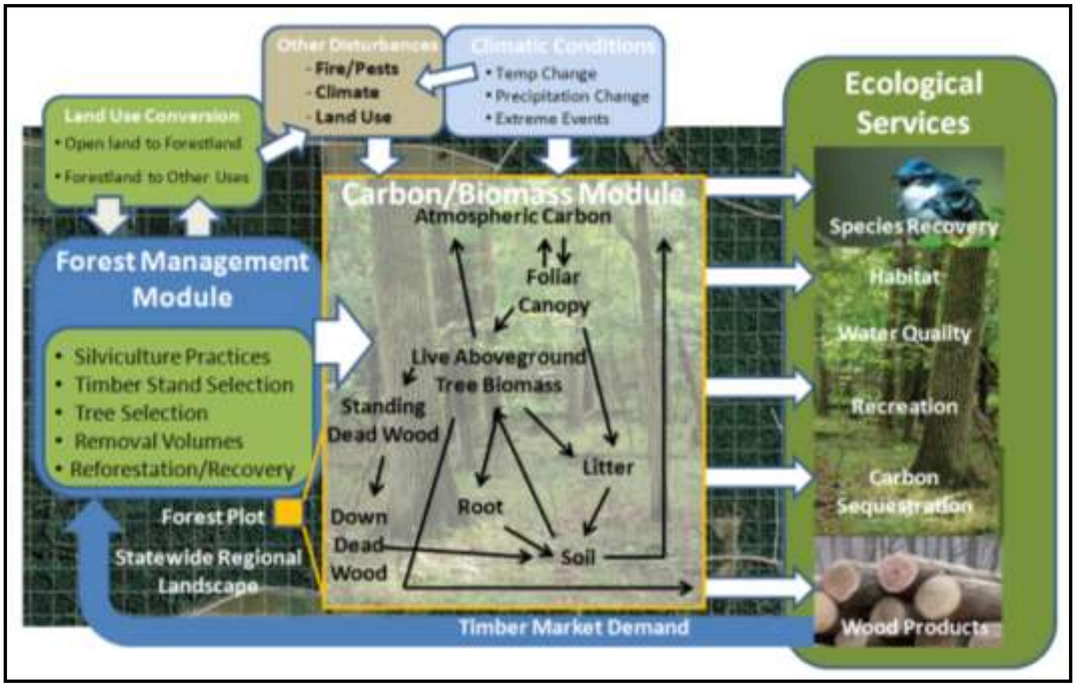

Figure 3-1 Conceptual Model of the System Being Modeled

Based on this conceptual model, a detailed modeling framework was developed for CFM, which is presented in Figure 3-2. All endogenous processes and their associated scale are shown in the boxes labeled: T – timbering; G – growth; and C – carbon and biomass. These endogenous components of CFM, i.e., T, G, and C, are further discussed in Sections 4, 5, and 6/7, respectively. More detailed flow diagrams depicting timbering and growth processes are presented in Sections 4 and 5, respectively. All exogenous processes are show in the white boxes. Timbering processes (T) are initially influenced by national/international scale timber markets, which impact regional stumpage prices for individual tree species within 5 market zones of West

Virginia. Annual changes in these regional prices along with changes in stand and tree growth, ultimately change the value of individual trees and stands across West Virginia. The economic value of trees and stands, as well as other site conditions, lead to the selection of forest stands for timbering events, and the selection of individual trees for removal. Timbering events then remove biomass from forest stands and add biomass to the wood products pool at the state level. Biomass removal then impacts the stands growth the following year due to changes in remaining tree volumes, stems, and stand density/competition. As part of the growth module (G), changes in stand biomass also occur as a result of disturbance events, mortality events, tree regeneration, and tree growth (both positive and negative), which in turn impact estimates of live tree and stand biomass/carbon, volume, BF, and value. Tree growth is also influenced by stand competition factors, site characteristics, and tree size. As part of the carbon/biomass module (C), estimated changes in live tree aboveground biomass allows the model to estimate changes in other forest carbon pools, including understory, standing deadwood, and down deadwood; which are then added to exogenous estimates of soil carbon and litter (soil carbon and litter could not be modeled on an annual time step, as further discussed in Section 7). The net annual change in carbon fluxes at multiple scales associated with photosynthesis, respiration, and decomposition are modeled collectively, not as separate fluxes. Ultimately, these modules enable the calculation of forest ecosystem indicator metrics and carbon fluxes at the stand- and state-level, including carbon fluxes, offsets (relative to state anthropogenic emissions), and carbon stocks. Several cross-scale feedback loops are addressed in this analysis including the effect of changing tree and stand value (due to growth, disturbance, timbering, and stumpage prices) on future stand and tree timbering rates. The effect of these feedback loops and other endogenous processes are discussed in more detailed in Sections 6 and 7, respectively.

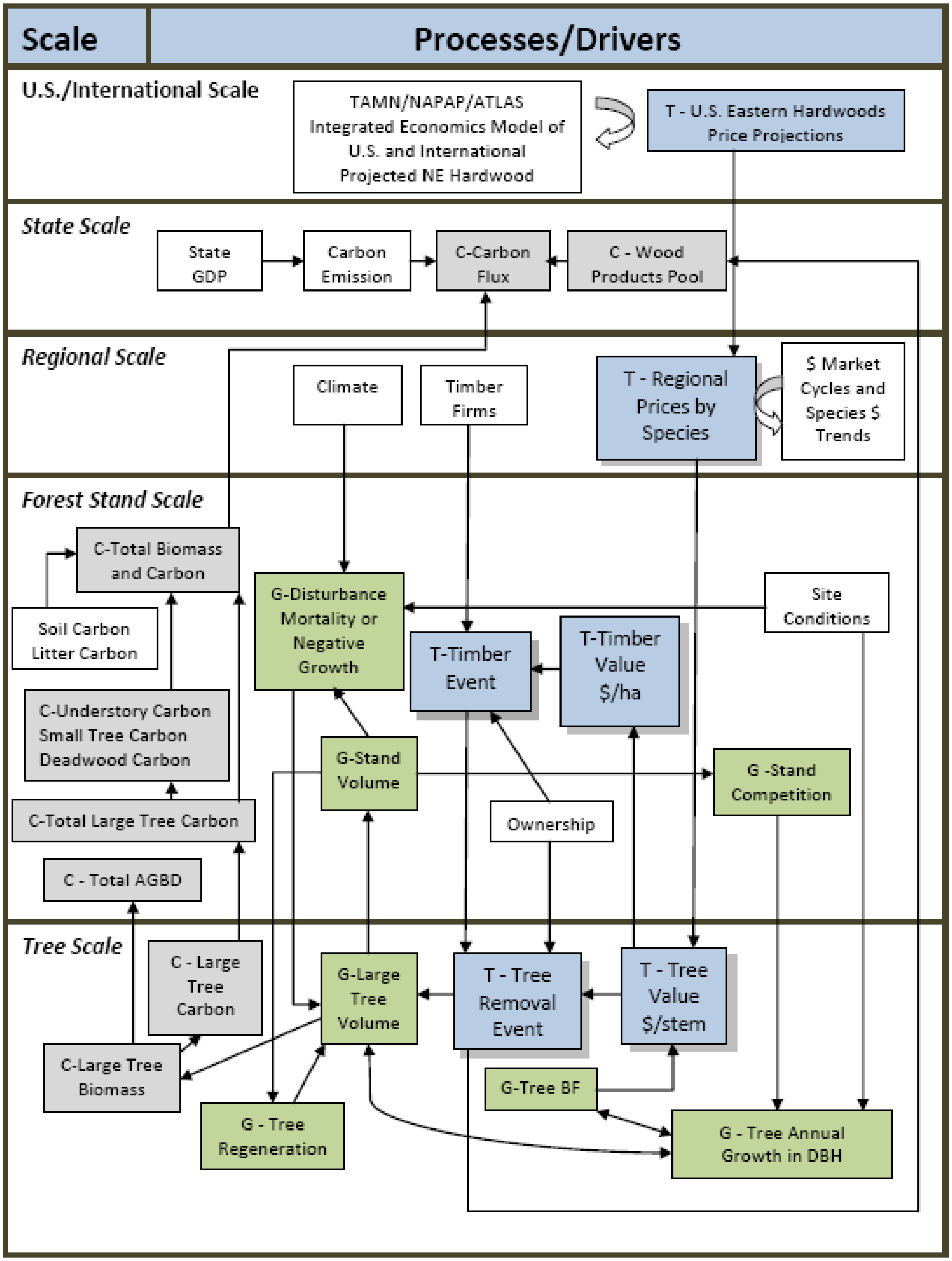

Figure 3-2 Flow Diagram of Endogenous Timbering Processes (T), Growth Processes (G), and Carbon/Biomass Processes (C), and Exogenous Processes (white boxes) at Multiple Scales Modeled in CFM

3.2 Data Compilation

3.2.1 Data Sources

The entire FIA database for West Virginia for sampling year 2000 were compiled and evaluated for this study (USFS 2009a, 2010a). These data were generated as part of a nationwide USFS program to monitor forest conditions and practices across the forested states (USFS 2009a). For this study, field monitoring data collected from approximately 2000 forested plots located randomly across West Virginia were used to conduct the analysis. In general, the USFS FIA data collection is based on a fixed plot design consisting of 4 subplots, with smaller micro-plots that are used to measure trees below 1" DBH. Plot-specific weighting factors are included in the database to extrapolate tree data collected on subplots and micro-plots to density measures (e.g., volume per acre), as well as to the state-level using extrapolation factors. The FIA database for West Virginia is a complex relational database with over 200,000 records and hundreds of variables that describe plot conditions, ownership regimes, tree species, tree volumes, commercial BF estimates, biomass, timber removals, and management approaches across West Virginia. The pertinent data (further described below and in Sections 4.2, 5.2, 6.2, and 7.2) were obtained from the FIA website and loaded into Microsoft Access 2007.

It should be noted that although the coordinates for FIA plots are provided in the FIA data, 20% of the plot locations are swapped with other plots within the same county. In addition, plot coordinates are modified (called fuzzing) to be within 1 mile of the actual location, in order to protect private landowner information, as required under the Food Security Act of 1985 (USFS 2009, 2010a). Thus, the exact location of the plots is not fully known.

In 2010, USFS significantly expanded the FIA database to include tree and plot-level carbon estimates for soils, litter, down dead trees, standing dead trees, and understory for all of the 2000 sampling plot data (USFS 2010). The 2009 released data already included tree-level estimates of aboveground and belowground carbon. These updated FIA data released in 2010 for the sampling year 2000 dataset were used for this study to initialize CFM for these specific carbon pools.

In addition to the 2000 FIA dataset, tree data collected during the 2004, 2005, and 2006 sampling periods were also evaluated for inclusion in this study. However, there were several problems encountered with the 2004, 2005, and 2006 data, and as such only the 2000 data were used for statistical analysis. For example, only a limited number of plots were sampled in any given year after 2000 (ranging from ~6 to 22% of the plots that were sampled in 2000). Therefore, the 2004, 2005, and 2006 datasets are relatively small and provide limited added value to the analysis. Furthermore, after 2000, the sampling plots were renumbered to hide their identity and thereby their relevance to previous sampling efforts. In addition, it was evident that large blocks of records from the sampling rounds after 2000 contained duplicate records for the same tree and plot. Due to these problems, this study utilized only the 2000 FIA dataset.

With respect to timber price data, baseline plot value data in the year 2000 were based on regional timber price data (1/4" International Scale $/thousand board-feet [MBF]) for commercially important tree species (see Section 3.2.2) that are compiled by the West Virginia Appalachian Hardwood Center (AHC) (2010) (see Table 3-1). Defined tree species category codes were used to link the FIA tree species codes (shown in FIA's TREE database) with West Virginia AHC codes and price data. Note that the table shows only average statewide stumpage price data for the year 2000 for illustration purposes only. Average regional prices for each year from 1988 to 2009 were actually used in the analysis, as discussed further in Sections 4, 5, and 6 (AHC 2010).

Table 3-1 International Scale ($/MBF) 2000 Tree Prices and Species Categories Applied to the TREE FIA Database

Common name	Category	FIA SPCD	Genus	species	WVAHC	$/MBF
black cherry	BC	762	Prunus	serotina	black cherry	$703
northern red oak	RO	833	Quercus	rubra	red oak	$335
sugar maple	HM	318	Acer	saccharum	hard maple	$287
black maple	HM	314	Acer	nigrum	hard maple	$287
Norway maple	HM	320	Acer	platinoides	hard maple	$287
black walnut	WN	602	Juglans	nigra	walnut	$282
ash spp.	AS	540	Fraxinus	spp.	ash	$189
blue ash	AS	546	Fraxinus	quadrangulata	ash	$189
American mountain-ash	AS	935	Sorbus	americana	ash	$189
green ash	AS	544	Fraxinus	pennsylvanica	ash	$189
black ash	AS	543	Fraxinus	nigra	ash	$189
white ash	AS	541	Fraxinus	americana	ash	$189
pumpkin ash	AS	545	Fraxinus	profunda	ash	$189
white oak	WO	802	Quercus	alba	white oak	$165
red maple	SM	316	Acer	rubrum	soft maple	$157
striped maple	SM	315	Acer	pensylvanicum	soft maple	$157
maple spp	SM	310	Acer	spp.	soft maple	$157
silver maple	SM	317	Acer	saccharinum	soft maple	$157
boxelder	SM	313	Acer	negundo	soft maple	$157
post oak	MO	835	Quercus	stellata	mixed oak	$152
oak spp. -- deciduous	MO	800	Quercus	spp.	mixed oak	$152
swamp white oak	MO	804	Quercus	bicolor	mixed oak	$152
scarlet oak	MO	806	Quercus	coccinea	mixed oak	$152
southern red oak	MO	812	Quercus	falcata	mixed oak	$152
bear oak, scrub oak	MO	816	Quercus	ilicifolia	mixed oak	$152
overcup oak	MO	822	Quercus	lyrata	mixed oak	$152
black oak	MO	837	Quercus	velutina	mixed oak	$152
chestnut oak	MO	832	Quercus	prinus	mixed oak	$152
bur oak	MO	823	Quercus	macrocarpa	mixed oak	$152
blackjack oak	MO	824	Quercus	marilandica	mixed oak	$152
swamp chestnut oak	MO	825	Quercus	michauxii	mixed oak	$152
chinkapin oak	MO	826	Quercus	muehlenbergii	mixed oak	$152
pin oak	MO	830	Quercus	palustris	mixed oak	$152
shingle oak	MO	817	Quercus	imbricaria	mixed oak	$152
willow oak	MO	831	Quercus	phellos	mixed oak	$152
yellow-poplar	YP	621	Liriodendron	tulipifera	yellow poplar	$136
hickory spp.	HK	400	Carya	spp.	hickory	$67
bitternut hickory	HK	402	Carya	cordiformis	hickory	$67
pignut hickory	HK	403	Carya	glabra	hickory	$67
shellbark hickory	HK	405	Carya	laciniosa	hickory	$67
shagbark hickory	HK	407	Carya	ovata	hickory	$67
mockernut hickory	HK	409	Carya	tomentosa	hickory	$67
other species	O				other	$71

Species-specific pricing data were obtained for all commonly harvested tree species, and categorical price data used by AHC were applied for less commonly harvested species (AHC

2009) (see Table 3-1). Data queries were conducted to ensure that all trees in the FIA TREE database could be identified to ensure pricing was applied appropriately.

Much of the other data necessary for the research project has been compiled through past efforts by other members of the research team, including: biophysical and stand-specific data needed for the carbon sequestration model runs (i.e., PnET-CN model), climate data, timber mill travel time data, and socioeconomic statistics for counties of West Virginia.

3.2.2 Data Management and Analysis

Data from FIA were managed using Microsoft Access 2007 and analyzed using models built using STAT11 and Visual Basic 2007. Univariate and multivariate statistical techniques, probability analysis, and Monte Carlo stochastic model simulation methods are discussed in Sections 4.2, 5.2, 6.2, and 7.2. An overview of data filtering and management techniques applied to the FIA data that pertains to all analyses are outlined below:

- Data records from the entire West Virginia data structure for the year 2000 were downloaded from the USFS FIA website (http://www.fia.fs.fed.us/) and imported into Microsoft 2007 Access (Vista Platform). A relational database was created, which includes imported data compiled by other researchers to be discussed further below.

- Although, each plot can be split into subplots, conditions (1 to 3 different condition types that cut across the plot network), and micro-plots, USFS has developed expansion factors to allow for the calculation of density metrics at the *plot-level*. As the plots are randomly selected locations across the state and the FIA data and state-wide expansion factors are all structured for plot-level analysis, it was appropriate to pool the four subplots to represent the conditions of a plot location when conducting stand level analysis (e.g., estimating AGBD). It should also be noted that the subplots are not independent of each other, but are collected in a systematic manner around the center of the plot; therefore, it was appropriate to use all four subplots to represent the condition of the plot. Furthermore, most of the data that were integrated with the forest stand data, such as carbon in the soil, litter, standing dead trees, and understory were all collected only at the plot-level; therefore, all carbon statistics needed to be compiled at this level. In addition, certain field data were not collected for all subplots (removals, mortality, and growth estimates). Therefore, stand-level variables were estimated at the plot level, by pooling subplot data when available. For 2/3rds of the plots, site conditions provided in the COND database were the same across all subplots for a given plot. In the event that two or more site conditions were recorded in the COND database (e.g., two different slope estimates across the 4 plot network) for a plot, then the predominate condition specified for the plot based on area weighting was used to represent the condition for the plot.

- Just over 2,000 forested plots were sampled during the 2000 sampling event. Of those, 70 percent were randomly selected for detailed analysis (1473 forest plots), while the remaining 30 percent (626 forest plots) were retained as an out of sample dataset for model validation purposes.

- A series of standard query language (SQL) programs were written in Access 2007 to compile data primarily from TREE, PLOT, and COND datasets to generate files to be used for statistical analysis. Key parameters used from the FIA database are presented in Table 3-2 (see USFS 2010a for a detailed listing of variables and definitions; http://www.fia.fs.fed.us/). Note that the parameters listed in Table 3-2 are not independent variables, but are variables from FIA that were important in deriving certain independent variables that are discussed in detail in the sections to follow.

Table 3-2 Key Variables from the FIA Database

FIA Parameter	Value	Description
PLT_CN	number	FIA plot number
DIA	in	Diameter at breast height
SPCD	code	FIA species code
REMVCFGS	cft/year	Tree removal volume for growing stock trees (> 5” DBH), between sampling periods. Tree removals for stands were calculated using FIA variables and the equation below. Removal (cft/ac-yr) =REMVCFGS*TPAREMV_UNADJ TPAREMV_UNADJ is an adjustment metric for converting REMVCFGS to volume per acre.
VOLCFGRS	cft	Tree volume (cft) of the central stem for growing stock trees (> 5” DBH).
RMVBSFSL	cft/year	Removed tree commercial BF (International ¼” rule) between sampling periods.
VOLBFNET	cft	Tree commercial net BF volume (International ¼” rule) for commercial sawtimber trees > 11” of the sawlog portion of the tree central stem.
DRYBIO_BOLE DRYBIO_TOP DRYBIO_STUMP DRYBIO_SAPLING	lbs	Oven dry biomass of the bole, top, stump, samplings (> 1” DBH) of the tree.
CARBON_AG	lbs	Tree (> 1” DBH) aboveground carbon mass, which is based on estimated tree biomass estimates above (50%)
GROWCFGS	cft/year	Positive and negative net annual merchantable volume of growth for growing stock trees (> 5” DBH) (only available for certain subplots) between sampling periods.
GROWBFSL	cft/year	Positive and negative growth of net annual MBF (International ¼” rule) of commercial sawtimber trees (>11” DBH) between sampling periods.
MORTCFGS	cft/year	Field measured tree mortality volume between sampling periods, used to calculate tree mortality volumes and annual rates for growing stock trees (> 5” DBH).
MORTBFSL	cft/year	Field measured commercial BF loss between sampling periods, used to calculate tree mortality BF volumes and annual rates for sawtimber trees (> 11” DBH).
STANDING_DEAD_CD	0 or 1	Identifies trees that are dead, which includes trees that died since 1989 as shown in MORTCFGS and MORTBFSL variables, as well as trees that died prior to 1989.

FIA Parameter	Value	Description
TPAMORT_UNADJ **TPAGROW_UNADJ** **TPA_UNADJ**	$acres^{-1}$	Plot-level expansion factors to convert TREE volume, biomass, and carbon statistics to density estimates.
COND_STATUS_CD	1 or 2	binary variable based on COND_STATUS_CD from the COND database that identifies plots as either forestland (plots with at least 50% coverage of timberland and as defined by FIA, i.e., COND_STATUS_CD = 1 was the predominant land use condition of the plot [USFS 2009a]) or other types (plots with less than 50% coverage of timberland as defined by FIA, i.e., COND_STATUS_CD = 2 was the predominant land use condition on the plot).
ELEV	ft	Derived from FIA 2000 Plot Data http://www.fia.fs.fed.us/, supplemented by USGS National Elevation Dataset (NED) and Global Elevation Data (SRTM). USGS. 2009 http://www.latlontoelevation.com/dem_consume.aspx
LAT **LONG**	degrees	Latitude and longitude recorded in decimal degrees based on NAD 83 datum.
SLOPE	% slope	Predominant slope on plot obtained from FIA 2000 database http://www.fia.fs.fed.us/
OWNCD	Code	Ownership regime code (identifies private and public lands).
FORTYPCD	Code	FIA forest type code.

4. Multi-scale Modeling of Timbering Events using Logistic and Multilevel Random Effects Logistic Regression Analysis

4.1 Introduction

Over the past several decades, forest resources throughout the northeast, including West Virginia, have continued to increase in biomass, stand size, and commercial value following large timber production that occurred in the first half of the 20th century (WV Division of Forestry 1990, USFS 1977, USDA 2008, Brown et al. 1997). Towards the end of the 20th century natural recovery of forest resources in the state, along with timber market conditions, gave rise to significantly higher timber removal rates, as shown in Figure 4-1. During this same period, average timber stumpage prices at the end of the 20th century more than doubled from 1990 to 2000 in West Virginia (see Figure 4-2), consistent with U.S. price trends, indicating the potential for a causal relationship between timber prices and timber removal rates. As forest resources continue to increase in commercial volume in the 21st century and stumpage prices change (e.g., rates have now leveled-off or declined since 2000, but long-term rates may rise again), it is uncertain how these changes will alter timber removal rates and patterns in the future. Also, there are significant differences in species-specific stumpage price trends, which may alter timber removal patterns and tree selection (see Figure 4-2). For example, black cherry stumpage prices doubled from 1989 to 2009 (when adjusted for inflation), while recent red oak stumpage prices have nearly fallen to their 1989 levels due to lower demand for this species. It is unclear to what

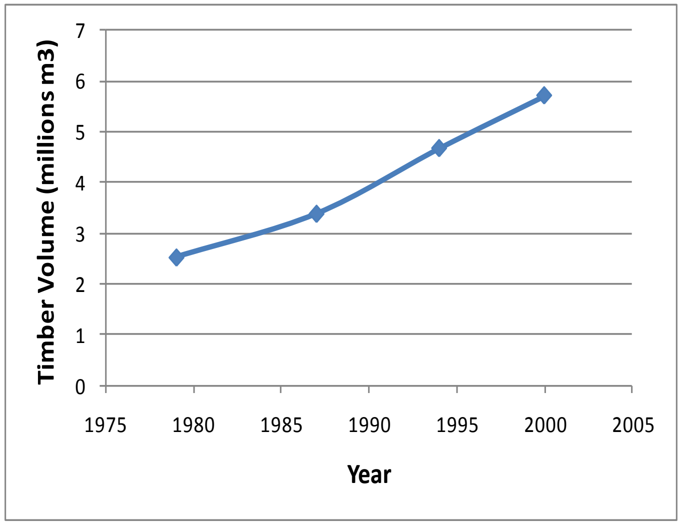

Figure 4-1 Forest Volume Removed in West Virginia from Timbering between 1979 to 2000 (millions m^3, lumber production in 1979 equaled 464 MMBF) (USFS/Hansen et al. 2005)

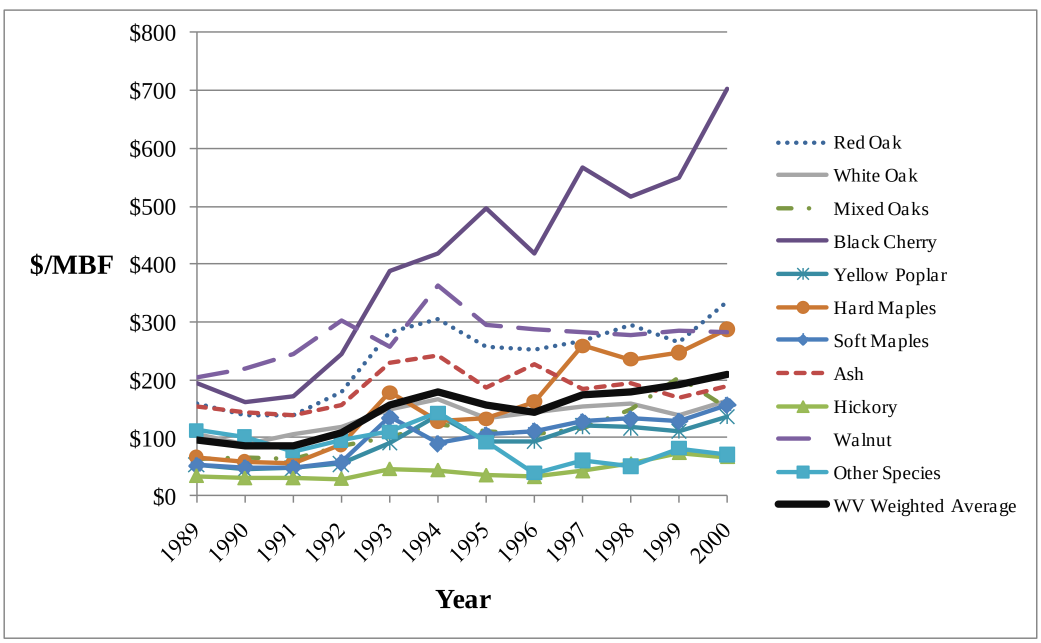

Figure 4-2 West Virginia Stumpage Prices from 1989 to 2000 ($/MBF) (AHC 2010)

extent these price trends impact long-term sustainable use of these species and alter species composition and forest community structure. Given the volume of timber removed in the northeast, it is important to better understand how national and international timber markets, coupled with continued regrowth of forest resources, impact micro-scale and statewide timber patterns, removal rates, forest condition, sustainability, and carbon sinks into the 21st century.

This portion of the research project focuses specifically on better understanding the relationships between timber market prices and stand characteristics on timber removal rates, stand selection, and tree selection. By modeling these relationships, it will then be possible to couple these results into an integrated modeling framework that will allow for more detailed analysis of the impact of market and policy scenarios on tree-, stand-, and state-level forest resources and carbon sink implications for long-term forecasting (as developed in Sections 5, 6, and 7).

Although several forest management and carbon models have been coupled for scenario analysis (e.g., numerous applications of the USFS Prognosis Model/Forest Vegetation Simulator [FSV] Model [USFS 2010b,c], Sohngen and Brown 2006, Sohngen and Sedjo 2006), this proposed approach is novel as it applies a micro-scale approach to simulate timber stand- and tree-selection as an endogenous process based on economic and site characteristic drivers, with cross-scale feedback mechanisms (i.e., impact of continued timbering, increased forest growth, and changing markets on future forest resource conditions, which in turn changes future timbering intensity and tree selection patterns). Thus, timbering events are modeled as an endogenous process, rather than as an exogenous process where the modeler typically imposes user-defined forest management constraints and timber removal estimates on the system. For example, the USFS Prognosis Model/FVS (as well as other growth models discussed in Section 5) requires the user to specify timber removal volumes and events as an exogenous variable, while micro-scale growth dynamics are modeled at the tree- and stand-level as an endogenous process. On the other hand, other large-scale economic models (Sohngen and Brown 2006, Sohngen and Sedjo 2006) simulate larger scale timber removals as an endogenous process based on economic models, but these models focus on evaluating land use change and conversions (between agriculture and other uses) at a multi-state regional-level or country-level. These economic models do not simulate micro-scale growth dynamics or selection processes at the tree-level, which allow for evaluating tree-and stand-level effects.

Application of forest management models, such as Prognosis/FVS, are well suited for addressing scenario analysis on public lands where foresters evaluate and carefully plan the extent of forest volume that will be removed, stand selection, frequency and rotation cycles, and specific timber techniques for tree selection. However, on private lands such factors are driven more by timber market conditions, forest resource conditions, and decisions by timber firms and/or private landowners as part of negotiations (i.e., depending on whether or not the timber firm owns the land rights). As timber market and forest resource conditions change over time and interact through cross-scale feedback mechanisms, it is important to evaluate these processes endogenously at a finer scale, as over 80% of the forest resources reside on private lands in West Virginia. Coupling these micro-scale economic processes into a multi-scale forest growth and carbon model, then allows for a more complete understanding of the long-term effects of timbering, continued forest growth, market conditions, and policy on forest biomass, resource sustainability, stand structure, biodiversity, and carbon at multiple scales.

To accurately model forest loss, it is important to understand the proximate causes and underlying forces driving these systems. Anthropogenic loss of forest resources is most often driven by local to regional proximate and underlying driving forces and conditions, and indirectly influenced by regional, national, and global drivers (Geist and Lambin 2002, Angelsen and Kaimowitz 1999). As indicated in a comprehensive study of driving factors of forest cover change conducted by Geist and Lambin (2002), the conditions influencing forest cover are diverse and location-specific. These driving forces cut across an array of policy, socioeconomic, and natural processes at multiple scales, including biophysical local conditions, national/global policies and regulations, corporate globalization, culture, history, human behavior, social decision-making at several levels (household, networks at different scales and types, governments), crop suitability and yields, technology applications, education, economics at several scales (land use, rent, export potential, prices), politics, infrastructure access, enforcement, natural succession forces, and other factors (Geist and Lambin 2002, Angelsen and Kaimowitz 1999). Most often a combination of factors will drive forest system change in certain locations. Their influence can vary over temporal, causal and spatial scales. Furthermore, these factors can also operate within complex temporal and cross-scale feedback mechanisms that can impact long-term outcomes.

In West Virginia, loss of live forest biomass can be attributed to a number of anthropogenic proximate causes including timbering and land use pressure associated with mining, agriculture, development, creation of open space, and other land uses (Hansen et al. 2005, USDA 2008, Drummond and Loveland 2010). From 1990 to 2005, the USFS estimates that forest cover in West Virginia declined nearly 0.6 percent over a 15 year period due to timbering and land use conversion (USDA 2008). This is consistent with recent findings by Drummond and Loveland (2010) that land-use pressure has resulted in declines in forest extent from 0.9% to 3.3% over a nearly 30 year period (early 1970s to 2000) in the Western Allegheny Plateau, Central Appalachians, and Ridge and Valley ecosystems of West Virginia, principally due to expanded mining, mechanical disturbances, and development. However, the loss of forest biomass due to land use change was still minor compared to the losses due to commercial timbering operations. From 1989 to 2000, estimated state-level forest volume removal rates due to commercial timbering events on forestland were approximately 20 times greater than the volume of timber removed from land clearing activities (i.e., clear cuts, which may or may not result in actual land use conversions, and forests removed from lands designated as other land use types) (USFS 2010a). Thus, commercial timbering continues to have a far greater impact on forest biomass and forest resources in West Virginia as compared to land use conversion. Therefore, it is important to understand the proximate causes behind timbering removal rates and selection processes in order to more accurately model long-term forest biomass and carbon pools. Timber harvesting was also found to be the key dynamic for projecting forest carbon cycling in the Pacific Northwest (Song and Woodcock 2003). As many other states in the northeast are experiencing similar land use pressures and timbering activities (Drummond and Loveland 2010; USDA 2008, 2010; Brown et al. 1997), the results of this analysis may provide further insights into the long-term cumulative effect of timbering and other processes on forest resources and carbon stocks.

Although timber events are the most important anthropogenic activity that results in loss of forest biomass in West Virginia, forest recovery during the 20th century and continued biomass growth exceeds forest biomass losses due to timbering. Altogether, the cumulative effect of timbering and land use pressure has not resulted in a net annual loss in forest biomass at the state scale. From 1990 to 2005 forest biomass in West Virginia was estimated to increase by 9% at a net annual rate of 0.5% / year (USDA 2008, USFS 2010a), despite the slight reduction in the spatial extent of forestlands and timbering in West Virginia. As timbering reduces biomass by about 0.44% / year and the rate of timbering significantly increased from 1990 to 2000, it is unclear whether forest resources in West Virginia will continue to increase at the current rate in consideration of future timber market conditions and long-term growth rates. As forests continue to mature following recovery during the 20th century after significant losses that occurred at the turn of the 19th century, it is possible that long-term growth rates will decline into the 21st century as these systems fully mature. Even slight changes in annual timbering and regrowth rates could alter the long-term balance and sustainable use of forest resources in West Virginia and potentially reverse current recovery trends. Thus, it is important to properly evaluate and model these processes in greater detail when conducting long-term projections of timber resources, forest biomass, and ecosystem recovery.

To explore timbering processes in West Virginia further, the first basic research question is: *What are the factors affecting timbering rates and stand and tree selection?* For example, in any given year, why are certain timber stands selected for commercial timber removal and not others? To what extent do economic drivers impact stand selection, removal volumes, and removal methods, including species composition, age class, biomass, plot/tree accessibility, ownership, and/or proximity to a mill for processing? If timber firms operate in a system with full knowledge of the timber resources and full access to these resources, it stands to reason that timber stand selection and removal methods would be based in large part on economic drivers in order to maximize the objectives of the firm to maximize profit. *Thus, it is hypothesized that timber stand and tree selection for commercial timbering operations and removal volumes are driven by underlying economic drivers.*

Given the complexity of the system under investigation, it is important to identify and evaluate the unique principal drivers that may influence timbering processes in West Virginia and carefully consider how the system will respond to change over time. Understanding these elements is important for LUC model development and conceptualization. Some of the key issues and observations regarding West Virginia's forest resources and related industry are outlined in several publications (Parker et al. 2008, USFS 2003, and analysis of FIA and National Woodland Ownership Survey (NWOS) data [USFS 2009a,b]). These publications provide a conceptual framework of the overall timber market in West Virginia, which is highly dependent on interactions between timber firms and non-industrial private forest landowners (NIPFs). Nearly 80% of the forestlands in West Virginia are privately held and over 70% of those lands are owned by NIPFs who may or may not be willing to sell timber rights in any given year. NIPF surveys (NWOS 2009a,b) indicate that 19% of NIPFs in West Virginia would be willing to sell commercial timber on their lands in the next five years (USFS 2009b). Given that the frequency of annual timber events on forest stands is low in West Virginia (0.5 % of all forest stands are timbered per year [USFS 2010a]), the NWOS results suggest that timber firms may have sufficient access to timber resources in West Virginia for commercial timbering.

If it is assumed that timber firms operate in a system with full knowledge of the timber resources and full access to these resources, it was deduced that timber stand selection and removal methods would be based in large part on economic drivers in order to maximize the objectives of the firm to maximize profit. Thus, it was hypothesized that economic drivers that increase the market value will increase the frequency and volume of timber removals. Forest stands and trees of higher total value (species with higher stumpage value per volume and stands with higher BF density) would be more likely to be selected for timbering. Forest stand ownership was also considered to have an indirect effect on forest stand selection, tree selection, and removal rates, as stands owned and managed by public agencies may be less likely to allow large-scale commercial removals. Forest stands located on steeper slopes may also be less likely to be timbered due to reduced access. Other socioeconomic variables, such as population density change, income within the county in which the forest stand was located, and other land use types (i.e., other than forestland, such as agriculture or developed land) may also have an indirect effect on timbering frequencies. Essentially, population density change, income, lower elevation, and other land uses are measures of human occupation of the landscape and development, and such areas may be more likely to be timbered in order to maintain open areas or convert land uses from forests to open or developed areas. Population density change and income also serve as proxy variables of infrastructure (processing mills, trucking) and access (e.g., road networks), which impacts removal costs. Similarly, timber removals may occur closer to production mills in order to reduce costs. Thus, forest stands located near timber mills would be more likely to be timbered, all other factors being equal. Inferred hypothesized relationships between specific economic drivers and timber stand selection for commercial timber removals are presented in Table 4-1.

Table 4-1 Economic Drivers of Timber Stand and Tree Selection for Commercial Timber Removals

Economic Independent Variables	Effect
Stand/tree value	+
Stand/tree volume	+
Distance to mill	-
Slope	-
Private ownership	+
Public ownership (for profit timbering allowed)	-
Population density	+
Income	+
Elevation	-

4.2 Methods

4.2.1 Overview of Multilevel Modeling Approach

As detailed in Figure 3-2, selection of forest stands and specific trees on those stands were modeled as two separate events, which considered both stand and tree characteristics. A flow diagram outlining the basic timbering modeling approach is presented in Figure 4-3. To identify key drivers of timber stand selection, independent variables that reflect the economic factors outlined in Table 4-1 and Figure 4-3 were evaluated and tested using multivariate logistic regression and multilevel random effects logistic regression techniques. Independent variables included: total stand volume density, total stand value density (log transformed), slope, elevation, average income, population density growth, ownership (binary variable: public/private), travel time to the nearest mill, and ecoregional province (2 categories). This model was then used for selecting timber stands using Monte Carlo analysis as part of an integrated model presented in Figure 3-2 (see boxes labeled with T) and discussed further in Sections 5 and 6.

Since the dependent variables were binary and the independent variables were continuous and binary, multivariate logistic regression modeling was applied using STAT11 for predicting stand and tree selection probabilities (Johnson and Wichern 2007, Xiao et al. 2010, Greene 2008). For modeling tree-selection, there is a hierarchical structure to the data, which required alternative statistical techniques. In this hierarchical structured data set, each tree observation is not statistically independent of other tree observations within the same stand, precluding simple pooling of the data and ignoring stand-level interactions and effects. Therefore, a multilevel

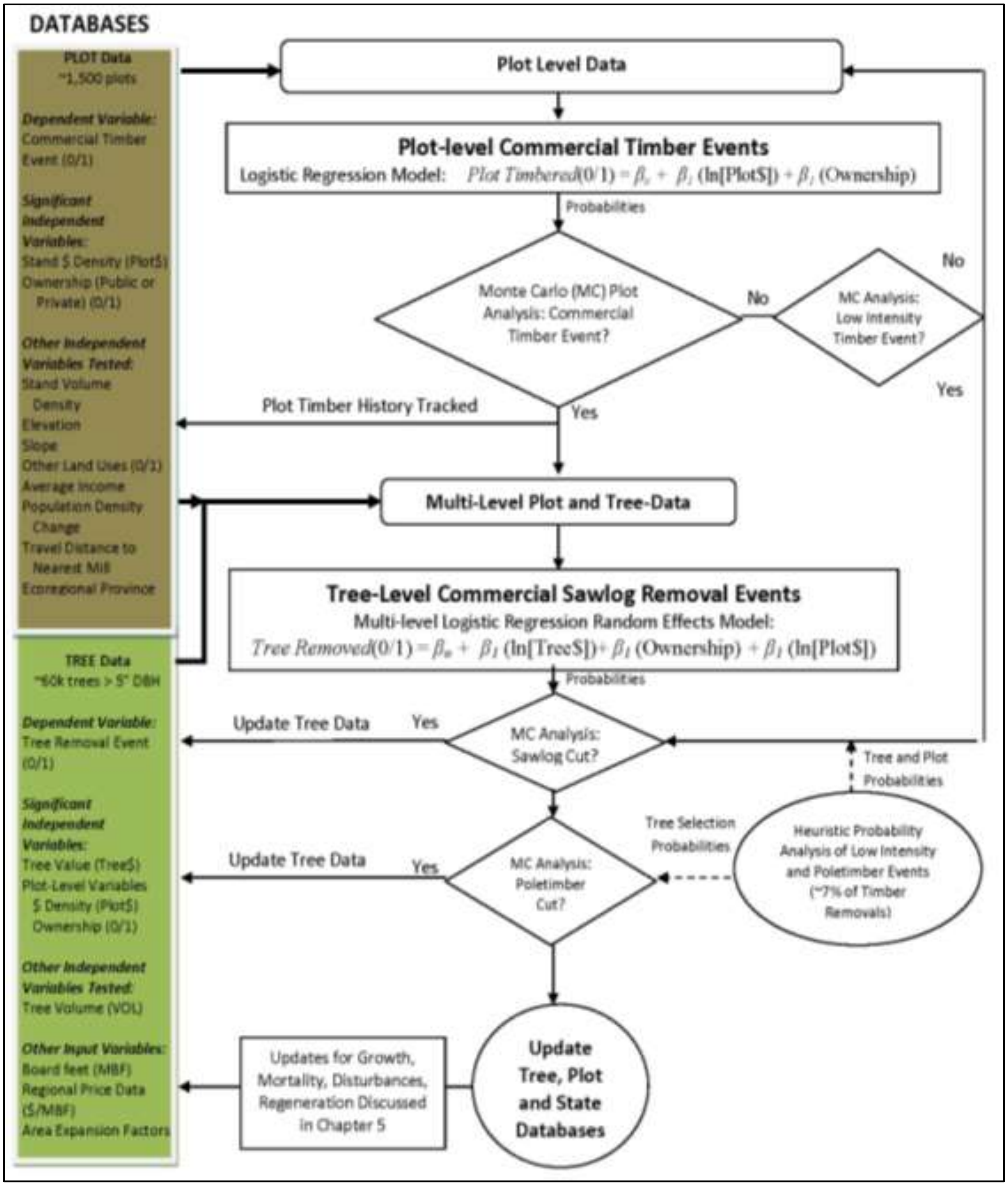

Figure 4-3 Flow Diagram of Multiple Scale Commercial Timber Selection Models and Processes

random effects logistic regression model was also tested in order to determine if the hierarchical structure contributed a significant amount to the observed variance. The stand effect variance is modeled either as a fixed effect that varies for each sample location (which can be logistically difficult to apply when modeling probabilities) or as a random effect depending on model diagnostics (Greene 2008, Xiao et al. 2010). This modeling approach provides an appropriate way for statistically analyzing tree-level data collected at the forest stand level, which are similar in structure to data often encountered in the fields of microeconomic behavior, social science, and education research.

The multilevel model included all the independent variables previously discussed, as well as tree-level variables (price of the commercial tree, volume of the sawlog, and DBH for non-commercial trees). Multilevel random effects logistic regression models were applied to all large trees above 5” DBH, trees with commercial value as sawlog timber (i.e., trees with BF in the central stem), and non-commercial trees (i.e., large trees above 5” DBH that lacked commercial value as sawlog timber). The model results were used to identify any key economic drivers of tree selection and to develop models for simulating stand and tree selection as part of the integrated model using Monte Carlo analysis (as shown in Figures 3-2 and 4-3).

In addition to the methods discussed above, alternative modeling approaches were also tested for simulating forest stand selection and forest removal intensity. Instead of using binary dependent variables and logistic regression, an ordinal variable was tested using ordered probit regression and ordered logistic regression for modeling defined categories of timber events. For this analysis, three ordinal categories of timbering intensity were defined based on heuristic techniques further discussed in Section 4.3.1. Preliminary results indicated that the binary/logistic and multilevel modeling approaches were able to generate favorable model fit statistics (as further detailed in Section 4.3) unlike the ordered discrete statistical models ($p > 0.7$, with R^2 = 0.03). Therefore, use of ordered discrete statistical modeling methods were no longer pursued.

Stumpage prices were based on the state regional timber prices for each of the five regions (International Scale $/MBF) for commercially important tree species that are compiled by AHC (2010). Since timbering events occurred between the 1989 and 2000 sampling events and the actual year of the removal was unknown, a weighted average tree price was derived for each species category and region using timber production trends in West Virginia (Hansen et al. 2005, see Figure 4-1) with adjustments for inflation to 2000 prices based on the Producer Price Index (PPI) (BLS 2009). This weighting approach was necessary because stumpage prices steadily increased between the two sampling period from 1989 to 2000 (nearly doubling), and it is not known in which year the actual timbering event occurred. To properly model the relationship between timber price and timbering events it was therefore necessary to estimate the value of the timber when it was actually removed from the stand. If the 2000 price data were used to fit the logistic regression model when stumpage prices were highest, then the constant term for the model equation would not be calculated properly and would underestimate timber removals (as most removals occurred when prices were lower than levels recorded in 2000, see Figures 4-1 and 4-2). On the other hand, if average prices between 1989 and 2000 were used, then the logistic regression equation could overestimate timber removals (as most removals occurred toward the end of this time period when prices were much higher than the average, see Figures 4-1 and 4-2). Thus, a weighted average approach was used to estimate the average stumpage prices for timber that was actually removed. To approximate the stumpage prices when timber was removed, timber production records for West Virginia compiled by the USFS were used to estimate the volume of timber removed each year from 1989 to 2000 (using interpolation, see Figure 4-1).

These data, along with PPI adjustments, were then used to develop annual weighting factors for timber stumpage prices at the regional level.

4.2.2 Timber Stand and Tree Selection Variable Selection and Analysis Methods

An overview of the dependent and independent variables for the timber stand and tree selection analyses are presented in Table 4-2. All the independent variables were evaluated in the stand and tree selection models, with the exception of tree value and tree volume, which were only evaluated for the tree selection model (as footnoted in Table 4-2). Stand-level independent variables were still evaluated when modeling tree selection, because such variables could impact tree selection probabilities (e.g., a tree may be more likely to be removed if the overall stand has higher value and/or lower removal costs). Stand and tree price distributions were highly skewed and exhibited lognormal distribution characteristics, thus log transformations were applied to these variables to enhance normality. The relationships between dependent and independent variables were also evaluated to verify that none exhibited a unimodal or bimodal distribution pattern.

Multivariate logistic and multilevel random effects logistic regression models were fit using the original independent variables as presented in Table 4-2, as well as principal component analysis (PCA). Initially, PCA and correlation analysis were performed to evaluate the dimensions and intercorrelations of independent variables so as to create a full explanatory model, but without over fitting the data. In order to identify the key PCs, the eigenvalues with the largest explanatory power were selected based on the recommended criteria specified for the Latent Root test, where PCs with eigenvalues above 1 are selected for further analysis (McGarigal et al. 2000). Since PCA variables include only continuous independent variables, all binary independent variables that were statistically significant ($p < 0.1$) in contributing to the model fit were also included in the model.

Table 4-2 Plot and Tree Selection and Removal Variables

Model Parameter	Value	Derivation and Source Information
Dependent Variables		
Stand Commercial Timber Event	1 or 0	Commercial timber removal with > 30% of stand volume removed (USFS 2010a)
Tree Removal Event	1 or 0	Tree removal event (USFS 2010a)
Independent Variables		
Stand Value ($) Density	$/ha 2000$	Price density based on species-specific BF and WV 1989 to 2000 price data, using a weighted average across years based on timber production (Hansen et al. 2005), PPI, and regional price data (AHC 2010)
Tree Value ($)[2]	$/stem	Same methods as above
Stand Volume Density	m^3/ha	USFS 2010a
Tree Volume[2]	m^3	Central stem tree volume (USFS 2010a)
Stand Travel time [1]	minutes	GIS network analysis of the travel time from stand (USFS 2010a) to nearest production mills
Stand Slope [1]	% slope	Predominant slope on plot (USFS 2010a)
Stand Elevation	FIA stand value (m)	USFS 2010a and USGS National Elevation Dataset and Global Elevation Data (2009)
Stand Ownership	1 or 0	Public or private lands (USFS 2010a)
Population Density Change of County	%	County population density change (U.S. Census Bureau 2005)
Average Income of County	$/person	2005 U.S. Census Bureau
Ecoregional Province	1 or 0	Bailey's Ecoregional Provinces: Eastern Broadleaf Forest (Oceanic) Province or Central Appalachian Broadleaf Forest Province (March 1995)

[1] proxy for removal costs [2] tree selection model only

In order to develop a model that could be readily applied in CFM and other models, such as FVS, simpler and more practical statistical models that required only the key independent variables impacting stand and tree selection were also developed. Similar model reduction measures have been applied by USFS in developing simpler forest growth models that were integrated into FVS (Teck and Hilt 1991; USFS 2010b,c). This is important for broader application and technology transfer, as the simpler models may yield similar results to the models fit using PCA, but require far fewer variables and reduced data collection effort. For example, the distance to the nearest mill is a labor intensive variable to compute, requiring GIS-based network analysis to estimate travel times between each stand and the nearest mill for processing. If it is found that this variable does not statistically contribute to the overall model fit and that applying a simpler model without this variable yields commensurate results to the PCA approach, then this simpler model may be sufficient for predicting stand and tree selection patterns.

To develop these simpler models, multivariate logistic regression and multilevel models were developed using all independent variables presented in Table 4-2, as a first step. Independent variables that did not contribute significantly to model fit were removed individually. The independent variable least likely to contribute to the model fit was removed initially, and then the remaining variables were refit. Next a statistical significance test was run to determine whether the fit of the first and second logistic regression models were significantly different from one another using the likelihood ratio chi-squared test ($p < 0.1$) as computed in STAT11 (Xiao et al. 2010). If the model coefficients were statistically different between the two models ($p < 0.1$), then the fuller model was selected and no additional variables were removed, otherwise the variable was removed and these steps were repeated. This higher statistical threshold of $p < 0.1$ was utilized for variable selection (as opposed to 0.05 or 0.025) in order to reduce the concern of dropping important independent variables from the analysis.

The final models were then verified by comparing estimated and observed stand and tree selection for the 70% dataset within ten quantile partitions of the data. The quantiles were categorized based on a rank order of the estimated probabilities of an event using the logistic regression model; and then the data were split into ten equal partitions. For model validation, the final models were then applied to the 30% out of sample dataset and observed and estimated stand and tree removals were compared for model fit.

4.3 Results and Discussion

4.3.1 Overview of Timber and Tree Stand Selection Patterns

Overall, forest stands were timbered at a frequency of 0.5% annually between 1989 and 2000. Of those stands that were timbered, 64% of the stand value was removed on average, which consisted of over 50% of the tree stem volume for those stands that were timbered. At the state-level, approximately 0.8% of commercial timber value was removed each year from West Virginia forests, while only 0.44% of the total tree stem volume was removed on average. These results suggested that tree selection was being targeted to the most valuable tree species on the stand (e.g., black cherry, red oak, and hard maples).

Commercial timbering events were defined as a timbering event where at least one commercial sawlog tree was removed from a stand (accounts for 96% of all timber removal events by volume). Commercial timbering events that occurred in West Virginia from 1989 to 2000 were classified into three levels of timbering event intensities, which exhibited different relationships to the explanatory variables:

1. High intensity events were defined as timbering events where 60% or more of the total central stem volume was removed from the plot for trees > 5" DBH. Tree selection patterns typically involved removal of the largest commercially valuable trees from the stand (e.g., diameter limited cuts, where trees above a specific DBH were removed, e.g., > 11" DBH), with a small portion consisting of clear cuts (where 95% to 100% of all tree stem volume for trees above 5" DBH were removed). Clear cuts were relatively infrequent (only 6% of all timber removal events); therefore, it was not evaluated separately.

2. Medium intensity timbering events were defined as timbering events where 30% to 60% of the total central stem volume was removed from the plot for trees > 5" DBH. Tree selection patterns typically involved removal of a select portion of the larger commercially valuable trees from the stand, as well as thinning practices, which include mixed aged tree removals.

3. Low intensity timbering events were defined as timbering events where less than 30% of the total central stem volume was removed from the plot for trees > 5" DBH.

One-third of all timber removal events in West Virginia were high intensity and they generated 47% of total state timber removals by volume. Over half (54%) of all timber removal events were medium intensity and they generated 47% of total state timber removals by volume (similar to the high intensity events). About 13% of all commercial timber removal events were low intensity and they generated only about 6% of total state timber removal volume.

In evaluating stand and tree selection patterns in the raw data, it was evident that stand selection and tree removal patterns in the low intensity category were clearly different than the type of commercial timbering practices seen in the medium and high category. The medium and high intensity events involved diameter limited cuts of the highest valued timber, select cuts of the highest valued timber, and clear cut events. Based on the results of the heuristic analysis, stand and tree selection patterns appeared to be similar for both the medium and high intensity events; therefore, there was no justification for splitting the dataset using the defined categories discussed above. However, distinct differences were seen between the low intensity category and the higher intensity categories. For example, as shown in Figure 4-4, as the stand value density increases, the probability of the stand being selected for medium/high intensity removals in West Virginia steadily increased. In contrast, stand selection for low intensity removals did not exhibit any apparent economic trend, as tree selection appeared to be driven by other factors not evident in the data. For example, low intensity events may involve removal of diseased trees, firewood collection, high grading, thinning, clearing, or removals for other purposes, other than the selection of high value trees. Similar results were seen for individual tree selection patterns (Figure 4-5). The probability of tree selection generally increased with increased stumpage value for medium/high removal events, while no such pattern was seen with the low intensity events or with other explanatory variables. Given the differences in stand and tree selection patterns between medium/high versus low intensity timbered plots, the low intensity timber removal events were modeled separately. For the purposes of this project, the medium/high timber removal events were classified as “commercial timbering events”, to distinguish them from the low intensity removal events. The logistic regression modeling effort was focused on analyzing timber removal dynamics for these commercial timbering events, as they accounted for 91% of all timber removals statewide.

Spatial patterns in stand removal rates, intensity, and stand value were also evaluated across West Virginia using data compiled at the regional level, based on the WV AHC (2010) regional categories used for reporting timber production and stumpage prices at the state level. As shown in Figure 4-6, the highest average stand value density ($3,300/ha) were found in the West Virginia Highlands area (particularly the northern counties of Region 3), which also had the

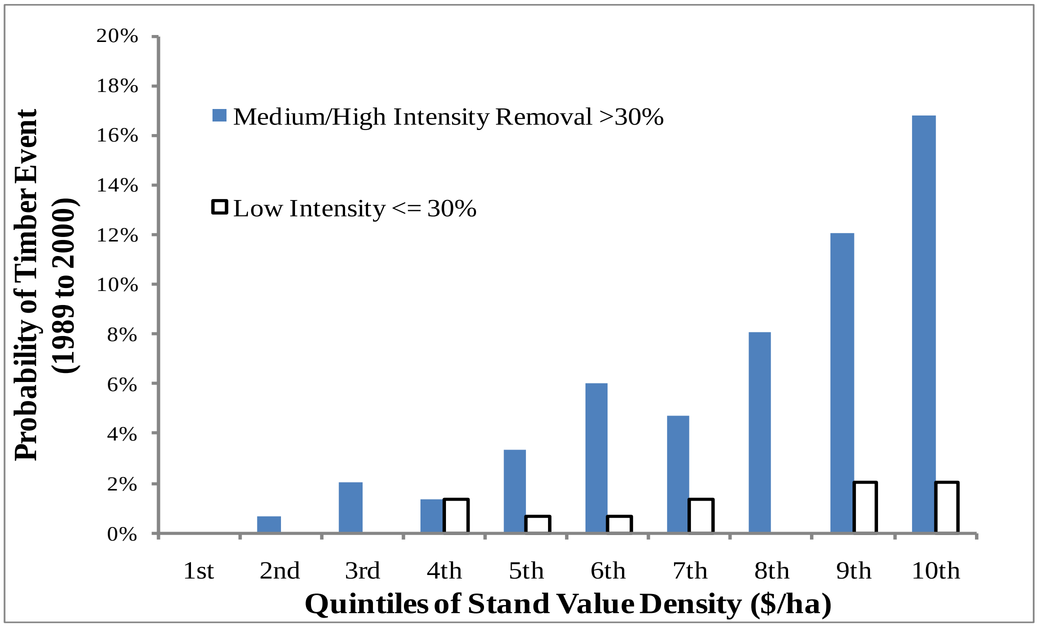

Figure 4-4 Stand Selection Patterns for Medium and High Commercial Timbering Events Versus Low Intensity Timbering Events

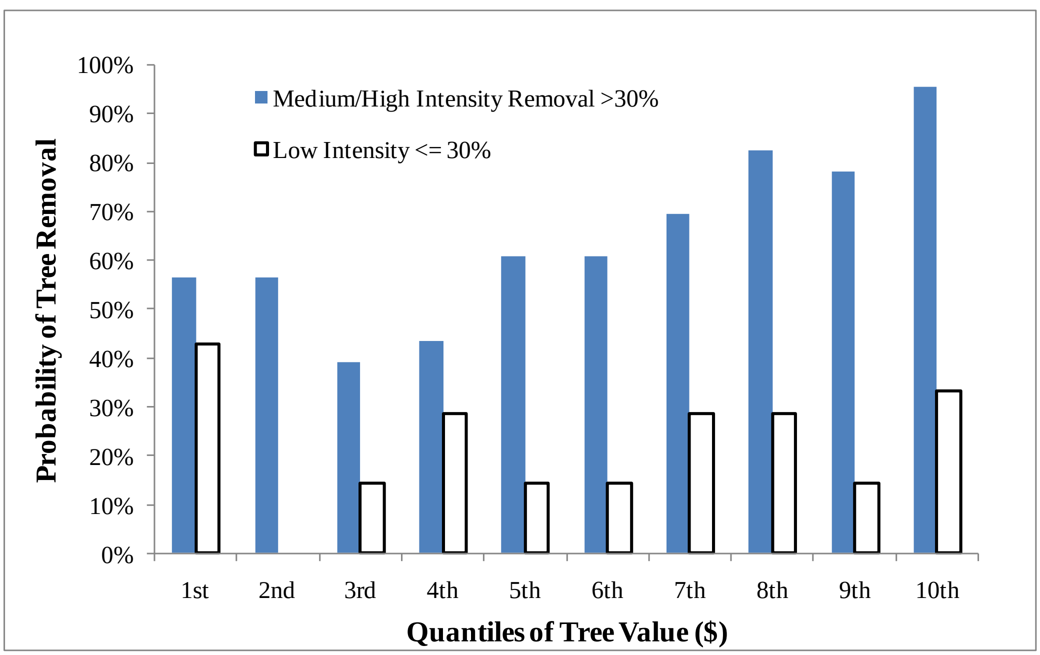

Figure 4-5 Commercial Tree Removal Patterns for Stands with Medium/High Commercial Timbering Events Versus Low Intensity Timbering Events

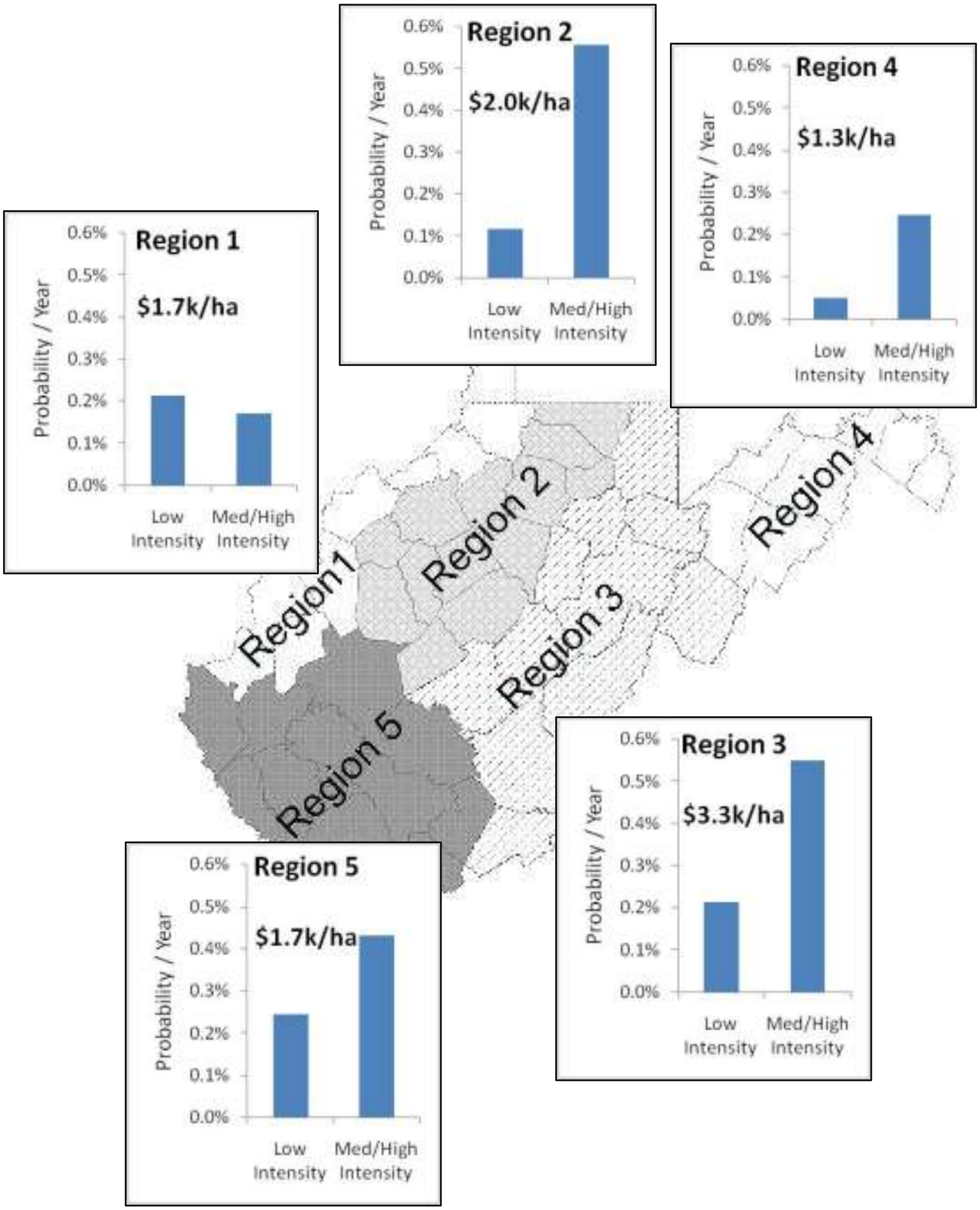

Figure 4-6 Commercial Stand Selection Patterns Across West Virginia

highest incidence of medium/high timber removals in the state, while the eastern panhandle had the lowest average stand value density ($1,300/ha) as well the lowest incidence of timber removals. The incidence of medium/high intensity timber removals appeared to generally increase across the state with higher stand value density, while no such patterns were evident for the low intensity events. At the county level, the spatial differences in timber value appears to be an artifact of spatial differences in biophysical characteristics of the stands (e.g., higher rainfall), which promote the greatest growth potential for high valued species, such as black cherry and hard maples, which are prevalent in the West Virginia highlands area (Region 3), and highest potential for annual growth rates (increased precipitation, higher elevations, lower average maximum temperature). The effects of biophysical characteristics, species composition, and regional cost differences are incorporated into the independent variables used for modeling timber removals discussed further below, as well as for forest growth discussed in Section 5. However, there may still be other stand characteristics, such as historic disturbance effects, terrain classification, slope orientation, access, regional industrial networks, and other factors that may create spatial patterns and explain some of the variance in stand and tree selection not captured in this analysis. Further studies and research are needed to determine whether some of these other factors are important and whether other spatial patterns exist in the West Virginia data. Modeled estimates of timber removals by region versus observed data are discussed in Section 4.3.4.

4.3.2 Principal Component and Correlation Analysis of Independent Variables of Stand Selection

As discussed in Section 4.2, PCA was conducted on the independent variables that were used to predict timber removal events. Using the Latent Root criterion test, there were 4 principal component vectors with eigenvalues of nearly 1 or more (McGarigal et al. 2000). These four vectors explained 83% of the variance in the independent variables presented in Table 4-3. The four key vectors in the principal component analysis and factor loadings are presented in Table 4-4 and discussed below:

PC1. Human Development: Change in population density and income were both highly correlated with this vector, and with each other (+0.67), as shown in Tables 4-4 and 4-5. This vector explained 33% of the total variance.

PC2. Sawtimber Value: Value and volume of timber on the stand were both highly correlated with this vector, and with each other (+0.71), as shown in Tables 4-4 and 4-5. This vector explained 22% of the total variance.

PC3. Plot Access: Elevation and slope were both significantly correlated to this vector, as shown in Table 4-4. This vector explained 16% of the total variance.

PC4. Travel Costs: Travel distance to the nearest mill was highly correlated with this vector, while slightly negatively correlated with increases in population density and income as expected (-0.19 and -0.25, respectively), as shown in Tables 4-4 and 4-5. This vector explained 13% of the total variance.

Table 4-3 Principal Component Proportions and Cumulative Variance for Independent Variables

Component	EigenValue	Variance Proportion	Variance Cumulative
1	2.29	0.33	0.33
2	1.52	0.22	0.54
3	1.11	0.16	0.70
4	0.89	0.13	0.83
5	0.61	0.09	0.92
6	0.32	0.05	0.96
7	0.26	0.04	1.00

Table 4-4 Principal Components and Factor Loadings

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7
Slope	0.29	-0.03	-0.62	0.46	0.57	0.00	0.03
Stand Vol Density	0.41	0.55	0.04	-0.12	-0.07	-0.07	0.71
Log Stand $ Density	0.38	0.58	-0.08	-0.08	-0.13	0.05	-0.69
Income	-0.47	0.41	0.05	0.28	0.09	0.72	0.09
Population Density	-0.44	0.40	0.18	0.34	0.18	-0.68	-0.05
Elevation	0.29	-0.07	0.70	-0.02	0.63	0.12	-0.09
Travel Distance	0.31	-0.16	0.29	0.76	-0.47	0.03	0.01

Table 4-5 Correlation Matrix for Independent Variables

Variables	Slope	Vol/ha	$/ha	Income	Pop	Elevation	Travel
Slope	1						
Stand Vol Density	0.14	1					
Log Stand $ Density	0.17	0.72	1				
Income	-0.22	-0.13	-0.08	1			
Population Density	-0.24	-0.12	-0.09	0.67	1		
Elevation	-0.08	0.21	0.11	-0.26	-0.15	1	
Travel Distance	0.17	0.12	0.09	-0.25	-0.19	0.26	1

4.3.3 Drivers of Timbering and Forest Stand Selection

4.3.3.1 Results of Modeling Commercial Timbering Events

Modeling Commercial Timbering Events Using PCA. The logistic regression model fit using the principal components (defined and discussed in Section 4.3.2) for predicting commercial timbering events is presented below:

$$Timber\ Event = 0.49(PC1) + 0.72(PC2) + 0.06(PC3) - 0.25(PC4) + 0.74(Ownership) - 3.99 \quad \{1\}$$

The logistic regression analysis of the principal components indicated that the incidence of stand selection increased with increasing human development (PC1) ($p < 0.001$), stand value (PC2) ($p < 0.001$), closer proximity to mills (PC4) ($p = 0.051$), and private ownership ($p = 0.065$) (the only statistically significant binary variable). Of the principal components, stand value was the primary variable that drove the incidence of a timbering event, followed by human development and proximity to the mill. The plot access principal component (PC3) did not appear to be significant ($p = 0.59$).

In terms of model fit, the principal component model was highly statistically significant (Likelihood Ratio test was highly significant at $p < 0.0001$). The estimated R^2 was quite low, 0.12, due to the inability of the model to accurately predict infrequent removals at a fine spatial and temporal resolution. The Hosmer and Lemeshow Goodness-of-Fit Test, which is routinely used for evaluating logistic regression model performance, was applied to test model outcomes (Hosmer and Lemeshow 2000). The Hosmer and Lemeshow Goodness-of-Fit statistic indicated that the null hypothesis (i.e., predicted events estimated using the model for dataset partitions are statistically the same as the observed data) cannot be rejected (p = 0.76) indicating good model fit for the ten quantile partitions (or deciles) of the data (Xiao et al. 2010). The Partition of the Hosmer and Lemeshow Test (see Table 4-6 and Figure 4-7) indicated that the model performed well at modeling the overall pattern in the data for the ten quantile partitions of the dataset. The use of ten quantile partitions is a standard method applied in the Hosmer and Lemeshow Test (Hosmer and Lemeshow 2000), and is the default setting in SAS and STAT11 for evaluating logistic regression model performance. The ten quantile partitions were based on rank ordering the stands by probability of being selected for a timbering event and comparing the total number of observed timbering events versus most-likely expected number of events within each quantile partition. Overall, there was a 1.5% error rate in the classification of timbered plots estimated

Table 4-6 Partitions of the Hosmer and Lemeshow Test for Modeling Timber Removals at the Plot Level Using Principal Components

Quantile	Total	Plots Not Timbered		Timbered Plots	
		Observed	Expected	Observed	Expected
1	149	149	148.5	0	0.5
2	149	148	147.1	1	1.9
3	149	149	146.0	0	3.0
4	148	144	144.0	4	4.0
5	149	141	144.0	8	5.0
6	149	141	142.7	8	6.3
7	148	140	140.1	8	7.9
8	149	140	138.8	9	10.2
9	149	134	134.6	15	14.4
10	148	119	119.1	29	28.9

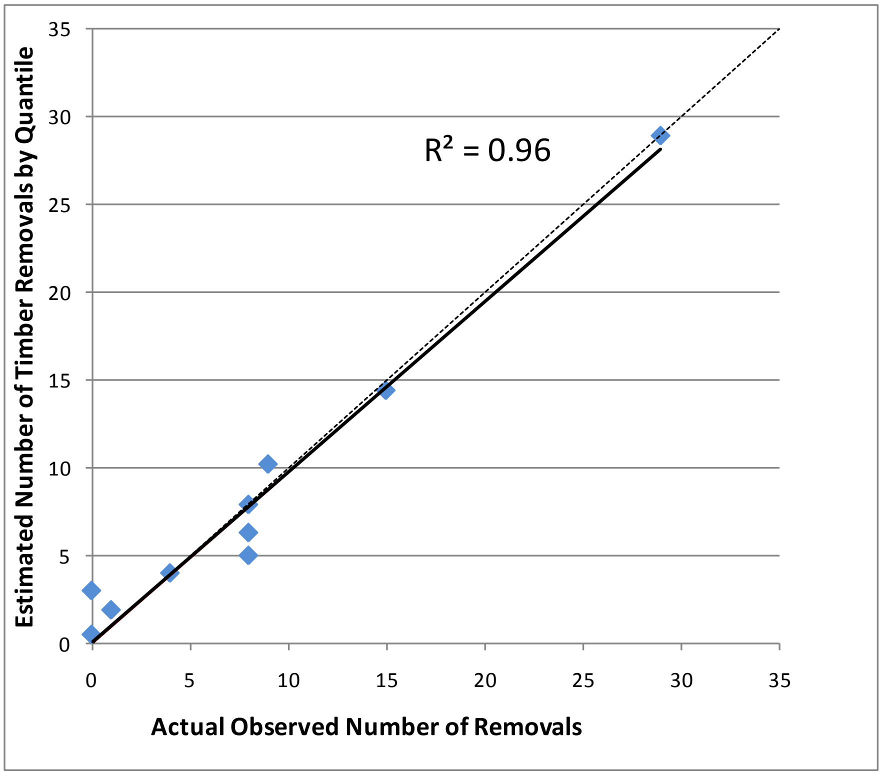

Figure 4-7 Timber Removal Model Fit: Estimated Versus Observed Number of Plots Selected for Timber Removals by Quantile from 1989 to 2000 using Principal Component Variables

within each of the quantile partitions shown in Table 4-6. The apparent error is calculated as the total number of misclassifications divided by the total sample size, which is a standard measure of calculating error for logistic regression (Johnson and Wichern 2007). Figure 4-7 shows that the expected number of timber removals within each quantile partition was highly correlated with the observed number of timbering events (R^2 = 0.96). These results indicated that the logistic regression model performs well at describing the overall pattern of stand selection (e.g., number of timbering events within each quantile partition) as shown in Table 4-6 and Figure 4-7, but it cannot predict the exact plot in which a timbering event occurred (as evident by the low estimated

R^2 of 0.12 derived at the plot level). This model scale issue is due in part to the very low frequency of annual occurrences (the probability of a plot being timbered is only 0.5% annually).

Modeling Commercial Timbering Events Using Independent Variables. The logistic regression analysis of the selected independent variables indicated that only stand value density (log transformed \$/ha) ($p < 0.001$) and plot ownership ($p = 0.08$) were statistically significant in predicting stand selection for commercial timbering events. Other independent variables, including stand volume density ($p = 0.49$), travel time ($p = 0.84$), slope ($p = 0.20$), elevation ($p = 0.50$), population density ($p = 0.67$), ecoregion ($p = 0.22$), and income ($p = 0.75$), were not statistically significant in improving model performance based on a likelihood ratio chi-squared test (using a threshold of $p < 0.1$) (Xiao et al 2010). Therefore, these variables were removed from the model. The logistic regression model fit using the original independent variables for predicting commercial timbering events is presented below:

$$Timber\ Event\ (1) = 1.17(ln(TOT\$/2.47)) + 0.66(Ownership) - 11.32 \quad \{2\}$$

where:

TOT\$ = total value density of sawtimber commercial tree > 11" on the plot (\$/ha); and

Ownership = private ownership is 1 and public ownership is 0.

In terms of model performance, the results of the model fit using the original independent variables are shown in Table 4-7 and Figure 4-8. The Hosmer and Lemeshow Goodness-of-Fit statistic ($p = 0.88$) and the R^2 (0.13) for the independent variable model were slightly higher than the results obtained for the principal component model ($p = 0.76$ and $R^2 = 0.12$). The apparent error rate for the quantile partition level classification was slightly higher for the independent variable model (i.e., 1.9% versus 1.5% error), as compared to the PCA model.

Table 4-7 Partitions of the Hosmer and Lemeshow Test for Modeling Timber Removals at the Plot Level Using Independent Variables

		Plots Not Timbered		Timbered Plots	
Quantile	Total	Observed	Expected	Observed	Expected
1	149	149	148.9	0	0.1
2	149	147	148.0	2	1.0
3	149	147	146.7	2	2.3
4	148	146	144.3	2	3.7
5	149	144	143.9	5	5.1
6	149	139	142.3	10	6.7
7	148	141	139.4	7	8.6
8	149	140	138.0	9	11.0
9	149	135	133.7	14	15.3
10	148	117	119.8	31	28.2

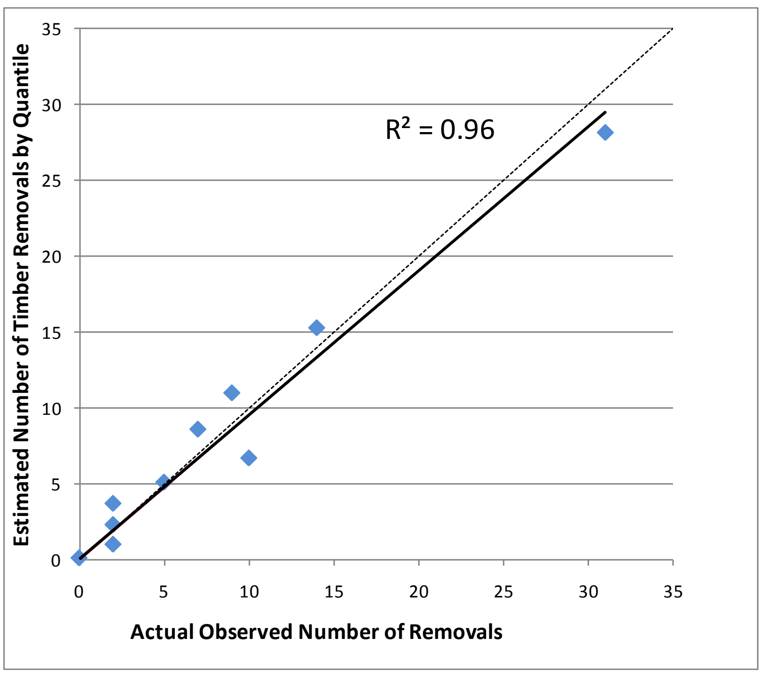

Figure 4-8 Timber Removal Model Fit: Estimated Versus Observed Number of Plots Selected for Timber Removals by Quantile from 1989 to 2000 using Models fit Using Independent Variables

4.3.3.2 Discussion of Commercial Timbering Event Models

Given the small difference in the error rate (1.9% for the PCA model versus 1.5% for the independent variable model) and the similarity in quantile partitions, the results suggest that the simpler independent variable model based only on stand value and ownership regime performed reasonable well, in comparison to the full model based on PCA. Applying simpler regression models that provide reasonable results and focus only on the key variables is a modeling technique that has been applied by the USFS for modeling and simulating forest management (e.g., Prognosis/FVS models) in order to increase the computational efficiency and reduce data collection and analysis requirements (Teck and Hilt 1991; USFS 2010b,c). As such, the simpler model, based on the original independent variables, was used for conducting long-term timbering event simulations to 2050 in the integrated model, which is further discussed in Sections 5 and 6. These results also indicate that existing variables in the FIA database could be used for developing similar models for other states and regions that are similar (e.g., in the northeast), without the need to conduct more labor intensive GIS-based network analysis for calculating distances to mills, although further research is needed to test this for other regions.

4.3.3.3 Modeling Annual Incidence of Timbering Events

The logistic regression model based on the original independent variables was used to derive individual plot probabilities for a timbering event between 1989 and 2000. Using the FIA database, it is not known when an actual timbering event occurred; therefore, it was necessary to fit the logistic regression model for all events that occurred between sampling periods (i.e., 1989 and 2000) and then utilize probability theory to derive annual probability estimates. To that end, the first step is to convert the logistic regression model (Equation 2) for predicting timber removal events into a probability model.

The above logistic regression equation can be used to calculate the probability of a timbering event for the time period between 1989 and 2000, as shown below (Greene 2008, Johnson and Wichern 2007).

$$\ln\left[\frac{p}{1-p}\right] = 1.17(\ln(TOT\$/2.47)) + 0.66(Ownership) - 11.32 \qquad \{3\}$$

Equation 3 is then solved for *p*, which represents the probability that at least one timbering event occurred between 1989 and 2000.

$$p = \frac{1}{\left(1+e^{-(1.17(\ln(TOT\$/2.47))+0.66(Ownership)-11.32)}\right)} \qquad \{4\}$$

The probability that no timbering event occurred between 1989 and 2000 then can be calculated as: $q = (1 - p)$. Bernoulli's equation can then be applied to derive the annual probability that a plot is not timbered from 1989 to 2000 (q) (actual time interval was approximately 12.6 years), as $q = \binom{12.6}{0} {q_a}^0 p_a^{12.6} = p_a^{12.6}$; thus, the annual probability $p_a = q^{1/12.6} = (1-p)^{1/12.6}$. Substituting Equation 4 into this last equation yields the following formula for calculating the annual probability of a timbering event.

Annual Probability of Stand Selection for Commercial Timbering Events

$$p_a = \sqrt[12.6]{\mathbf{1} - \frac{\mathbf{1}}{\left(\mathbf{1} + e^{-(-\mathbf{1.17}(\ln(TOT\$/\mathbf{2.47}))-\mathbf{0.66}(Ownership)+\mathbf{11.32})}\right)}} \qquad \{5\}$$

This equation can be simplified to:

$$p_a = \frac{\mathbf{1}}{\sqrt[\mathbf{12.6}]{\mathbf{1}+e^{(\mathbf{1.17}(\boldsymbol{ln}(\boldsymbol{TOT}\$/\ \mathbf{2\ .47})+\mathbf{0.66}(\boldsymbol{Ownership})-\mathbf{11.32})}}} \qquad \{6\}$$

Timber Stand Selection Model Validation. To validate the above model, the 30% sample dataset and models above were used to evaluate model performance by comparing observed versus predicted timbering events. When the data are evaluated by quantile (Table 4-8 and Figure 4-9), there was a 4.8% apparent error rate in the classification of stands for the 30% validation dataset for the quantile partitions in the dataset. These results indicate that the model performed reasonably well at predicting the general pattern of removals, although stands with the highest probability for timber events (particularly the upper two deciles) were not timbered to the same

Table 4-8 Logistic Regression Model Fit for 30% Validation Sample Set

Group	Plot Not Timbered		Plot Timbered	
	Observed	Expected	Observed	Expected
1	63	63	0	0
2	62	63	1	0
3	62	62	1	1
4	62	62	1	1
5	63	61	0	2
6	61	60	2	3
7	62	59	1	4
8	59	58	4	5
9	59	56	4	7
10	53	49	10	14

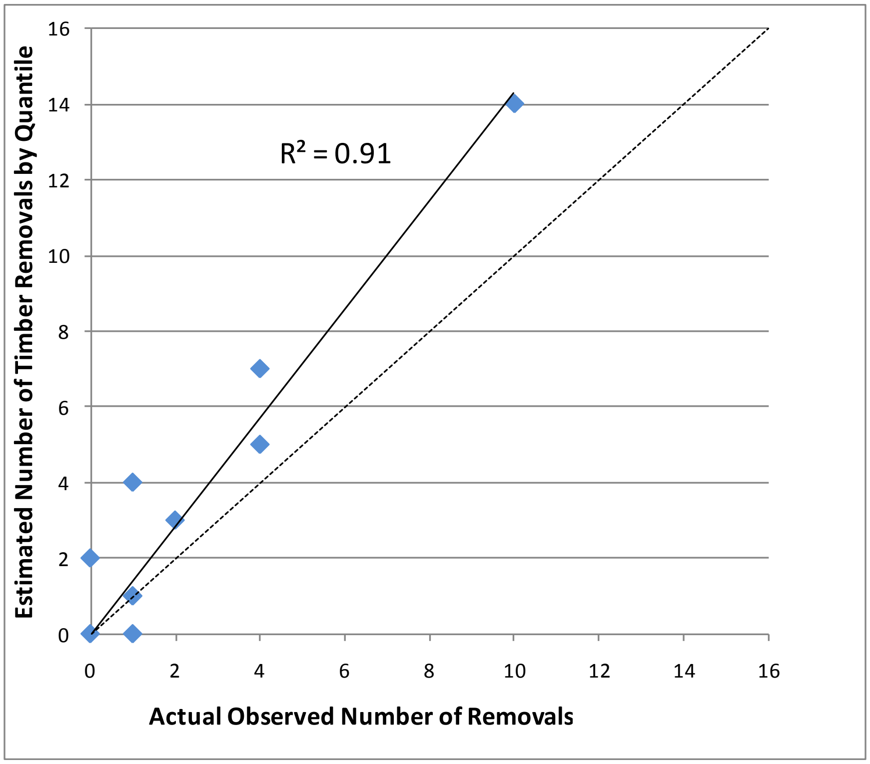

Figure 4-9 Timber Removal Model Fit: Validation of Estimated Versus Observed Number of Plots Selected for Timber Removals by Quantile from 1989 to 2000 using the 30% Out of Sample Dataset

intensity as predicted by the model. It is unclear why the model overestimated the number of timbering events for stands with higher probabilities for selection. Figure 4-9 presents predicted versus actual timbering events derived for each quantile partition (derived by rank ordering the stands by estimated probability of an event). The results show that the model did reasonably well in predicting timbering patterns relative to the probability of plot selection at the quantile partition level (R^2 = 0.91) (with group 1 having the lowest probability of a timber event, while group 10 has the highest probability of a timbering event).

Low Intensity and Noncommercial Timbering Events. In addition to the selection of forest stands for medium/high intensity commercial timber events, plots were also selected for low intensity removals and noncommercial timbering events (i.e., stands where no commercial sized trees were removed [DBH < 11”]). A logistic regression model could not be developed for predicting the selection of these low intensity commercial events, which represents only 6% of the forest stand removals by volume. Furthermore, a model could not be developed for predicting noncommercial timbering events, which represents only 3.8% of the total forest stand removals across the state by volume. Given that these timbering events represent a small proportion of the forest biomass removals, these events were predicted using Monte Carlo analysis using probability estimates from heuristic analysis of the FIA data, as further discussed in Section 6.

4.3.4 Tree Selection

4.3.4.1 Results of Modeling Commercial Tree Removal Events

Modeling Commercial Tree Removal Events Using PCA. The addition of the tree-level variables did not appreciably change the interpretation of the principal component analysis previously discussed in Section 4.3.2 as these tree variables were mostly correlated with the stand value principal component (although the order of the components and minor variable assignments changed). Using the Latent Root criterion test, there were 4 principal component vectors with eigenvalues above 1. These four vectors explained 75% of the variance in the independent variables presented in Table 4-9. The four key vectors in the principal component analysis and the factor loadings are presented in Table 4-10 and discussed below:

Table 4-9 Principal Component Proportions and Cumulative Variance for Tree Selection Independent Variables

Component	EigenValue	Variance Proportion	Cumulative
1	2.63	0.29	0.29
2	1.82	0.20	0.49
3	1.24	0.14	0.63
4	1.06	0.12	0.75
5	0.97	0.11	0.86
6	0.50	0.06	0.91
7	0.38	0.04	0.96
8	0.28	0.03	0.99
9	0.12	0.01	1.00

Table 4-10 Principal Component and Factor Loadings for Tree Selection Independent Variables

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8	Comp 9
Slope	-0.03	-0.31	-0.37	0.72	-0.03	0.41	-0.24	0.17	0.00
Stand Vol Density	0.46	-0.17	0.02	0.10	-0.51	-0.20	0.37	0.26	0.49
Log Stand $ Density	0.53	0.01	0.06	0.17	-0.33	-0.10	-0.11	-0.45	-0.60
Income	-0.04	0.62	0.09	0.25	-0.07	0.49	0.46	-0.27	0.12
Population Density	0.04	0.61	0.22	0.27	-0.10	-0.27	-0.42	0.49	-0.05
Elevation	0.23	-0.22	0.65	-0.20	-0.01	0.59	-0.21	0.21	0.00
Travel Distance	0.00	-0.21	0.52	0.51	0.48	-0.34	0.26	-0.11	0.02
Log Tree $	0.49	0.15	-0.16	-0.04	0.41	0.02	-0.40	-0.34	0.51
Tree Vol	0.45	0.10	-0.28	-0.11	0.47	0.10	0.36	0.47	-0.34

PC1. Sawtimber Value: Value and volume of timber in the stand, as well as tree value and volume, were all correlated with this vector, and correlated with each other (see Tables 4-5 and 4-10). This vector explained 29% of the total variance.

PC2. Human Development: Change in population density and income were highly correlated with this vector, and with each other (+0.67) (Tables 4-5 and 4-10). This vector explained 20% of the total variance.

PC3. Elevation: Elevation was significantly correlated to this vector (travel distance to the nearest mill was highly correlated with this vector, as well as PC4 below) (Table 4-10). This vector explained 14% of the total variance.

PC4. Plot Access: Slope and travel distance were highly correlated to this vector (Table 4-10). This vector explained 13% of the total variance.The results of the multilevel model indicated that the rho statistic for the random-effects model was not significant (rho = 0.11, sigma = 0.63, p = 0.094) indicating that the model results were not statistically different from analyzing the data as a pooled dataset using standard logistic regression (Johnson and Wichern 2007, Xiao et al. 2010, Greene 2008). The Hausman test was also conducted to evaluate the heterogeneity of the hierarchical data and to determine whether a fixed effects model would be more appropriate in the event of lack of heterogeneity. The Hausman test was insignificant (p = 0.20) indicating sufficient heterogeneity of the hierarchical data at the plot level for applying the random effects model. In any event, given that the random effects model yielded an insignificant rho statistic, the principal component data were analyzed as a pooled data set using standard logistic regression.

The logistic regression model fit using the principal components for predicting commercial timbering events is presented below:

$$Timber\ Event = 0.13(PC1) + 0.25(PC2) - 0.11(PC3) - 0.10(PC4) - 2.26(Ownership) - 2.70 \quad \{7\}$$

where: Ownership = private ownership is 1 and public ownership is 0.

The logistic regression analysis of the principal components indicated that the incidence of commercial tree removal during a timbering event increased with increased human development (PC2) ($p = 0.02$) and increased stand value (PC1), although the latter PC was not statistically significant ($p = 0.16$), which was not expected. Also surprisingly, the probability of tree removal also declined on privately owned land versus public land ($p = 0.004$). Although publically owned land was less likely to be initially selected for timbering (which may be due to policy constraints that may limit the frequency and rotation cycles of timbering events on public lands), once timber rights are granted on public lands for a particular stand, timbering firms appear to remove higher volumes of trees as compared to private lands, all other factors being equal. This may be due in part to a lack of ownership and vested interest in the long-term yield of public forest lands, or limited potential for future access to public forest stands as a result of ecological sustainable timbering policies (e.g., increased rotation cycles). The plot elevation and access principal components (PC3 and PC4) did not appear to be significant ($p = 0.40$ and $p = 0.51$, respectively).

In terms of model fit, the principal component model was highly statistically significant (Likelihood Ratio test was highly significant at $p < 0.0001$). Furthermore, the Hosmer and Lemeshow Goodness-of-Fit Test indicated that the null hypothesis (i.e., predicted events estimated using the model for dataset partitions are statistically the same as the observed data) cannot be rejected ($p = 0.99$) indicating excellent model fit. On the other hand, the estimated R^2 was quite low, 0.06, due to the inability of the model to accurately predict infrequent removals at a finer spatial and temporal resolution. The Partition of the Hosmer and Lemeshow Test (see Table 4-11 and Figure 4-10) indicated that the model performed well at modeling the overall pattern in the data for quantile partitions of the dataset. Overall, there was a 9% error rate in the classification of tree removals estimated within each of the quantile partitions shown in Table 4-

11. Figure 4-10 shows that the expected number of timber removals within each quantile partition was highly correlated with the observed number of tree removal events ($R^2 = 0.83$).

Table 4-11 Partitions of the Hosmer and Lemeshow Test for Modeling Tree Removals During Timbering Events Using Principal Components

		Trees Timbered		Trees Not Timbered	
Quantile	Total	Observed	Expected	Observed	Expected
1	23	20	20.3	2	1.7
2	23	17	18.3	6	4.7
3	23	18	16.1	5	6.9
4	23	17	15.4	6	7.6
5	23	16	14.6	7	8.4
6	23	13	14.0	10	9.0
7	23	12	13.5	11	9.5
8	23	12	12.9	11	10.1
9	23	12	12.0	11	11.0
10	22	10	10.1	13	12.9

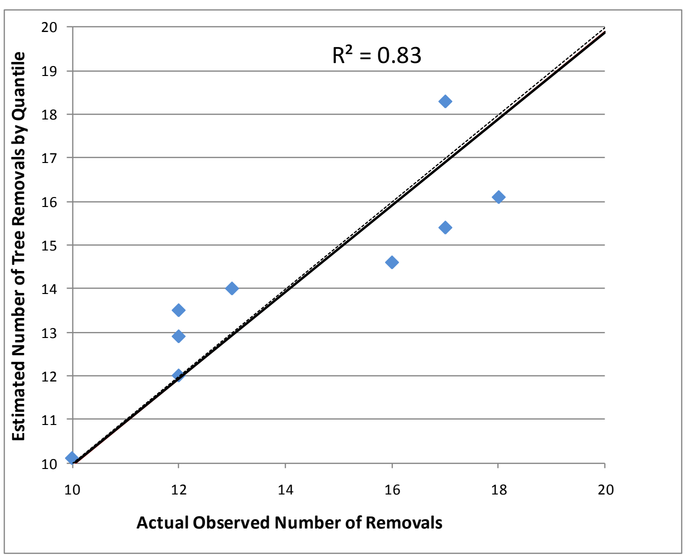

Figure 4-10 Tree Removal Model Fit: Estimated Versus Observed Number of Trees Selected for Removal by Quantile from 1989 to 2000 using Models fit Using Principal Component Variables

Collectively, these results indicated that the logistic regression model performs well at describing the overall pattern of tree removals (e.g., number of timbering events within each quantile partition).

Modeling Commercial Tree Removal Events Using Independent Variables. For the independent variable model, results of multilevel modeling indicated that a statistically significant portion of the variation in the data (approximately 20%) was attributed to the hierarchical structure of the data (rho = 0.19, $p = 0.026$). These results indicate that this stand effect would have a statistically significant impact on estimated model coefficients, as compared to using a pooled dataset and ignoring the hierarchical structure of the data. As such, the multilevel modeling approach was selected over pooling the data. The Hausman test was also conducted to evaluate the heterogeneity of the hierarchical data and to determine whether a fixed effects model would be more appropriate in the event of lack of heterogeneity. The Hausman test was insignificant ($p = 0.71$) indicating that it would be appropriate to apply the more efficient random effects model.

Statistically significant independent variables for predicting tree removals during a commercial timbering event included: tree value ($p < 0.001$), stand value density ($p < 0.001$), and plot ownership ($p < 0.001$). Other independent variables were not statistically significant in improving model performance based on a likelihood ratio chi-squared test, including: stand volume density ($p = 0.50$), travel time ($p = 0.46$), slope ($p = 0.98$), elevation ($p = 0.60$), population density ($p = 0.84$), ecoregion ($p = 0.99$), tree volume ($p = 0.40$), and income ($p = 0.12$) (Xiao et al 2010). Therefore, these other independent variables were removed from the model.

The following multilevel random effects logistic regression model was derived for predicting tree removal events when a stand has been selected for timbering:

$$Tree\ Removal\ (1) = 1.79\big(\ln(Tree\$)\big) - 1.61\big(ln(TOT\$/2.47)\big) - 3.27(Ownership) + 10.81 \quad \{7\}$$

where:

Tree$ = the value of a commercial tree > 11” ($)

TOT$ = the total value density of commercial tree > 11” on the plot ($/ha); and

Ownership = binary where private ownership is 1 and public ownership is 0.

The model coefficients indicate that as the tree value increases, so does the probability of the tree being removed. However, when the value of the stand increases the probability that an individual tree being removed decreases, as the timber firm may have more valuable trees to choose from. This multi-scale effect was not seen in the principal component analysis as tree- and stand-level price variables were both significantly correlated to the first principal component (i.e., stand value).

In terms of model fit, the independent variable model was highly statistically significant using the likelihood ratio test ($p < 0.0001$). The Hosmer and Lemeshow Goodness-of-Fit Test is not appropriate for a multilevel model; therefore it was not applied. Overall, there was a 21% error rate in the classification of tree removals within each of the quantile partitions shown in Table 4-12. However, Figure 4-11 shows that the expected number of timber removals within quantile partitions was highly correlated with the observed number of timbering events ($R^2 = 0.79$).

Table 4-12 Multilevel Random Effects Logistic Model Fit for Tree Removals During a Timbering Event

Quantile	Total	Tree Timbered		Tree Not Timbered	
		Observed	Expected	Observed	Expected
1	23	21	22.3	2	0.1
2	23	21	21.3	2	1.7
3	23	23	20.4	0	2.6
4	23	21	18.7	2	4.3
5	23	14	17.0	9	6.0
6	23	12	15.0	11	8.0
7	23	10	13.4	13	9.6
8	23	8	11.3	15	11.7
9	23	12	8.2	11	14.8
10	22	5	3.7	17	18.3

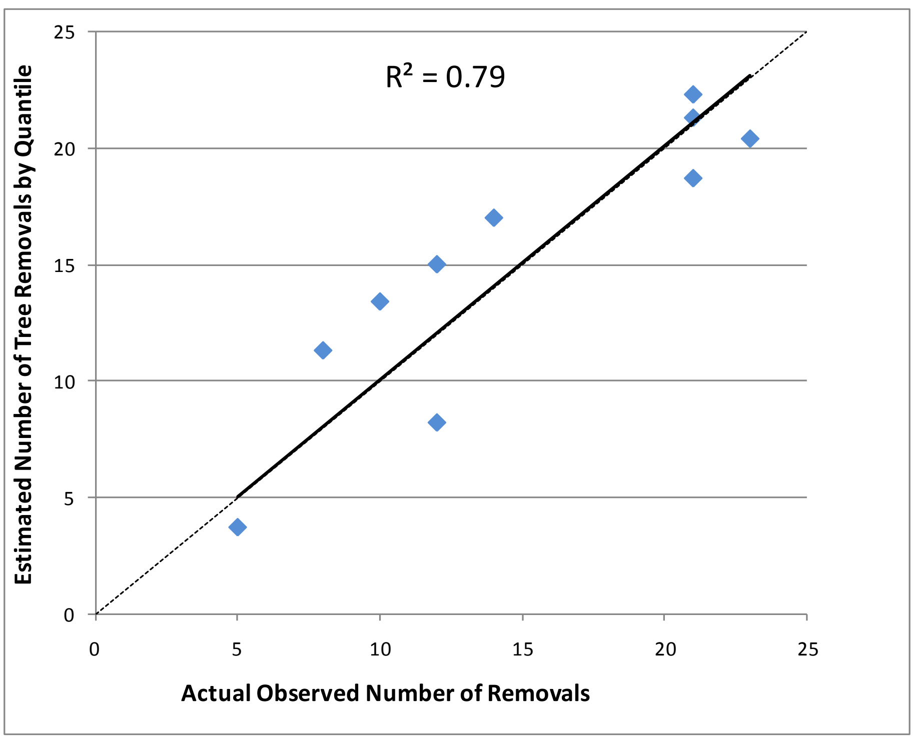

Figure 4-11 Tree Removal Model Fit: Estimated Versus Observed Number of Trees Selected for Removal by Quantile from 1989 to 2000 using Models fit Using Independent Variables

4.3.4.2 Discussion of Commercial Tree Removal Event Models

In terms of model performance metrics, the tree selection model fit using the principal component variables appeared to perform better that the model using a subset of the independent variables, but the results were similar. The R^2 for the independent variable model (R^2 = 0.79, see Figure 4-11) for the ten quantile partitions were similar to results obtained for the PC model (R^2 = 0.83). The error rate based on classification of tree removals at the quantile partition level was higher for the independent variable model (21%), as compared to the PC model (9%). However, there was a marked difference in how variability in tree selection patterns was modeled between the two models, which could bias the comparison of this error estimate. As shown in Tables 4-11 and 4-12, the PC model estimated a smaller range of tree removal events (10 to 20), as compared to the independent variable model (4 to 22). Theoretically, the error rate calculated at the quantile level could be smaller, when the variance decreases. Another important difference seen was that the model fit using principal components did not address the interaction seen between tree price and stand price, as previously discussed. For the independent variable model, stand value and tree price were found to have opposite, and highly statistically significant ($p < 0.001$) affects on tree selection probabilities. However, this effect was masked in the principal component analysis, as both were highly correlated with the first principal component. In fact, this negative interaction between tree price and stand price may have resulted in the higher than expected p value (p = 0.16) for the first PC, which appeared to suggest that tree price may not have been significant in determining tree selection patterns, which was counterintuitive and inconsistent with pattern seen in Figure 4-5. Overall, it could be argued that the model fit using the PC analysis may be mathematically better, but the simpler model using the independent variables yielded results that were similar and appeared to better characterize tree removal patterns (relative to tree and stand price interactions and removal distribution patterns). Furthermore, the independent variable model yielded an average prediction error of only 1% for estimating stand removal volumes (see *Tree Value Removal Verification and Validation* section below), as discussed in the section to follow. Thus, the simpler independent variable model performed reasonable well for predicting stand removal volumes for the purposes of this project. Therefore, the tree selection model based on the original independent variables was used for simulating tree removals during commercial timbering events in the integrated model, which is further discussed in Sections 5 and 6.

4.3.4.3 Modeling Annual Incidence of Tree Removal Events

Estimating Tree Selection Probabilities. Using methods previously discussed for deriving the stand selection probability model, the equation below was derived for estimating the probability of individual tree selection for timbering events. To simplify this analysis, it was assumed that if a timbering event occurred, then all removals occurred during a single year between 1989 and 2000. This assumption has the potential to slightly overestimate removal volumes as there is a small probability that two or more timbering events could have occurred between 1989 and 2000. However, simulations using the stand and tree models indicated that the probability of a stand being selected more than once during a 12 year interval was 1%, and the removals represented only 0.1% of total removals during a 12 year interval, as stand volume was significantly reduced following the first removal event. Therefore, this assumption was considered to not have a significant impact on the results. Since tree removals occur only when a timbering event occurs and this was assumed to occur only once during the 12 year sampling interval, it was not necessary to adjust the probability model further as was done for the stand selection model.

The following equation was derived for estimating the probability of tree removals using Equation 7 above.

Tree Selection for Timbering Events

$$p(event) = \frac{1}{(1+e^{-(1.79(ln(Tree\ \$))-1.61(ln(TOT\ \$/2.47))-3.27(Ownership)+10.81)})} \qquad \{8\}$$

Tree Selection Model Validation. For validation purposes, the 30% out of sample dataset and tree selection model were used to evaluate model performance by comparing observed versus predicted tree removal events. The partitioning results presented in Table 4-13 and Figure 4-12 below indicates the level of model fit for predicting individual tree removals. Due to the low number of commercial tree removal events in the 30% validation data set (i.e., 41 commercial tree removals on 24 plots), five partitions were established for comparing model performance rather than ten. Overall, 80% of the trees were correctly classified within the 5 partition groups (R^2 of 0.79).

Tree Value Removal Verification and Validation. To evaluate the value of timber removed for verification purposes, the most-likely estimated value of timber removed per plot was estimated and compared to the actual value of timber removed from plots that were commercially timbered between 1989 and 2000. Predicted versus observed results for the 70% dataset (which was used to parameterize the model) are presented in Figure 4-13 below. Overall, the predicted values of timber value removed per hectare were highly correlated to observed values, with a model R^2 of 0.88. The model estimated that on average \$3,364/ha was removed from these plots, while the predicted value was \$3,324/ha, which was 1% lower. As demonstrated in Figure 4-14, the model was able to replicate regional differences in timber removal patterns to some extent, but further research in this area is recommended.

Table 4-13 Multilevel Random Effects Logistic Model Fit for Tree Removals During a Timbering Event for the 30% Data Set

Partition	Total	Tree Not Timbered		Tree Timbered	
		Observed	Expected	Observed	Expected
1	12	3	1	9	11
2	12	1	2	11	10
3	12	1	3	11	9
4	12	6	6	6	6
5	12	8	9	4	3

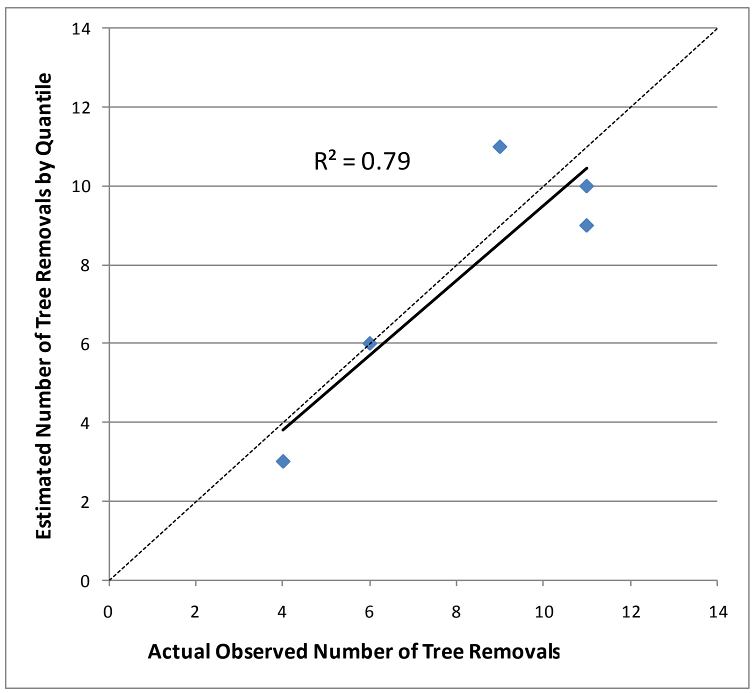

Figure 4-12 Tree Removal Model Fit: Validation of Estimated Versus Observed Number of Trees Selected for Removal by 5 Partitions from 1989 to 2000 using the 30% Out of Sample Dataset

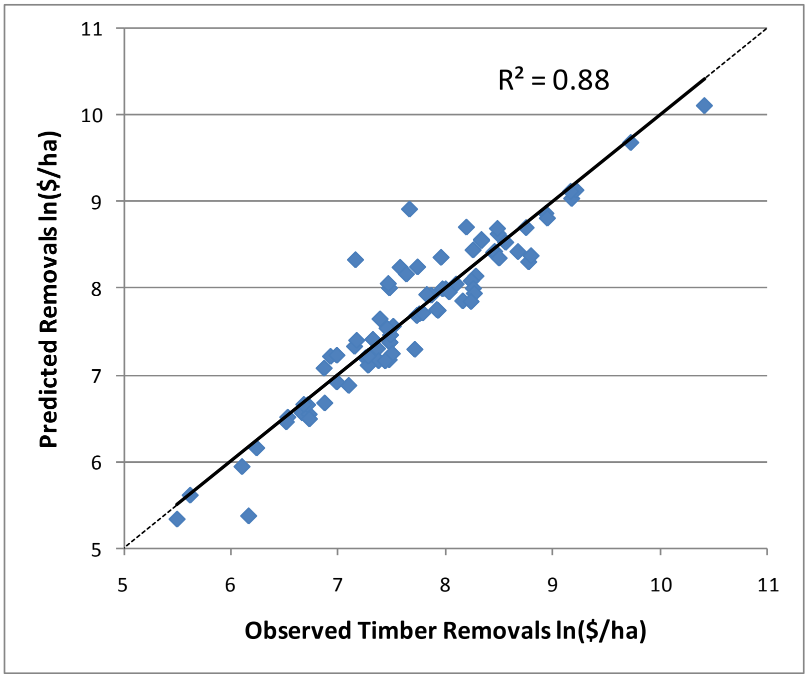

Figure 4-13 Timber Removal Model Fit: Actual Versus Observed Values for the 70% Data Set for Model Verification

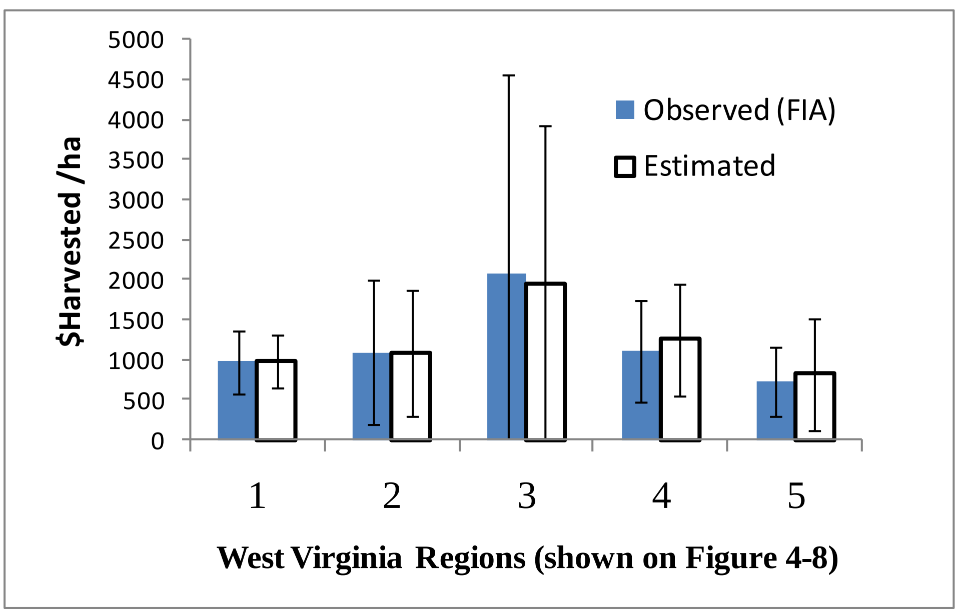

Figure 4-14 Timber Removal Model Fit by West Virginia Region (See Figure 4-8 for locations)

The commercial tree removal model was also applied to the 30% out of sample data for the purposes of model validation. Overall, the predicted values of timber value removed per hectare were highly correlated to observed values, with a model R^2 of 0.81 (see Figure 4-15). The model estimated that on average $3,920/ha was removed from these plots, while the observed value was $3,253/ha, which was 17% lower. The difference was principally associated with a single outlier event where only a small amount of timber was removed from the forest stand with highest timber value in the 30% dataset (because of the much higher value, the model predicted much higher tree removals than actually occurred). If this outlier is removed, then the model estimated that on average $3,017/ha was removed from these plots, while the observed value was $3,166/ha, which was 4.7% higher than the predicted value. Overall, the results of the validation indicate that the model does reasonably well at predicting the total value of timber removed.

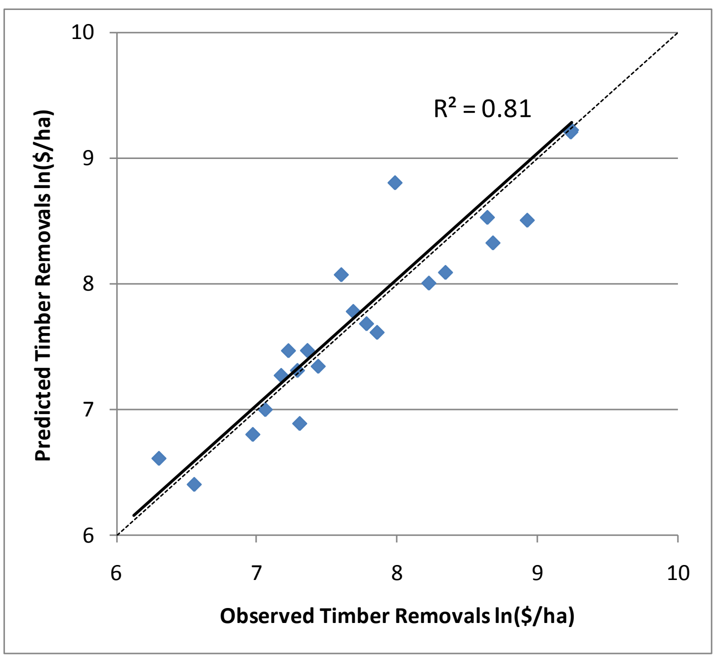

Figure 4-15 Timber Removal Model Fit: Validation of Actual Versus Observed Values using the 30% Out of Sample Dataset

Poletimber Tree Selection. Patterns of non-commercial tree removals (i.e., poletimber with DBH < 11”) appear to differ from commercial removal events, as shown in Figure 4-16. Poletimber removals were not correlated (< 0.3) to commercial tree removals. Furthermore, none of the independent variables were able to predict poletimber tree selection. In general, poletimber removals represented only 14% of the total volume of timber removed from a stand. For the purposes of the integrated model, poletimber tree removals were estimated using Monte Carlo simulation using an estimated frequency of poletimber removals during timbering events based on FIA data (USFS 2010a).

Figure 4-16 Non-Commercial Tree Removals by Tree Size Class (10 Quantiles)

Tree Selection for Low Intensity Timbering Events. For low intensity timbering events, a small portion of commercial trees were selected for removal. A logistic regression model could not be developed for predicting the selection of commercial trees during low intensity events, which represent only 6% of the forest stand removals. As shown in Figure 4-5, no clear relationship between tree value and selection frequencies could be seen with the low intensity timbering events. For the purposes of the integrated model, commercial tree removals on low intensity plots were estimated using Monte Carlo simulation using an estimated annual frequency of low intensity timbering events based on FIA data (USFS 2010a).

4.4 Conclusions

The logistic and multilevel models developed in this section provide an important and novel way of simulating timbering events at the tree and stand scale as an endogenous process, that will allow for simulating cross-scale feedbacks and other processes for evaluating the long-term impact of timbering on forest stand metrics, biomass, and carbon at multiple scales, as further discussed in Sections 6 and 7. These models also provide a means for simulating stand and tree selection processes reflective of different timber market conditions and price levels for scenario analysis. In addition, the multilevel random effects logistic regression approach used for tree selection provides an appropriate way for statistically analyzing forest stand data, which are similar in structure to hierarchical data often encountered in the fields of microeconomic behavior, social science, and education research.

Overall, the results of the timber stand and tree selection analysis indicated that timber stand value density, tree prices, and plot ownership were key drivers in predicting timber stand and tree selection for removal events. The models predicted timbering practices and tree selection patterns reflective of observed data for quantile partitions of the dataset. Increased tree stumpage prices, which increased overall stand value, significantly increased the probability of a stand being selected, on both private and public lands. Private lands were much more likely to be selected for timbering than public lands, as expected. At the tree-level, increased value of the commercial tree (based on stumpage price and BF) significantly increased the probability of the tree being selected. The model also indicated that forest stand conditions also impacted individual tree selection probabilities, as tree selection probabilities increased on public lands (which was not expected) and stands of higher value decreased individual tree selection probabilities (presumably due to increased competition for selection when conducting select cuts).

Although both the plot and tree-selection models were able to predict observed patterns in the data for quantile partitions of the data set, there was variability in stand and tree selections that the models could not explain. Furthermore, the highest valued stands and trees were not always selected for timbering in any given year. Thus, there are other factors not captured by these models that contribute to timber and stand selection. Such factors may include: incomplete knowledge of the value of forest resources on forest stands across West Virginia, real estate ownership class (fee title held by timber firms versus private landowners), real estate market transactions, the inability for timber firms to gain timber contracts on private and public lands with higher stand value, corporate regional networks and infrastructure, access problems, and/or self imposed sustainable forest management. Detailed surveys, participatory modeling, and spatial agent-based modeling techniques may help capture some of these micro-scale processes that cannot be addressed through statistical analysis of FIA data (Parker et al. 2003, Bousquet and Le Page 2004).

By developing and comparing logistic regression models developed using principal component variables and the original independent variables, it was possible to determine the predictive power of multiple variables. In addition to the effect of stand value and ownership regime, the principal component analysis indicated that timber events increased with increased human development and closer proximity to production mills, which both serve as proxy variables for reducing removal costs. However, reasonable model performance was also achieved when these variables were excluded using a simpler model that only included stand value and ownership regime. In addition, the independent variable modeling approach provided additional insights that would have been difficult to ascertain with the principal component analysis approach at the tree-level, as stand value and tree price were found to have opposite effects on tree selection probabilities.

This effect was masked in the principal component analysis, as both were highly correlated with the first principal component. In any event, overall model performance for predicting stand and tree selection were similar using either the principal components or the significant subset of independent variables, which yields a simpler model. Since the statistically significant independent variables are all currently available in the FIA database, it suggests that this modeling approach may be applicable for other states and regions for simulating timber and tree selection events as an endogenous process, which enables a finer-scale analysis with cross-scale feedback mechanisms for predicting the long-term impact of timber removals on forest biomass, stand structure, and carbon (as discussed in Sections 5, 6, and 7). Additional research would be required to confirm that this approach is appropriate for other geographical regions.

There are limitations with the stand and tree modeling approaches, which could be further refined through additional research. For example, there may still be other stand characteristics, such as terrain classification, slope orientation, access, regional industrial networks, and other factors that may create spatial patterns and explain some of the variance in stand and tree selection patterns not captured in this analysis. Furthermore, more detailed ownership regime and timber history data would be helpful for evaluating stand and tree selection patterns. Evaluation of many of these variables would be difficult to analyze with the FIA dataset, as the exact plot locations and ownership regimes are not publically available. Working with the privately-held data managed by USFS, would enable a more robust analysis of these factors. Further studies and research are needed to determine whether some of these other factors are important and whether spatial patterns exist in the data.

Since West Virginia stumpage prices are highly correlated with U.S. hardwood timber markets (as further discussed in Sections 5 and 6), the linkage between timber prices and removal events suggests that U.S. hardwood prices may be a good environmental indicator of timber removals in West Virginia, and perhaps other states. Furthermore, the results suggest that tree species with higher value and higher demand (e.g., black cherry) may undergo significant timber pressure, relative to less valuable species thereby impacting species composition and dominance in decades to come. The impact of these processes will be further explored when the stand and tree models are coupled with forest growth, mortality, disturbance, and regeneration models for estimating system level dynamics and feedback mechanisms over a half century of continued timbering under different timber market and forest management scenarios.

5. Cumulative Effect of Timbering and Other Key Processes on Net Annual Forest Growth at Multiple Scales in West Virginia

5.1 Introduction

Towards the end of the 20th century, the increase in timber prices and growth of forest resources in West Virginia gave rise to significant increases in commercial timber removals (see Figure 4-1). This timbering activity not only directly impacts forest biomass, but indirectly, timbering could also potentially affect the rate of other key processes that impact long-term estimates of forest biomass and carbon, such as mortality rates, forest growth rates, landscape disturbance rates, and regeneration rates. Thus, it is important to evaluate the indirect effect of timbering on these processes, thereby creating the means to model cross-scale feedbacks, as well as to assess the cumulative effect of all these processes on long-term AGBD fluxes. This portion of the study focuses on analyzing the indirect effect of timber removals on forest growth, mortality rates, disturbances, and regeneration, and integrating these results with the direct biomass removal effects (discussed in Section 4) to evaluate the cumulative effects of timbering on net annual growth in forest volume across West Virginia in 2000. These results will then be used to develop an integrated, multi-scale model to simulate the long-term effect of timbering on forest ecosystem indicators and timber resources from 2000 to 2050 (discussed in Section 6), as well as carbon sequestration to 2050 (discussed in Section 7).

Overall the research question is: *What is the cumulative effect of timbering and other key processes on net annual forest growth in West Virginia?* The primary processes (i.e., model compartments) that may significantly alter forest volume and BF metrics include: forest growth (both positive and negative), tree mortality rates, regeneration, and timbering rates and intensity. Negative growth (i.e., large portion of the tree dies in a given year which exceeds the annual increase in biomass due to positive growth) and increased tree mortality may be associated with a number of anthropogenic and natural disturbance regimes. In West Virginia, the principal disturbances to trees identified in the FIA database (USFS 2010), other than timbering, included: vegetation (suppression, vines) (28%), extreme weather events (principally ice storm damage) (27% of identified disturbances), animal damage (principally animal grazing) (16%), insect infestations (9%), diseases (8%), other human disturbances (8%), and fire (3%). These results are based on an analysis of FIA plots from 2004 through 2007, as disturbances were not recorded for the 2000 sampling period.

Although disturbances were identified for many West Virginia plots in 2004 through 2007, only 20% of the plots that experienced a negative net growth were identified as being disturbed by a visible disturbance agent. Disturbances for the other 80% of the plots were not known or recorded. On the other hand, 15% of the plots with net positive growth were also identified to have experienced these same visible disturbance agents. These results suggest that the factors driving net negative growth at the plot level in West Virginia are not being captured by the disturbance metrics recorded in FIA (USFS 2010a). If specific disturbance vectors were not apparent, then other environmental attributes (e.g., variations in microclimatic conditions including precipitation and temperature) may be impacting West Virginia forest growth, which is further explored in this section.

With respect to timbering disturbances, there is the potential that such events may indirectly impact net annual forest growth, mortality rates, other disturbances, and stand regeneration of saplings and poletimber on the plot; thus it is important to further explore these processes. Timbering in West Virginia principally involves the removal of large size class trees (approximately 60% of the forest stand volume on average), which reduces the basal area of forest stands. Reduction in basal area of the forest stand decreases crown cover, increases light penetration, and reduces competition, thereby increasing the basal area growth (BAG) of trees that remain in the forest stand (USFS 2010b,c). Individual-tree diameter growth models are based on the principle that BAG declines in a negative exponential manner as basal area competition increases (i.e., basal area for all trees of larger basal area size than the tree in question, which is referred to as the basal area large [BAL] variable) (Holdaway 1964; Teck and Hilt 1991; USFS 2010b,c). As timbering events reduce basal area competition, timbering events would therefore increase the potential growth rate of trees that remain, which is the principle behind forest thinning. Opening up the canopy as a result of timbering may also provide opportunities for saplings to grow and regenerate; thereby, increasing the survival and growth rates of saplings (DBH < 1") and poletimber (DBH between 1" and 5") leading to increased stand regeneration rates. Timbering event disturbances could also increase the mortality rates for the trees that remain on the plot due to direct injury, soil and surface water flow disturbances, and/or increased potential for natural disturbances (fire/pest infestations). On the other hand, timbering may lower the potential for mortality by reducing species competition. Studies have shown that reduced tree competition through thinning can reduce tree mortality rates and reduce stand susceptibility to drought (Cotillas et al. 2009, Powers et al. 2010). Thus, if timbering affects tree-growth rates, mortality rates, other disturbances, or regeneration rates, then it may have an indirect effect on live tree volume estimates, beyond the direct effect of volume removals. Since these are largely inferred relationships, four *null hypotheses will be tested that timbering has no effect on growth rates, mortality rates, disturbances, or regeneration rates*.

To evaluate the cumulative effect of timbering on forest system dynamics as discussed above, it was necessary to also model net forest growth processes, independent of timbering activities. Specifically, it was necessary to select a model that would accurately estimate the growth (both positive and negative) in aboveground wood volume and biomass over time. This was important because measures of aboveground timber volume and growth directly impact the economic value of plots and individual trees and therefore timber stand selection and removal decision probabilities in a given year (as detailed in Section 4), which are simulated using CFM on an annual time step. CFM predicts plot-level timbering events and tree-specific removals based on changes in stand value density ($/ha) and tree value ($/stem), which change annually (due to timber price market fluctuations and timber growth). This modeling effort therefore requires accurate estimates of plot- and tree-specific BF and tree-specific aboveground growth in terms of volume (m^3/ha) and biomass (g/m^2) (both positive and negative growth). This objective to accurately model the live aboveground wood pool volume/biomass is important for properly simulating human-environmental interactions, which is the focus of this study.

To accomplish this objective two forest growth modeling approaches were evaluated: 1) an empirically-based forest growth modeling approach, and 2) a process-based modeling approach. In this context, empirical approaches involve developing statistical models that relate forest growth to independent variables that characterize conditions of the tree, stand, and climatic conditions. Process-based models can be used to estimate forest growth based on simulating tree physiological response to environmental conditions and biogeochemical cycling processes. In general, empirical modeling approaches provide the means to capture observed patterns, but if future environmental conditions change enough to alter underlying modeled relationships, then future projections may be suspect. Process-based modeling approaches can help overcome the limitations of empirical modeling methods, so long as these key processes and growth responses are sufficiently incorporated into the model and calibrated to the conditions under study.

For this study, readily available empirical models and field data from FIA were utilized to model net forest growth processes at the tree- and stand-level, using incremental tree growth models utilized in the FVS program; and mortality rates, regeneration rates, and disturbance patterns statistically modeled from FIA data. The empirical growth models developed by USFS have been validated for the Northeast Region using field measured tree growth FIA data, as further discussed in Section 5.2.2.2 (Teck and Hilt 1991; USDA 2010a,b).

For the process-based model, the PnET-CN model, which has been successfully applied in the Fernald Experimental Forest (FEF) in West Virginia, was selected and tested (Aber and Federer 1992; Aber et al. 1995, 1996, 1997). PnET-CN includes feedback mechanisms for assessing forest growth response in relation to nitrogen and carbon cycling mechanisms, which would also allow for estimates of carbon dynamics in soil and other important carbon pools that are difficult to address through empirical methods. Although the PnET-CN model has been validated for NPP and NEP at a local scale in the FEF in West Virginia (Aber and Federer 1992; Aber et al. 1995, 1997; Aber and Goulden 1996; Davis et al. 2008, 2009; Stange et al. 2000), the model has not been validated for a state, across multiple ecosystems, disturbance regimes, for the live aboveground wood pool, which is important for estimating timber removal probabilities that were discussed in Section 4.

PnET-CN is based on established relationships between net photosynthetic rate and percent nitrogen in leaf matter, and vapor pressure deficit in the air that regulates transpiration and photosynthetic rates (Aber and Federer 1992; Aber et al. 1995, 1996, 1997). These relationships are built into PnET-CN to calculate net photosynthetic rates per leaf surface area (amount of CO_2 per m^2 per second). Essentially, PnET-CN is a model of the net photosynthetic engine aggregated at the stand or plot level. Since its introduction in the early 1990s, the PnET-CN model has undergone significant enhancements. A modified version of this model, PnET-CNsat (Davis et al. 2008, 2009), was also tested for simulating AGBD and growth for forest stands, which are likely to have nitrogen saturated soils.

5.2 Methods

5.2.1 Conceptual Modeling Approach

To estimate changes in forest volume and BF over time, a multi-scale integrated model was developed (i.e., CFM model) (see Figure 3-2 and Section 3.1 for a description of the conceptual model). The models developed in this portion of the study were used for estimating tree growth, mortality, disturbance, and regeneration rates for CFM shown in Figure 3-2 (boxes labeled - G). Several cross-scale feedback loops are addressed in this analysis including the effect of changing tree and stand value (due to growth, disturbance, timbering, and stumpage prices) on future stand and tree timbering rates. Figure 5-1 provides further details on the specific modeling processes addressed in this section, including forest growth (both positive and negative), disturbance, mortality, and regeneration.

To address fine-scale tree-level silviculture impacts, the model tracks the life history of approximately 60,000 trees across 1,500 forest stand plots in West Virginia including: forest type, species, AGB, total biomass (root, stump, bole, tree top), aboveground volume, BF, annual growth (positive or negative) in AGB, annual growth in BF (positive or negative), and birth and mortality. Tree- and plot-level dynamics are simulated on an annual time-step, with summary statistics derived at the tree-, plot-, and state-level to assess impacts to tree volume, BF, and other metrics. Since timber events may have an indirect impact on forest growth, mortality, disturbances, and regeneration at a plot or tree-level, it was necessary to test these relationships and incorporate these findings into the integrated model, as appropriate. The sources of field data used in the analysis were discussed in Section 3.2.

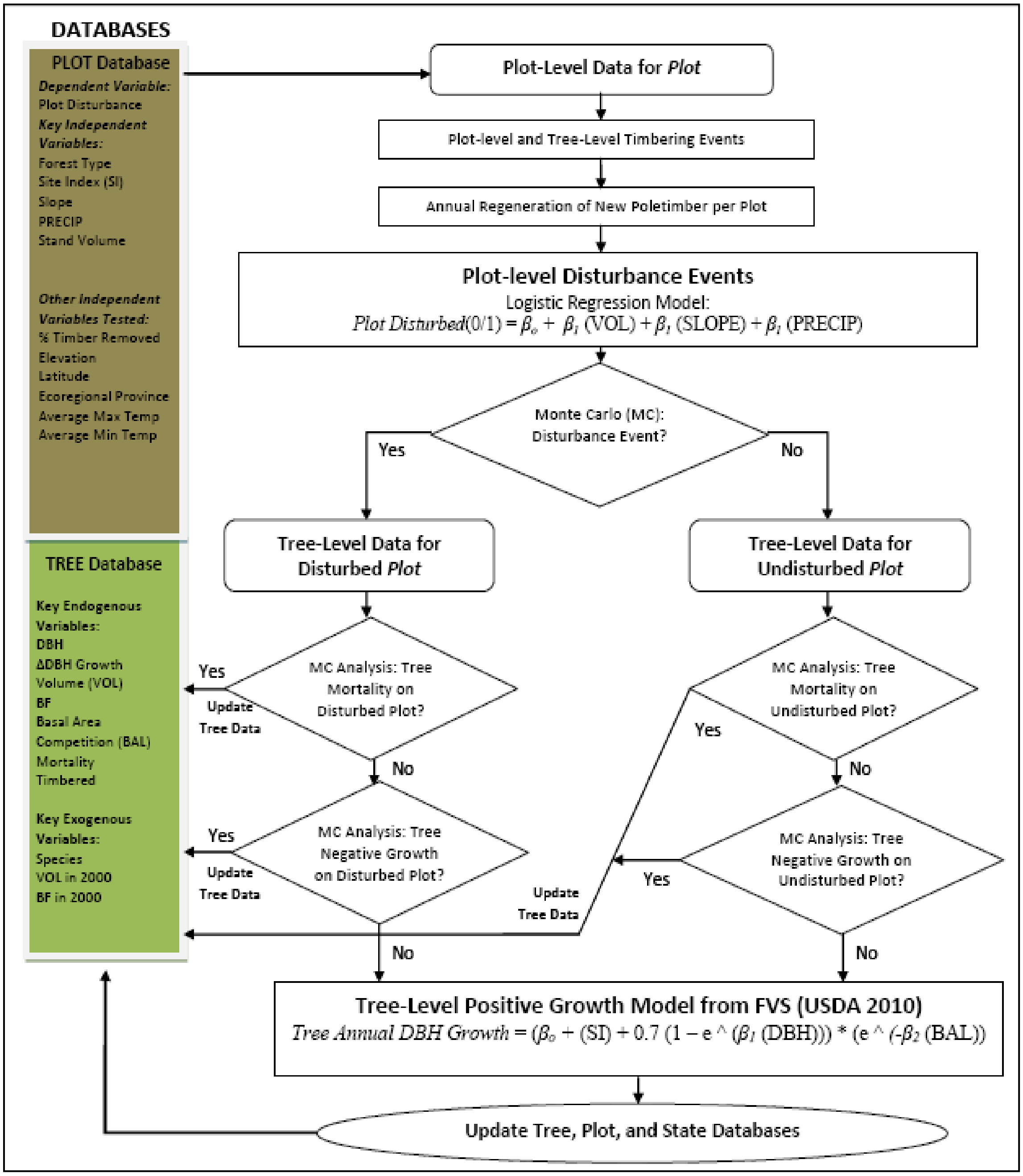

Figure 5-1 Flow Diagram of Forest Growth Modeling Compartments

5.2.2 Modeling Forest Growth and Timber Effects

5.2.2.1 Modeling Timbering Effects on Forest Stand Net Annual Growth

The first part of this study was to assess the indirect effect of timbering on the net annual growth rates of forest stands across West Virginia. Net annual incremental growth estimates are provided for only about 1/3rd of the FIA plots (583 plots) and only for the center subplot, which were sampled in the field during the 1989 and 2000 field sampling events. Field measured incremental annual growth in volume of live poletimber and sawtimber trees located on these 583 forest subplots were obtained and analyzed from the FIA database. The net growth (either negative or positive) of the remaining live trees (not including timber removals) was analyzed and summed for each plot. The percent annual change in forest volume was derived for each plot and live tree by dividing the FIA field measured growth per unit area estimates by the total tree volume per unit area for plots for which field data were collected (a subsample of approximately 40% of the plots in West Virginia). Multiple regression and logistic regression techniques were then used to analyze the effect of timbering events (intensity of removal [i.e., percent volume of poletimber and sawtimber trees removed]) and other forest stand independent variables (see Table 5-1) on net annual growth of the plots, as further discussed below.

Table 5-1 Plot and Tree Growth, Mortality, and Regeneration Variables

Model Parameter	Value	Field Data Source/Derivation
DEPENDENT VARIABLES		
% Net Growth in Tree Volume and BF	%	FIA 2000 Plot Data
Disturbed Plots (Plots with Net Negative Growth)	1 or 0	FIA 2000 Plot Data
Plot-Level Mortality Rate: Volume of Dead Trees	stems m^3/ha	FIA 2000 Plot Data
Plot-Level Regeneration Rate: Total Poletimber	m^3/ha	FIA 2000 Plot Data
INDEPENDENT VARIABLES		
% Timber Removal	%	FIA 2000 Plot Data
Tree Volume Density	m^3/ha	FIA 2000 Plot Data
Latitude	degrees	FIA 2000 Plot Data
Forest Stand Elevation	FIA stand value (m)	FIA 2000 Plot Data, supplemented by USGS National Elevation Dataset and Global Elevation Data 2009 http://www.latlontoelevation.com/dem_consume.aspx
Forest Stand Slope	% slope	Predominant slope on plot FIA 2000 database
Average Minimum Annual Temperature	^oC	NOAA National Climate Data Center, Weather Station nearest the plot that is located within the same climatic zone as the plot (16 weather stations). Plot-specific weather data were not available. http://www.ncdc.noaa.gov/oa/ncdc.html
Average Maximum Annual Temperature	^oC	NOAA National Climate Data Center, Weather Station (see further explanation above).
Average Annual Precipitation	cm/year	NOAA National Climate Data Center, Weather Station (see further explanation above).
Ecoregional Province	1 or 0	Bailey's Ecoregional Provinces: Eastern Broadleaf Forest (Oceanic) Province or Central Appalachian Broadleaf Forest Province (March 1995) http://www.fs.fed.us/land/ecosysmgmt/index.html

5.2.2.2 Modeling Forest Growth

Many types of forest growth models have been developed for a wide range of applications, including: stand-level distance dependent and independent models; tree-level distance dependent and independent models; and gap models (Porte and Bartelink 2001). These models include empirical models, process-based models, and hybrid models. In a comparative analysis of these models, research by Porte and Bartelink (2001) suggests that the empirically-based stand models appeared to perform better than tree-level models at predicting stand-level growth, although detailed comparative measures of accuracy for each model were not provided. Furthermore, the empirical models performed better than process-based models at predicting growth for the region being modeled, although this applied only when the empirical models were applied to the area in which it was parameterized (Porte and Bartelink 2001). In any event, empirical and process-based models should not be applied to locations beyond their model domain where they were developed, calibrated, and validated, until they can be re-tested and evaluated.

Overall, forest managers and researchers generally prefer tree-level models over stand-level models for assessing the effect of tree competition, species growth dynamics, forest management, and disturbance impacts (timbering/insect hosts) on the stand and larger scales (USFS 2010 b,c; Porte and Bartelink 2001). The distance-dependent and gap tree-level models provide an added benefit over distance-independent models for simulating the growth of a specific tree in a stand, as they evaluate tree-specific competition for light and resources that directly impact growth potential for a specific tree. However, this requires more rigorous computation and tracking of two- or three-dimensional stand structures. If the objective of the analysis is focused on stand-level yields and effects, rather than individual-tree effects, then simpler distance independent tree models are commonly used for evaluating forest stand growth (Colbert et al 2004; Jogiste 1997; Kolbe et al 1999; Porte and Bartelink 2001; Schuler et al. 1993; Teck and Hilt 1991; USFS 2010b,c; Zhao et al. 2004). Such models routinely incorporate DBH, basal area [BA], site index factors, and stand-level competition factors (e.g., basal area large tree competition factor, which is the total stand BA for trees of greater BA than the tree being modeled) for addressing both tree-specific growth potential (based on DBH, species, and site conditions), and stand competition factors. Such models provide a simpler approach for addressing tree-specific distance and competition variables, which can impact long-term growth and yields. Validation of the Teck and Hilt (1991) tree growth model that was ultimately incorporated into the USFS FVS model for simulating tree growth for the entire northeastern United States indicated that the mean annual growth diameter prediction error was 0.013 inches for over 16,000 observations, representing 28 species from the FIA database. As the observed mean annual growth was 0.113 inches, this prediction error represented an 11% difference in the mean growth rate. Overall, the Tech and Hilt model (1991) over predicted incremental growth for 16 species, while it under predicted growth for 12 species. Based on these results, the USFS has incorporated this model into their FVS model as the principle means for simulating tree growth and conducting forest management planning at the northeast regional level, including forests of West Virginia. Thus, tree-specific, distance independent models provided an adequate means for addressing forest growth, when forest prescriptions or disturbance processes (e.g., timber removals, mortalities) are being modeled at the tree-level.

Tree-level, distance independent models are routinely used by the USFS (e.g., as part of FVS) to evaluate stand and larger scale forest growth and forest management simulations. Furthermore, the FIA database is structured for the use of such models, as tree-specific coordinates are not available for applying tree-level, distance dependent and gap models. The USFS has applied tree-level, distance-independent models for all regions in the United States, including parameterization and validation of individual-tree diameter growth models for predominant tree-species in the northeast (USFS 2010a,b; Teck and Hilt 1991). The model is based on a sigmoidal growth model routinely applied for tree growth applications, which also includes parameters for tree size (DBH, BA), site condition, and stand-level competition (BAL). The model was developed based on previous research on forest growth modeling in the United States, with extensive calibration and validation of test results using FIA data (USFS 2010a,b,c; Teck and Hilt 1991). These models were used in this study for simulating incremental tree diameter growth to 2050. The FVS diameter growth models were also linked to field-measured West Virginia tree volume growth estimates measured in the field between 1989 and 2000 to calibrate and convert the DBH growth estimates to field-based volume growth estimates provided in FIA for West Virginia. User defined disturbances and mortality also can be added to FVS growth simulations to better simulate landscape conditions. Thus, it is necessary to develop user-defined disturbances and related effects when applying the FVS, which was also done for CFM.

For modeling tree and stand growth for this project, two specific models were tested for estimating individual tree growth and forest stand growth, as discussed in Section 5.1. The empirically-based model discussed above (FVS) was utilized for modeling tree-specific and stand growth (through compiling tree-specific growth). Also, a process-based model, PnET-CN, was also tested for estimating stand growth. The methods used for estimating forest growth using FVS and PnET-CN are presented in the sections below.

Modeling Forest Stand and Tree Growth using FVS. As previously discussed, the individual tree diameter growth model developed by Teck and Hilt (1991) which is utilized in the Northeast Variant of the FVS model was used for modeling tree BA growth in CFM. The individual-tree diameter growth model estimates species specific annual growth in DBH based on site and tree attributes included in the FIA database, including species, site index, DBH, and a tree competition factor (basal area large [BAL]). The BAL statistic is a tree-specific competition metric that is the total basal area of all trees in the stand that are larger in DBH than the tree in question. USFS researchers found the BAL statistic to be the best measure of tree competition for deriving annual DBH growth measures. The model was developed specifically for modeling forest growth in the northeast and was integrated in both the Northeast TWIGS model (NE-TWIGS) and FVS (USFS 2010b,c). The model is customized to 28 species groups and 30 forest cover types based on an analysis of incremental growth of over 50,000 trees in the northeast, which includes the species categories and forest cover types found in this West Virginia study. Validation performance was discussed in Section 5.2.2.2. The growth equations and parameters for the species groups used for the entire northeast region that are pertinent to this study are presented in Table 5-2.

Table 5-2 Individual Tree Diameter Growth Models for the Northeastern United States (Teck and Hilt 1991)

Species Group	Basal Area Growth[1]
Ash	$BAG = 0.00090*SI*(1- e^{(- 0.093 * DBH)})* e^{(- 0.015 * BAL)}$
Black Cherry	$BAG = 0.00079*SI*(1- e^{(- 0.157 * DBH)})* e^{(- 0.017 * BAL)}$
Hickory	$BAG = 0.00080*SI*(1- e^{(- 0.078 * DBH)})* e^{(- 0.016 * BAL)}$
Hard Maples	$BAG = 0.00074*SI*(1- e^{(- 0.071 * DBH)})* e^{(- 0.016 * BAL)}$
Mixed Oaks	$BAG = 0.00082*SI*(1- e^{(- 0.079 * DBH)})* e^{(- 0.014 * BAL)}$
Other Species	$BAG = 0.00096*SI*(1- e^{(- 0.093 * DBH)})* e^{(- 0.021 * BAL)}$
Soft Maples	$BAG = 0.00079*SI*(1- e^{(- 0.065 * DBH)})* e^{(- 0.016 * BAL)}$
Red Oak	$BAG = 0.00089*SI*(1- e^{(- 0.098 * DBH)})* e^{(- 0.018 * BAL)}$
Walnut	$BAG = 0.00096*SI*(1- e^{(- 0.093 * DBH)})* e^{(- 0.015 * BAL)}$
White Oak	$BAG = 0.00074*SI*(1- e^{(- 0.087 * DBH)})* e^{(- 0.014 * BAL)}$
Yellow Poplar	$BAG = 0.00088*SI*(1- e^{(- 0.142 * DBH)})* e^{(- 0.020 * BAL)}$

[1] BAG = Basal area growth (ft3/acre), DBH = diameter at breast height (inches), SI = Site index (USFS 2010a), BAL = total BA for trees larger than the subject tree (tree competition factor)

Modeling Forest Stand Net Growth using PnET-CN. In addition to the FVS modeling approach, an analysis was conducted to determine whether the PnET-CN model could be integrated with CFM in order to predict net annual growth of the plot over time under various disturbance regimes. If the results of this analysis indicated that plot-level AGBD and growth from FIA could be replicated using PnET-CN, then it would be theoretically possible to integrate the Visual Basic code of the two models (PnET-CN and CFM) and use PnET-CN to govern plot-level growth and carbon pool estimates across West Virginia. The key advantage of using PnET-CN for this analysis is the ability of this model to simulate carbon and biomass dynamics in the forest system, including soil organic carbon (SOC) and other pools, which are important for estimating total carbon stocks and annual carbon fluxes. PnET-CN is also a process-based model, as previously discussed, which enables the user to simulate forest growth and carbon fluxes in response to changes in carbon and nitrogen cycling and anthropogenic disturbance regimes, which may not be reflected in the empirical data.

The key metric that must link PnET-CN and this CFM model is measures of live AGBD (g/m^2) at the plot level and the annual net growth in AGBD. Since the FIA database provides measures of AGBD and annual growth and PnET-CN also provides measures of AGBD, it was possible to compare the PnET-CN output with not only actual measures of current AGBD, but also net growth measured in the field from the FIA database. These results were also compared to modeled growth of total wood pool biomass using FVS/CFM. Specific performance criteria were developed to evaluate the viability of the approach.

1. *Plot Baseline AGBD g/m2.* Since PnET-CN cannot simply be initialized with 2000 field data, it was necessary to determine whether plot-level AGBD could be replicated using PnET-CN. PnET-CN must be run for about two hundred years (starting in 1700) prior to

the year 2000, to ensure that the historic disturbance regimes and nitrogen cycling are properly simulated in order to achieve current AGBD estimates in 2000. As a performance criterion, plot-level AGBD estimates from PnET-CN should be within +/- 10% of field measured data. Since FVS is an empirical model it can be initialized with the current data, and therefore it already meets this criterion.

2. *Plot Growth Rates.* Estimates of average plot-level growth using PnET-CN should be commensurate with field measured growth using FIA data and within the mean error of FVS (average within +/- 11%) (e.g., differences in annual growth of a plot from 0.5% to 2% will significantly impact long-term forest condition and conclusions, as current timber removal rates approach 0.5% annually).

Both performance criteria related to live AGBD system dynamics are important because each factor will significantly impact system level estimates of timbering and forest resources (carbon, biomass, BF, stand value) over time. If these criteria are not met, then PnET-CN cannot be effectively integrated with CFM for estimating AGBD and growth across West Virginia at this time.

The specific methods for conducting the PnET-CN analysis are presented below.

- All of the FIA plots from two counties were analyzed, namely Boone and Tucker Counties. Boone County, which is located in southwestern West Virginia, was selected because it is an area which is unlikely to have nitrogen saturated soils (NADP 2009). Forests in Boone County are fairly typical of the predominant oak-hickory association forest-type found throughout West Virginia. Tucker County was selected because: 1) it is known to contain nitrogen saturated forests and is located in the northern high elevation areas of West Virginia with known high nitrogen deposition rates (Davis et al. 2008, 2009; NADP 2009); 2) the forest types are typical of the highlands area of West Virginia (the second most common forest type in West Virginia, i.e., the maple/beech/birch group); and 3) it includes FEF where the previous studies had been conducted using PnET-CN and PnET-CNsat (Davis et al. 2008, 2009). Overall, about 50 plots were analyzed for different model runs. About half of these plots included field measured growth estimates from FIA.

- Nearby weather station data collected from these counties were used for each of the model runs (NOAA National Climate Data Center data collected near Madison, WV for Boone County; and FEF climate data for Tucker County, WV). Sampling data collected from the state-wide study were used in part to parameterize the PnET-CN/sat models. The FolNCon and SWLmax parameters were derived for each plot by calculating a weighted average based on the total aboveground biomass of each of the principal tree species on the plot. Both the PnET-CN (used for Boone County) and PnET-CNsat (used for Tucker County) models provided from the PnET website and Dr. Davis, respectively, were used in the analysis.

- For plot-level disturbance regimes, USFS/FIA record only near-term timber removals from 1988 to 2000 for each plot, as well as other disturbance impacts that occurred sometime during this time interval (e.g., mortality, negative growth from ice storms, fire, pests, etc.). Prior to 1988 when FIA data became available, no site-specific disturbance profile data exists for individual FIA plots. At the state level, timber production statistics are available which indicates that at the turn of the century there was significant timbering activity, followed by peaks around 1935 (WV Division of Forestry 1990, USFS

1977), and lastly a significant peak in the 1990s (see Figure 4-1). Between 1935 to 1988, estimates of timber removals were based on known removal rates in the 1990s (~5% of plots timbered per decade, with 63% average removal rates per plot) with the relative difference in timber production at the state level from 1935 to the present day. Overall, timbering rates between 1935 and 1990 were about half of the rate experienced in the 1990s and at the beginning of the 20th century. These trends are consistent with the assumptions presented in Davis et al. (2009). Similar assumptions were adopted in this analysis for estimating long-term historic timber removal for plots across the state. Initially, it was assumed that all plots were essentially clear cut at the turn of the 20th century (95% mortality with 70% removal of biomass) and that all plots experienced a smaller removal of 25% associated with the chestnut blight in the mid-1930s (with 25% removal of biomass) (Davis et al. 2009). During the 1990s, the average removal from all timbered plots was 63% of the timber resources. This same rate was assumed for events that occurred from 1935 to 1988 to estimate typical removals that would have occurred in that period.

- To address the performance criteria previously discussed, PnET-CN was run for different scenarios and conditions. A multi-tier strategy was tested for all plots in Boone and Tucker Counties with available growth estimates. As a first step, all plots were simulated using average disturbance regimes for all plots in Boone and Tucker Counties, as outlined in Table 5-3. Parameter values were based in part on statistics gleaned from Davis et al. (2009) and timber frequency data analyzed from FIA (2010a), as previously discussed.

Table 5-3 First Tier Timber Removal Disturbance Profiles for Plots in Boone and Tucker Counties, WV

Agriculture Disturbance (nitrogen Removal)	1915		1935		1950		1988	
	Mortality	Removal	Mortality	Removal	Mortality	Removal	Mortality	Removal
0 or 0.1	0.95	0.70	0.25	0.25	0.25	0.25	FIA % Removals	FIA % Removals

For those plots where the estimated AGBD was either below or above 10% of the field measured AGBD in year 2000, plausible adjustments (within the ranges discussed below) were made to the disturbance regimes in order to calibrate PnET-CN to observed AGBD in 2000. Ranges of values used to calibrate PnET-CN are outlined below. Specific adjustments are detailed in Appendix A.

- Agriculture removals between 1750 to 1850: 0 to 0.1;
- Turn of the 20th century timber removals at the peak removal year of 1915: 0 to 0.95 mortality (with approximately 3/4^{ths} of the biomass removed and 1/4th remaining on plot);
- Chestnut blight impacts and removal peaks in the mid 30s: 0 to 0.25 (mortality/removal); and
- Removal scenarios between 1935 to 1988: 0 to 0.8 removals. Based on state removal records and timbering frequencies in the 1990s, it was estimated that only 13% of the plots were likely to be timbered between 1935 and 1988. It was assumed that plots with the lower AGBD in 2000 were timbered at higher rates (0.5 and 0.8 removal rates), while plots with higher biomass were timbered at lower rates (0 to 0.25).

5.2.3 Modeling Plot-Level Disturbances

Exploratory analysis of plot-level and tree-level growth rates on the FIA plots indicated that landscape level disturbances were impacting the growth and mortality rates of multiple trees on the same plot, resulting in about 1/5th of the plots having a net negative growth rate (i.e., a net decline in the live volume of large trees > 5" DBH from 1989 to 2000). At the tree-level, higher tree mortality rates, higher incidence of tree negative growth rates, and lower positive growth rates were seen for multiple trees on the same plot, indicating that the stand was collectively experiencing the adverse effect of a disturbance of some type. The nature of these disturbances were not recorded in the FIA database, as previously discussed, but may have been due to local drought conditions or other micro-scale climatic conditions, disease and pest infestations that were not recorded or readily apparent. These disturbances caused greater habitat variability in stand conditions across West Virginia, as it altered future growth and habitat conditions for these stands (positive and negative growth appeared to be a continuous unimodal distribution). Overall, approximately 17% of the forest stands in West Virginia experienced a net negative growth rate at the stand level from 1989 and 2000, which was indicative of stands where higher tree-level mortality rates, negative growth rates, and reduced positive growth rates were found. To more accurately model such occurrences, plots with net negative growth rates per unit area were flagged using a binary variable (either 0 or 1) and the incidence of these events were modeled separately using logistic regression, as the dependent variable was binary and independent variables were both continuous and binary, as presented in Table 5-1. It was important to separate and model these disturbance events separately as they represent different processes from those that result in positive growth, and to ignore such effects could potentially result in overestimating growth and/or under-representing the variability of stand conditions across the landscape. A plot with a net negative growth was defined as a plot where the sum of the individual tree negative growth per unit area (either partial tree loss or mortality) exceeded the sum of the individual tree positive growth per unit area on the same plot. This approach identifies only large disturbances that are significant enough to yield overall net negative growth rates at the stand level. Smaller disturbance events that may impact only a few trees on the stand would not be identified using this approach, as the positive growth rates of other trees would still yield a net positive growth for the overall stand.

A multivariate logistic regression model was developed to predict the incidence of plot level disturbances (binary dependent variable) using the independent variables presented in Table 5-1, as well as new variables derived from these same independent variables using principal component analysis. A multivariate logistic regression was developed using all principal component variables that contributed to a significant portion of the variability in the data (discussed further in Section 5.3). For use in the integrated model CFM, a simpler model using only statistically significant independent variables was also developed. The methods for variable selection and model validation were the same as discussed in Section 4.2.

5.2.4 Tree Mortality and Timbering Effects

To evaluate the indirect effect of timbering on tree mortality, the total volume of tree mortalities per area (ha) for poletimber and sawtimber trees that died between 1989 and 2000 were compiled as the dependent variable. Mortalities were recorded on 1 of the 4 subplots from 583 forest plots located across West Virginia, and only on a subsample of plots across the state. The FIA database includes separate fields for identifying trees that died versus trees that were cut during a timbering event during this time period. The nature of the disturbance that may have caused the tree mortalities was generally not known, as previously discussed. As the dependent variable was continuous, multiple regression was used to analyze the effect of timbering events (intensity of removal based on the percent volume of poletimber and sawtimber trees removed) and other forest stand independent variables (see Table 5-1) on plot-level mortality rates. In addition, an analysis of variance (ANOVA) test was conducted to evaluate whether there was a statistically significant difference in the volume of tree mortalities on plots that were timbered in West Virginia versus those that were not timbered between 1989 and 2000.

For modeling mortality rates in CFM, a heuristic analysis was conducted to analyze the annual incidence and volume of tree mortalities that were generated between 1989 and 2000 on the 583 plots that were included in the 2000 field sampling event. As tree mortality rates were much higher on plots that were predicted to experience a plot-level disturbance (i.e., net negative growth rate), the probability distributions for tree mortality events were estimated separately for plots with net negative growth rates and net positive growth rates.

5.2.5 Tree Regeneration and Timbering Effects

As previously discussed, CFM models tree-level dynamics and life history for each poletimber (5" to 11" DBH) and sawtimber (>11" DBH) tree on the plot, and not individual saplings. The total of all individual saplings on a plot represents less than 5% of the biomass on average; therefore, sapling biomass was not modeled as individual stems in CFM (see Sections 6 and 7 for a discussion of modeling methods for sapling biomass and carbon). Regeneration of individual trees occurs when a sapling grows large enough to be considered a poletimber tree, i.e., it exceeds 5" DBH. Thus, the effect of timbering on poletimber tree regeneration rates is analyzed, rather than each individual sapling.

A heuristic analysis was conducted to analyze the annual incidence and volume of new poletimber trees that were generated between 1989 and 2000 on approximately 1,500 FIA plots that were sampled in the field during the 2000 field sampling event. Annual incremental growth statistics were used to determine the approximate DBH range of new poletimber trees in 2000 that would have been below 5” prior to 1989. These statistics were used to identify trees that became poletimber trees between 1989 and 2000, and to calculate the total volume that was generated per plot on an annual basis. The total volume of tree regeneration per area (ha) for poletimber and sawtimber from 1989 and 2000 were then derived for each plot using the FIA data. Since the dependent variable was continuous, multiple regression was used to analyze the effect of timbering events (intensity of removal based on the percent volume of poletimber and sawtimber trees removed) and other forest stand independent variables (see Table 5-1) on plot-level regeneration rates. In addition, an ANOVA test was conducted to evaluate whether there was a statistically significant difference in the volume of tree regeneration on plots that were timbered in West Virginia versus those that were not timbered between 1989 and 2000.

5.2.6 Model Integration

Results of the timber models discussed in Section 4 were integrated with the models developed for growth, disturbance, mortality, and regeneration in order to simulate net changes in forest volume. The models were applied to the entire plot- and tree-level datasets for the 70% sample to predict near-term net annual growth in forest volume. State-level metrics were compiled based on the plot- and tree-level simulations to predict state-level outcomes and changes in forest volume. The actual changes in forest volume at the state level in 2000 for the 70% sample set were then compared to the simulated changes of forest volume to verify the results. Similar analyses were performed on the 30% out of sample dataset for model validation. Sensitivity analysis, Monte Carlo uncertainty analysis, and long-term model simulations are presented in Section 6.

5.3 Results and Discussion

5.3.1 Forest Stand and Tree Growth

5.3.1.1 Effects of Timbering on Forest Stand and Tree Growth

As a result of the multiple regression analysis, several variables were found to be significant in explaining the variation in net annual percent growth rates across plots in West Virginia, including stand volume ($p < 0.001$), slope ($p = 0.003$), latitude ($p = 0.006$), elevation ($p = 0.018$), and average annual precipitation ($p < 0.001$). Lower net growth rates were found on plots that were timbered between 1989 and 2000 than on plots that were not timbered (38% lower growth on average), but this difference was not statistically significant ($p = 0.24$). Thus, timbering events did not have a statistically significant impact on net annual percent growth for trees that remained following a timbering event at the stand level. Rather, percent annual growth rates declined when stand volume increased, precipitation decreased, elevation increased, slopes increased, and for stands at higher latitudes. Higher precipitation and lower slopes would tend to increase infiltration and reduce the potential for drought stress, which may explain their effects on higher growth rates.

With respect to stand volume, increased stand volume did decrease net annual percent growth rates, which was consistent with a sigmoid growth response curve (Colbert et al 2004; USFS 2010a,b; Teck and Hilt 1991). Although the *percent* change in annual growth declined with increased stand volume, the total stand volume still grew more on stands with higher stand volumes (as the dependent variable analyzed above is based on the percent growth in tree volume, rather than total growth in volume). As shown in Figures 5-2 and 5-3, the highest growth in stand

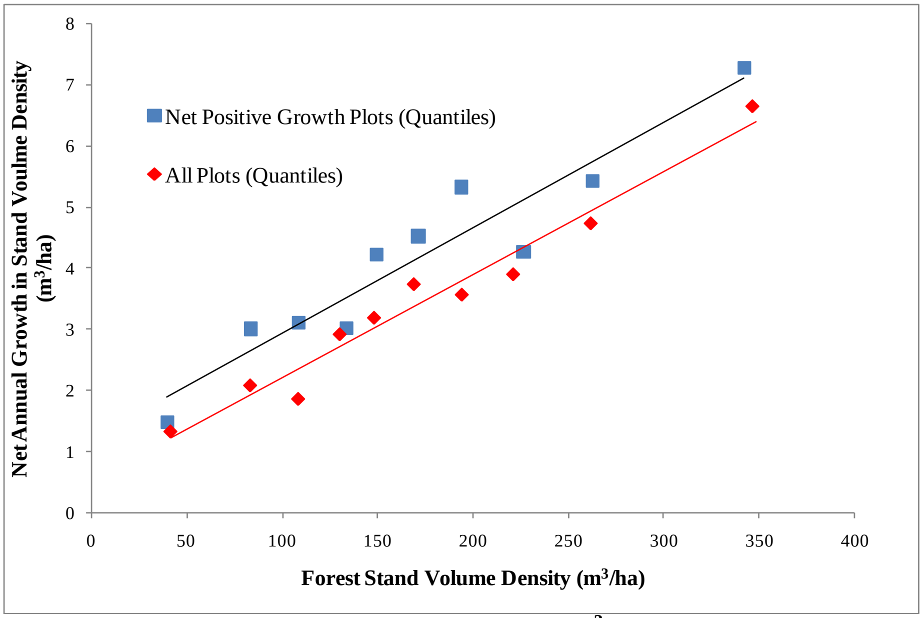

Figure 5-2 FIA Field Measured Forest Stand Growth (m^3/ha-year) by Forest Stand Volume (m^3/ha) Quantiles (squares: only net positive growth plots; triangles: all plots)

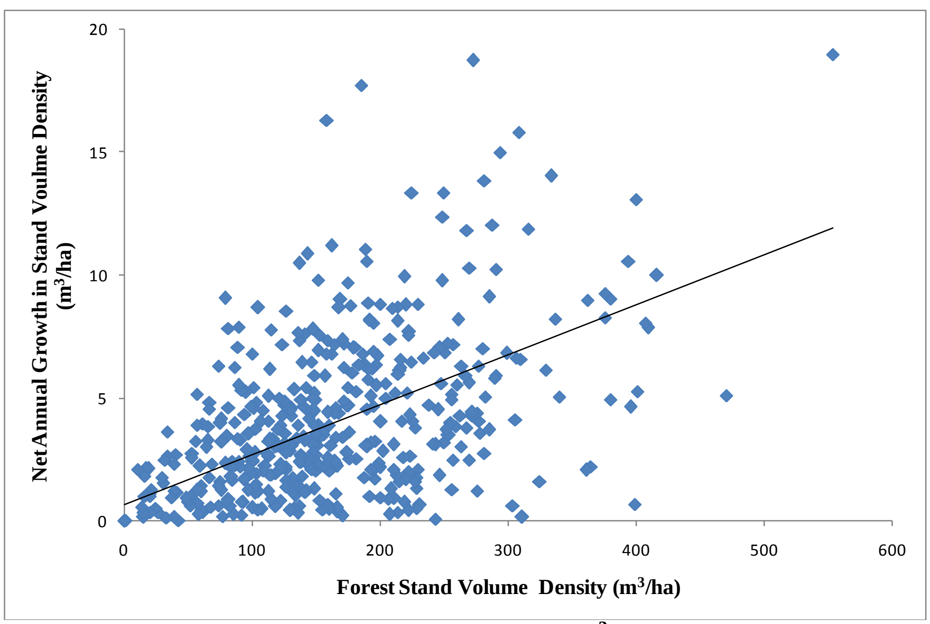

Figure 5-3 FIA Field Measured Forest Stand Growth (m^3/ha-year) by Forest Stand Volume (m^3/ha) for All Positive Growth Plots (increased variation with increased volume [similar results seen for increased biomass])

volume was still found on stands with the highest overall volume of timber, even though their annual percent growth rates were decelerating. There was a positive correlation (0.94) between stand volume and net annual growth rate in total volume for aggregated quantiles of forest stand volume (Figure 5-2). In fact, the net growth rate in total volume for forest stands with the highest 10% of forest volume (6.7 m^3/ha-year, for stands with AGBD typically above 25,000 g/m^2) exhibited net growth rates approximately two times higher than the average forest stand in West Virginia (3.4 m^3/ha-year), with a AGBD of approximately 13,000 g/m^2. Although the growth rate measured as a percentage of total biomass was lower for these older stands, the gross net increase in biomass was still greater for stands in advanced stages of recovery. Forest stands from the top quantile of forest stand volume have AGBD above 25,000 g/m^2 and total biomass commensurate with old growth forests (although they lack other stand structure characteristics of old growth forests, such as having > 30% of their biomass in large trees [Brown et al. 1997]). These results indicate that forestlands in West Virginia are continuing to recover and gain in volume and biomass, although their growth rate is decelerating as the stands continue to mature. These results are consistent with current trends and analysis by Brown et al. (1997).

Although several independent variables were significant in predicting stand-level net annual percent growth, the overall model fit was poor (R^2 = 0.25), and better results were achieved by modeling forest growth at the tree-level as further described in Section 5.3.1.2. The poor model performance was due in part to differences in tree-level variables, such as differences in species-specific growth rates, stand structure, and environmental settings between plots, which can result in large variability in growth response (Teck and Hilt 1991, USFS 2010c). Thus, forest growth was more appropriately modeled at the tree-level in order to more accurately model these micro-scale processes, as well as to analyze forest management effects at the tree-level.

5.3.1.2 Tree-Level Model Estimating Forest Growth

As previously discussed, the tree-level model used for the Northeast Variant of the FVS software were used to model tree- and stand-level growth rates in West Virginia. This model estimates annual incremental growth of trees based on the DBH, basal area, site index, and species (Tech and Hilt 1991). Although this model has already undergone significant calibration and validation in the northeast region, the model results obtained for West Virginia trees were compared to those reported by Teck and Hilt (1991) to verify that similar results were obtained. As this study only reported mean incremental growth rates for each of the tree species in the northeast, a similar statistic was derived for the major species groups evaluated for the West Virginia study (estimates are not reported in the FIA database). Applying this model yielded mean DBH annual growth measures that were very similar (within 10%) to observed annual growth for data collected for tree species groups on FIA plots located across the northeast for all major species categories when the mean DBH was similar, including hickories (within 8% of observed data), soft maples (within 9% of observed data), northern red oak (within 6% of observed data), white oak (within 9% of observed data), and yellow poplar (within 0.4% of observed data). Average black cherry and hard maple growth increment estimates in 2000 were not comparable to the observed field data reported by Teck and Hilt (1991) from the 1970s and 1980s. As expected, the average growth rate estimates for black cherry and hard maple for West Virginia in 2000 were higher than the rates reported by Teck and Hilt, because the average tree sizes in West Virginia in 2000 were much larger than those found in the 1970s and 1980s (Teck and Hilt 1991).

Annual increases in DBH for each tree were then converted to increased annual growth volume using species specific conversion equations that convert BAG and BA to tree volume growth in the central stem. These equations which converted BAG to volume growth measures were based on volume growth estimates for nearly 3,000 trees measured in the field in West Virginia as reported in the FIA database (USFS 2010a). These models were statistical significant ($p < 0.0001$) in predicting annual growth in tree volume for each tree species group and the models yielded R^2 ranging from 0.54 to 0.72; indicating good model fits (models are shown in Table 5-4). Aggregated quantile partitions of this data for each tree species yielded R^2 of 0.99, indicating excellent model fit for predicting the overall pattern in growth response. The annual incremental volume growth was then added to the previous year's tree volume to estimate the volume of the tree in the following year. These results indicate that the models performed well at replicating the overall pattern in positive growth observed in the field for the ten size classes of trees for each of the species groups across West Virginia. Plot-level volume density metrics were then estimated based on compiling tree-level growth estimates and area expansion factors included in the FIA database. To estimate annual growth in BF volume for each tree, a simple regression model was developed to predict annual growth in BF volume based on estimated annual incremental volume growth in the central stem. Annual incremental growth in tree volume was statistically significant in predicting annual growth in BF volume ($p < 0.0001$) and the model yielded an R^2 = 0.68; indicating a good model fit.

Table 5-4 Regression Equations for Converting Annual Incremental DBH Growth to Annual Growth in the Volume of the Central Stem and BF (Teck and Hilt 1991)

Species Group	Basal Area Growth to Central Stem Volume Conversion Equation[1]
Oak Group	VOL Growth = 5.010 * BAG + 0.5092 * BA + 0.0297 R^2 = 0.64 MSE = 0.30
Maple Group	VOL Growth = 4.4172* BAG +0.7187 * BA -0.00563 R^2 = 0.54 MSE = 0.32
Yellow Poplar	VOL Growth = 2.3643* BAG +0.9598 * BA + 0.01455 R^2 = 0.72 MSE =0.41
Other Species Group	VOL Growth = 1.411* BAG +0.7001 * BA +0.0012 R^2 = 0.59 MSE = 0.36
All Species	BF Growth = 4.245 * VOL Growth + 1.615 R^2 = 0.68 MSE = 2.24

[1] VOL Growth = annual volume growth of the central stem (cft^3); BAG (ft^2/acre) = estimated basal area growth of the tree (USFS 2010b,c); BA (ft^2/acre) = basal area of the tree (USFS 2010a) ; BF Growth = board foot growth of the tree (USFS 2010a)

5.3.1.3 Modeling Forest Stand Net Growth using PnET-CN

Overall, the results of the process-based modeling indicated that PnET-CN produced reasonable estimates of AGBD for many plots using plausible historic disturbance regimes; however, the net annual growth estimates for the wood pool were inconsistent with observed FIA measured growth across West Virginia plots. In addition, there were insufficient data at the state-level for properly parameterizing, adjusting, and validating the model to more adequately fit the model to the 1500 West Virginia plots, as was done for the more detailed site-specific study at FEF (Davis et al. 2009). The results of the comparison between the FIA plot data and PnET-CN output are presented below.

1. Plot Baseline ABGD (g/m2). State average historic disturbance profiles yielded plot-level AGBD estimates from PnET-CN for the live wood pool that were significantly above or below field measured AGBD for approximately 60% of the plots (see Appendix A for detailed results), depending on the assumptions applied for 1750 to 1850 agriculture disturbances and timber removals in the 20th century. By adjusting the historic disturbance profiles, it was possible to replicate AGBD using PnET-CN and PnET-CNsat that were within 10% of the field measured data for 85% of the plots tested. The specific adjustments to historic disturbance profiles that were made in order to achieve the field measured AGBD for each plot location are presented in Appendix A. The implication of these adjustments indicates that the model is sensitive to these historic disturbance regimes and unfortunately data are lacking to sufficiently parameterize the model across West Virginia. Arbitrarily adjusting model parameters to improve model performance, even if the values are “plausible” is not a viable modeling strategy. This is not to suggest that the model results are wrong or that PnET-CN is inaccurate, but simply that average statewide historic disturbance profiles are insufficient to parameterize this model, and

plot-specific data are necessary, but unavailable. Specifically, information on historic agricultural practices (soil disturbing activities) and disturbance from timber removals over the past two centuries prior to 1987 are needed at the plot level. Even if statewide data were readily available, it would be difficult to apply the data to the specific FIA plot locations due to the fuzzing and swapping of plot locations that USFS utilizes to hide the exact location of their plots, as discussed in Section 3. Further research is needed to evaluate strategies for developing historic disturbance profiles (agriculture soil disturbance and timber history) across large geographical areas in order to properly parameterize the PnET-CN model.

2. Plot Growth Rates. Overall, average net annual growth rates and plot-specific growth rates derived from PnET-CN were not commensurate with field measured growth rates derived from FIA data for these same plots. In general, plots that were not recently timbered had significantly higher growth rates as measured in the field than predicted by PnET-CN, as shown in Figure 5-4. For plots that were not recently timbered, the mean net annual growth as estimated by PnET-CN was 64% below field measured FIA observed data, which was statistically significant ($p = 0.004$ using a paired t-test), while the FVS estimate was 21% below FIA observed data, which was not statistically different ($p = 0.28$). In contrast, plots that were recently timbered had significantly lower observed growth rates than what were predicted using PnET-CN ($p = 0.02$), as shown in Figure 5-5. For plots that were recently timbered, the mean net annual growth as estimated by PnET-CN for plots was 101% higher than field measured FIA observed data, which was statistically significant ($p = 0.02$), while the FVS estimate was 16% above FIA observed data, which was not statistically significant ($p = 0.72$). When combining all plots from Tucker and Boone Counties, the mean net annual growth rate estimated by PnET-CN was 27% below the FIA observed data, while FVS was 11% below the FIA observed data. Since only a

very small percentage of plots are timbered in any given year, use of PnET-CN growth rates would have significantly underestimated field measured values of net annual growth in the live wood pool for West Virginia plots. Further research is needed to validate growth estimates and modeling processes within PnET-CN across larger geographical areas with diverse ecosystem communities and historic disturbance profiles.

The results of several PnET-CN modeling tests also indicated that long-term plot net annual growth was significantly impacted by historic disturbance regime assumptions, which resulted in very different maximum long-term AGBD potential for a plot. Although different locations may have significantly different maximum AGBD potential based on the environmental and climatic conditions that are specific to the location, this upper bound potential can be significantly altered by 18th and 19th century historic anthropogenic activities that disturb soil nitrogen cycling processes, such as agricultural crop production. As nitrogen and carbon are endogenous

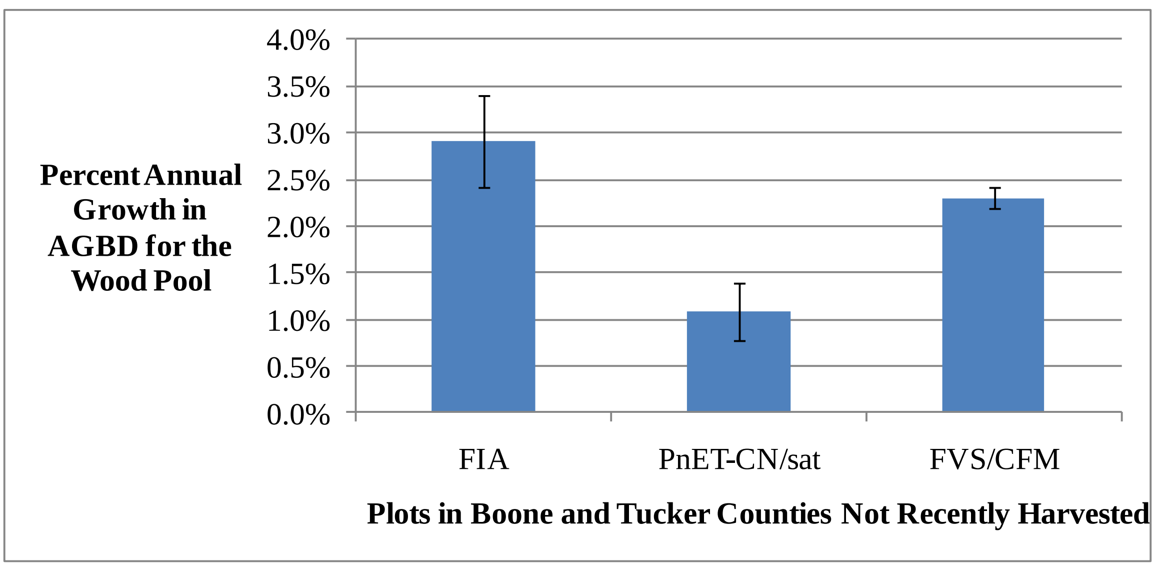

Figure 5-4 Comparison of Observed versus Estimated Stand Volume Growth (Aboveground Biomass in the Wood Pool) using PnET-CN/sat and FVS/CFM for Plots Not Timbered Since 1989 in Boone and Tucker Counties

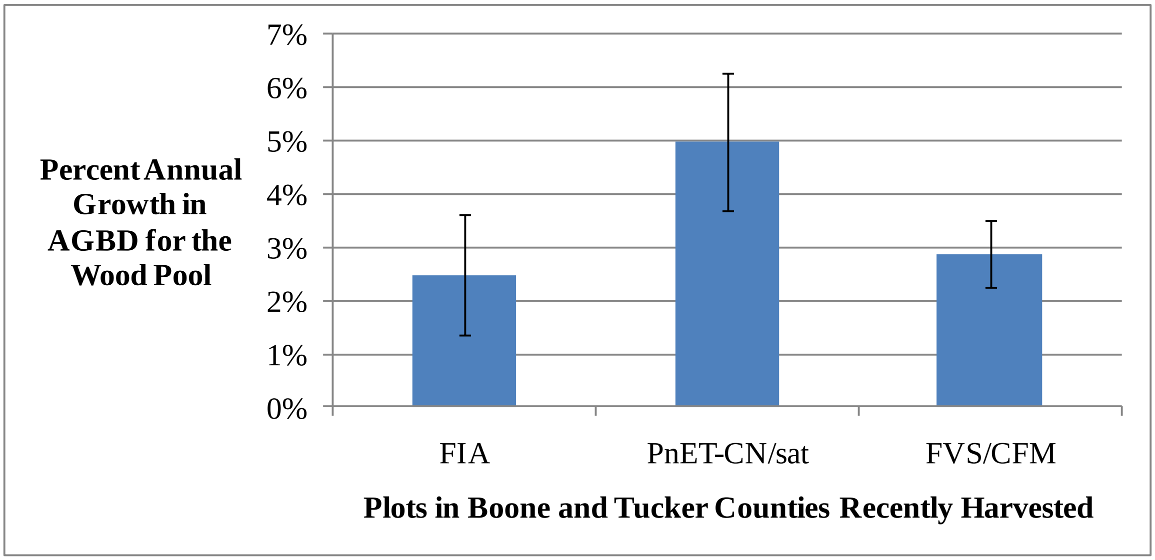

Figure 5-5 Comparison of Observed versus Estimated Stand Volume Growth (Aboveground Biomass in the Wood Pool) using PnET-CN/sat and FVS/CFM for Plots Timbered Between 1989 and 2000 in Boone and Tucker Counties

processes that are modeled iteratively over long time periods and achieve their own equilibriums, model parameters that affect nitrogen removal and cycle disturbance in the soil are particularly important in how the model derives these long-term upper-bound biomass equilibrium levels. These levels are not as affected by timber removal events, which do not disturb or remove nitrogen from the soil; however, they are significantly impacted by agricultural nitrogen removal practices that are typically assumed for PnET-CN model runs for the eastern U.S. from 1750 to 1850. Essentially, applying this disturbance regime in a PnET-CN model run reduces the upper bound AGBD and restoration potential of a plot by half, which is very significant (see Figure 5-6). Although this assumption may be reasonable for the many populated areas in the eastern coastal plain that experienced intensive agriculture practices during the 18th and 19th century, this assumption may not be appropriate for many mountainous parts of West Virginia. When nitrogen removals due to agriculture disturbances are assumed, then AGBD estimates predicted using PnET-CN were significantly below field observed values for most plots. However, when it is assumed that no agricultural disturbances occurred, the PnET-CN model was able to replicate upper-bound AGBD values on certain plots, but then it overestimated AGBD for other plots where AGBD values are much lower. In certain cases, there may be a number of land use factors that would explain the disparity in the results (e.g., forests without closed-canopies). In any event, the impact of this colonial period disturbance factor alone has a significant impact on the long-term future outcome, restoration potential, and growth of the forests to 2050; therefore, it is important that this undergo further study. For future research in this area, it is recommended that

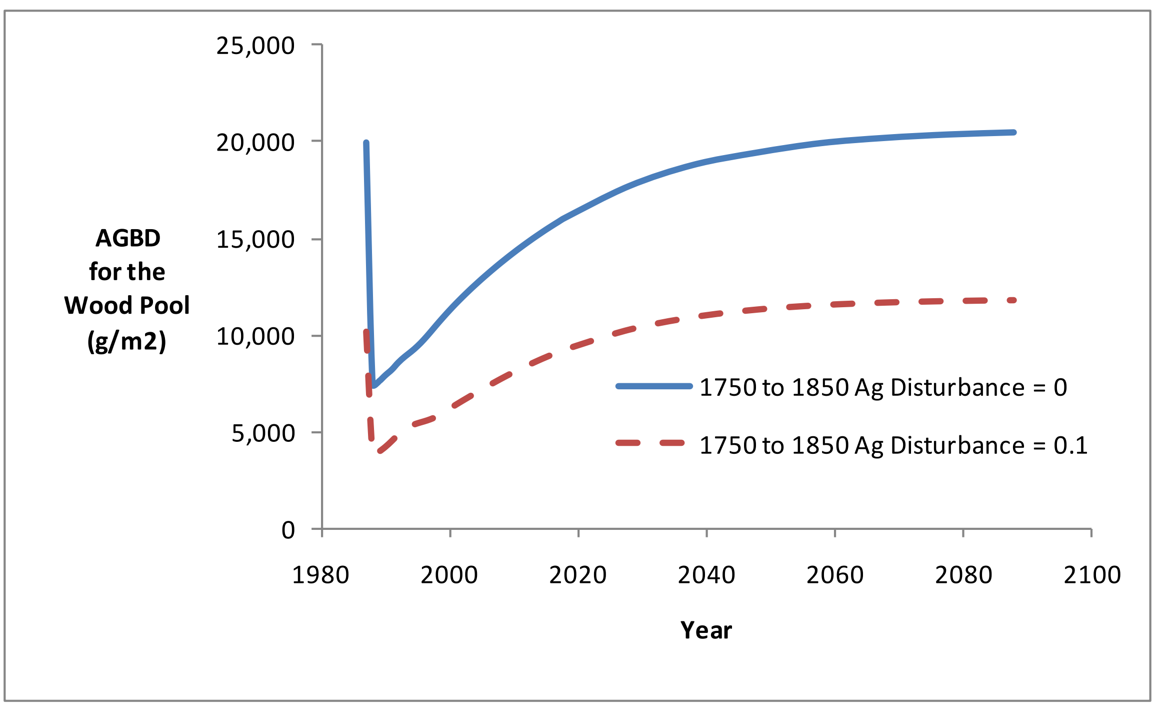

Figure 5-6 Long-term AGBD Potential Following a Hypothetical Removal in 1987 for an Average Plot (Boone County)

detailed field data necessary to fully parameterize PnET-CN be collected across a much larger regional area (e.g., ecoregion or province) and detailed historical profiles for FIA sample plots be developed to test PnET-CN estimates of biomass density in the aboveground wood pool against field measured growth and biomass estimates, stratified across an array of current and historic anthropogenic disturbance regimes (e.g., timbering, agricultural). Although such a study could be costly, it would enable the model to be properly tested, modified (if appropriate), and validated to ensure that it can be properly applied for larger regional areas.

As a result of the findings noted above, the PnET-CN was not used for simulating plot growth and biomass for this modeling project. Although FVS provides reasonable growth estimates that are commensurate with FIA, the inability to use PnET-CN on this project principally means that it cannot be used to model carbon cycling in Section 7. Although other empirical models are used to lieu of this model, SOC and many feedback mechanisms that are incorporated into PnET-CN cannot be modeled as endogenous processes. Perhaps with additional research, PnET-CN could be integrated into the model in the future as originally intended (as further discussed in Section 8).

5.3.2 Estimating Stand-Level Disturbance Effects and Net Negative Stand Growth

Nearly 1/5th (17%) of the plots in West Virginia experienced a net negative growth in live tree volume from 1988 to 2000. The negative growth and mortalities on these plots represented a total loss of 0.34% of live tree biomass annually and 4% of live biomass from 1989 and 2000. This landscape disturbance was similar in magnitude to all of the timbering losses that occurred during this same period; therefore, this landscape disturbance is a significant dynamic that impacts forest system volume, biomass, and carbon. On these plots, both significantly higher tree-level mortalities and negative growth rates were found, as compared to plots that experienced a net positive growth rate, as shown in Table 5-5. Overall, tree mortality rates were three times higher on plots with negative net growth, and nearly 20 times higher for large tree classes. In addition, the trees were two times more likely to experience negative growth on these same negative net growth plots, than on positive growth plots. In addition, the positive growth rate of trees on these disturbed plots was also reduced by about a 1/3rd, as compared to positive growth rates for trees located on other plots (i.e., plots where the net growth rate was positive). Thus, there appeared to be plot-level disturbances impacting multiple trees located on net negative growth plots, as mortality rates were higher, negative growth was more frequent, and positive growth was reduced.

To investigate the environmental conditions that may have resulted in this disturbance, independent principal component variables were analyzed using logistic regression to evaluate their effect on the incidence of net negative growth plots. Results of the principal component analysis are presented in Tables 5-6 and 5-7. Using the Latent Root criterion test there were 5 eigenvalue factors, which had nearly a value of 1 or more, which explained 87% of the variance in the independent variables presented in Table 5-1. The five key vectors in the principal component analysis are presented below:

Table 5-5 Comparison of Tree-level Mortality and Negative Growth Rate Frequencies on Forest Stands With Net Negative Versus Net Positive Growth Rates

Growth Rates	Tree Volume (cft)	Annual Frequency of a Tree Event: Landscape Disturbance: Net Negative Growth Plots	Annual Frequency of a Tree Event: No Landscape Disturbance: Net Positive Growth Plots	Ratio
Tree Negative Growth Rates	<3	6.6 %	9.1 %	0.7
	3 – 7	14.5 %	7.3 %	2.0
	7 – 14	21.4 %	9.4 %	2.3
	> 14	23.6 %	5.7 %	4.1
Tree Mortality Rates	<3	0.28 %	0.21 %	1.3
	3 – 7	0.67 %	0.25 %	2.7
	7 – 14	1.5 %	0.36 %	4.2
	> 14	2.9 %	0.17 %	17.1

Table 5-6 Principal Component Proportions and Cumulative Variance for Independent Variables

Component	EigenValue	Variance: Proportion	Variance: Cumulative
1	2.53	0.33	0.32
2	1.46	0.18	0.50
3	1.26	0.16	0.66
4	0.95	0.12	0.77
5	0.79	0.10	0.87
6	0.64	0.08	0.95
7	0.28	0.03	0.99
8	0.10	0.01	1.00

Table 5-7 Principal Component and Factor Loadings

Variable	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6	Comp 7	Comp 8
Slope	0.11	-0.48	0.39	0.21	0.58	0.48	0.07	0.03
% Timbered	-0.03	0.32	0.57	-0.40	-0.40	0.50	0.01	0.004
Latitude	0.11	0.70	-0.17	0.05	0.47	0.17	0.10	0.46
Elevation	-0.56	-0.09	-0.02	0.02	-0.06	-0.009	0.80	0.17
Average Min Temp	0.53	-0.26	0.18	-0.05	-0.26	-0.26	0.18	0.67
Average Precipitation	-0.002	0.25	0.34	0.86	-0.26	-0.08	0.01	-0.06
Average Max Temp	0.56	0.17	0.06	-0.09	0.11	-0.13	0.55	-0.56
Stand Volume	-0.24	0.13	0.58	-0.21	0.37	-0.63	-0.11	-0.006

PC1. Temperature: Average minimum temperature, average maximum temperature, and elevation were highly correlated with this vector. This vector explained 33% of the total variance.

PC2. Latitude: Latitude was most highly correlated with this vector and is an important variable included in PnET-CN for simulating growth. This vector explained 18% of the total variance.

PC3. Forest Stand Volume: Both total forest stand volume and the percent of timber removed during timbering events were both highly correlated to this vector. This vector explained 16% of the total variance.

PC4. Rainfall: Average annual precipitation was highly correlated with this vector. This vector explained 12% of the total variance.

PC5. Slope: Slope was most highly correlated with this vector. This vector explained 10% of the total variance.

Stand-Level Disturbance Events. The logistic regression model fit using the principal components for predicting stand-level disturbance events is presented below:

$$Disturbance\ Event = -0.13(PC1) - 0.11(PC2) + 0.20(PC3) - 0.42(PC4) + 0.67(PC5) - 1.71 \quad \{1\}$$

The logistic regression analysis of the principal components indicated that timber resources (PC3) ($p = 0.044$), precipitation (PC4) ($p < 0.001$), and slope (PC5) ($p < 0.001$) were all statistically significant in predicting the incidence of a landscape scale disturbance. The incidence of a stand-level disturbance increased with increasing stand volume (PC3), lower precipitation (PC4), and higher slopes (PC5). These results suggest that disturbance events may be related to increased stand competition and drought stress, as areas with lower precipitation and greater slopes would reduce long-term infiltration and soil moisture content (Cotillas et al. 2009, Powers et al. 2010), while increasing soil erosion and sun exposure.

In terms of model fit, the principal component model was highly statistically significant based on the Likelihood Ratio test ($p < 0.0001$). However, the estimated R^2 was quite low, 0.09, due to the inability of the model to accurately predict landscape disturbances at a fine spatial and temporal resolution. The Hosmer and Lemeshow (2000) Goodness-of-Fit statistic, which follows a chi-squared distribution, indicated that the null hypothesis (i.e., predicted events estimated using the model for dataset partitions are statistically the same as the observed data) cannot be rejected ($p = 0.94$) indicating excellent model fit. The Partition of the Hosmer and Lemeshow Test (see Table 5-8 and Figure 5-7) indicated that the model performed well at modeling the overall pattern in the data for the ten quantile partitions of the dataset. Overall, there was a 4.7% apparent error rate (i.e., total number of misclassifications divided by the total sample size, used for measuring logistic regression error) in the number of disturbance events estimated within each of the quantile partitions shown in Table 5-8 (Johnson and Wichern 2007). Figure 5-7 shows that the expected number of disturbance events within each quantile partition was highly correlated with the observed number of disturbance events ($R^2 = 0.91$). These results indicated that the logistic regression model performs well at describing the overall pattern of disturbance events as shown

Table 5-8 Partitions of the Hosmer and Lemeshow Test for Modeling Disturbance Events at the Plot Level Using Principal Components

Quantile	Total	Undisturbed Plots		Disturbed Plots	
		Observed	Expected	Observed	Expected
1	59	57	56.4	2	2.6
2	59	53	54.5	6	4.5
3	59	54	52.4	4	5.6
4	59	52	52.0	7	7.0
5	59	50	49.7	8	8.3
6	59	48	49.1	11	9.9
7	59	47	47.7	12	11.3
8	59	41	44.6	17	13.4
9	59	46	41.9	13	17.1
10	58	33	32.7	25	25.3

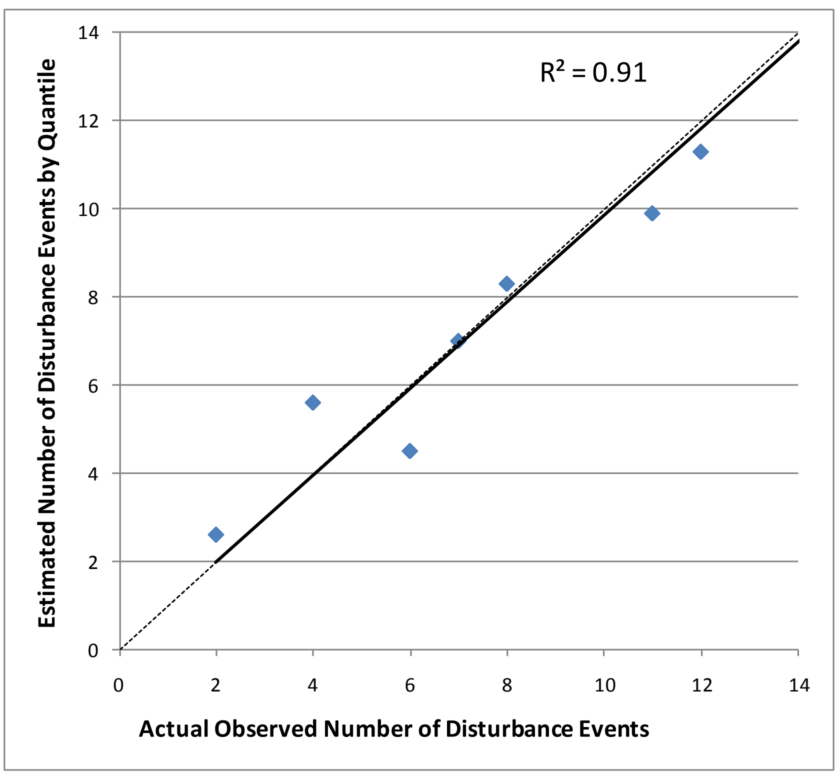

Figure 5-7 Disturbance Model Fit: Estimated Versus Observed Number of Disturbance Events by Quantile from 1989 to 2000 using Models fit Using Principal Component Variables

in Table 5-8 and Figure 5-7, but it cannot predict the exact location of a disturbance event at the finer resolution of an individual plot (as evident by the low estimated R^2 of 0.09 derived at the plot level). This model scale issue is due in part to the low frequency of occurrences (the percentage plots experiencing a disturbance event was 17% annually).

The logistic regression analysis of the selected independent variables indicated that only stand volume (m^3/ha) ($p < 0.001$), average annual precipitation ($p < 0.001$), and slope ($p = 0.01$) were statistically significant in predicting disturbance events across West Virginia as estimated using STAT11. Variables were removed from the model only if their inclusion did not significantly enhance the overall model fit based on a likelihood ratio chi-squared test ($p < 0.1$) (Xiao et al 2010). Other independent variables that were not statistically significant in improving model fit included: latitude ($p = 0.14$), elevation ($p = 0.72$), timber intensity ($p = 0.50$), ecoregion ($p = 0.65$), average minimum temperature ($p = 0.36$), and average maximum temperature ($p = 0.99$) based on the results of the likelihood ratio chi-squared test (Xiao et al. 2010). The logistic regression model fit using the original independent variables for predicting disturbance events is presented below:

$$Disturbance(1) = 0.00042(VOL/2.47) - 0.046(PREC) + 0.015(SLOPE) + 1.82 \qquad \{2\}$$

where:

VOL = the total stand volume of the central stems for all trees >5” DBH (m^2/ha);

PREC = Annual average precipitation (cm/year); and

SLOPE = percent slope (%).

Based on the logistic regression analysis, the following equation was derived using approaches discussed in Section 4 for estimating the probability of a plot experiencing a landscape scale disturbance that results in a net negative growth rate for the entire plot.

$$P(event) = 1 - 1/(1 + e^{(-1*(-0.006*VOL+0.0462*PREC-0.0153*SLOPE-1.82))}) \qquad \{3\}$$

In terms of model performance, the model fit using the original independent variables performed nearly the same as the model fit using the principal components. The Hosmer and Lemeshow Goodness-of-Fit statistic ($p = 0.95$) and the R^2 (0.08) for the independent variable model were very similar to the results obtained for the principal component model. The apparent error rate (i.e., total number of misclassifications divided by the total sample size) for the quantile partition level classification of 5.1% was very similar to the independent variable model of 4.7% (Johnson and Wichern 2007). The ten quantile partitions of the Hosmer Lemeshow test are shown in Table 5-9 and Figure 5-8. These results indicate that the simpler independent variable model yielded similar results to the principal component model. In order to improve computational efficiency, the simpler model based on the original independent variables, was used for conducting long-term disturbance event simulations to 2050 in the integrated model.

Table 5-9 Partition of the Hosmer and Lemeshow Test for Modeling Disturbance Events at the Plot Level Using Original Independent Variables

Quintile	Total	Undisturbed Plots		Disturbed Plots	
		Observed	Expected	Observed	Expected
1	59	57	56.3	2	2.7
2	59	56	54.2	3	4.8
3	59	52	52.1	6	5.8
4	59	50	51.9	9	7.1
5	59	51	49.8	7	8.2
6	59	49	49.2	10	9.8
7	59	46	47.4	13	11.6
8	59	41	44.8	17	13.2
9	59	44	42.2	15	16.8
10	58	35	33.0	23	25.0

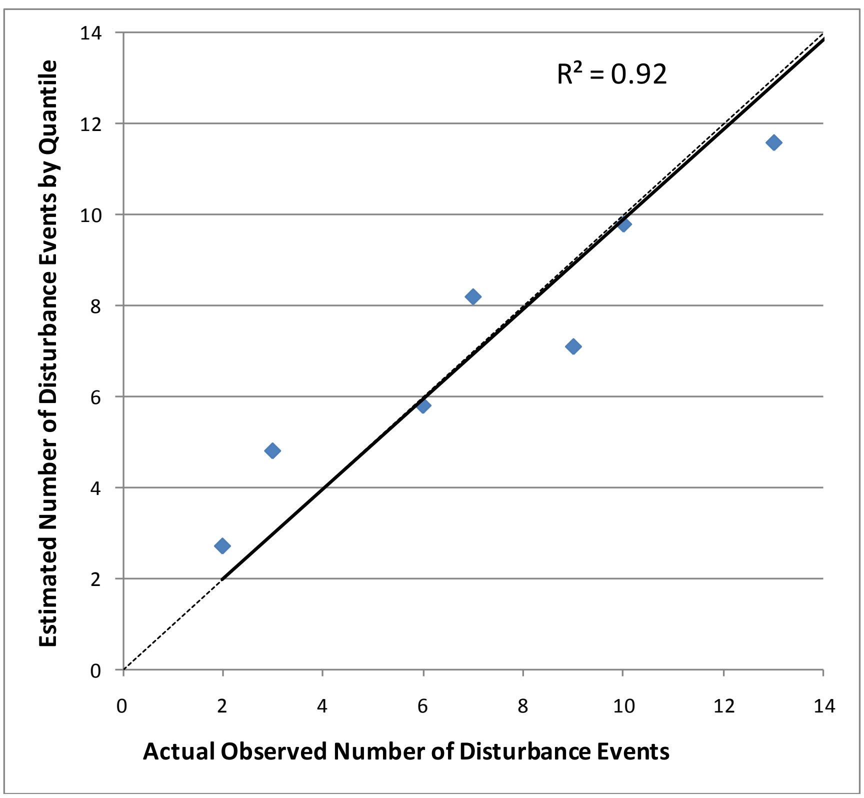

Figure 5-8 Disturbance Model Fit: Estimated Versus Observed Number of Disturbance Events by Quantile from 1989 to 2000 using Models fit Using Independent Variables

For conducting a long-term simulation to 2050, it was also important to determine if forest stand biomass projected in the long-term would fall within the model domain of the regression analyses discussed in Section 5. For example, if the integrated model were to predict forest stands with biomass in excess of those currently observed in West Virginia, then these empirical regression models may not adequately capture the relationships between forest biomass and disturbance frequencies for stands that exceed the bounds of this analysis. Based on CFM simulations discussed further in Section 6, it was estimated that at least 97% of the plots still had projected forest stand volumes in 2050 that were within the bounds of stand volumes seen in West Virginia in 2000 (albeit that a higher percentage of stands were in a higher state of recovery). Therefore, the empirically modeled relationship between stand volume and probability of disturbance modeled using current data was considered adequate for simulating long-term disturbances to 2050.

The results of the logistic regression analysis indicated that past timber removals did not significantly affect the probability of whether a plot would experience a net negative growth rate ($p = 0.5$), based on a likelihood ratio chi-squared test. Therefore, timbering events do not appear to affect this important disturbance dynamic. Furthermore, differences in ecoregional province location were not statistically significant in impacting disturbance potential ($p = 0.65$). Slope ($p = 0.01$), average annual precipitation rate ($p < 0.0001$), and estimated stand volume ($p < 0.0001$) were the only statistically significant variables that explained the incidence of plot-level disturbances. Overall, plots with steeper slopes, lower annual precipitation, and greater stand volume were more likely to experience a net negative growth rate, than other forest plots. Plots with steeper slopes and lower average annual precipitation would more likely receive lower water infiltration (due to higher runoff rates due to the slope, and lower potential for precipitation), which may stress the trees resulting in higher tree mortality, negative growth, and reduced positive growth observed in the data. Trees on steeper slope may also be more susceptible to erosion impacts and sun exposure.

The results also show that higher stand volume increased the incidence of landscape disturbances, which could be due to the added effect of competition, particularly during periods of stressed environmental and/or climatic conditions (e.g., reduced rainfall, higher or lower temperatures), and/or increased susceptibility to disease or infestation. Increased incidence of landscape scale disturbances has also been seen in other forest research in maturing forests in North America as a result of an array of disturbances, including drought stress, pest infestation, and fire (USGCRP 2008, Bouchard et al. 2008, Cotillas et al. 2009, Powers et al. 2010).

The increased incidence of disturbance for stands with higher volumes/biomass would inevitably create higher variability in net growth for forest stands in advanced stages of recovery, which is seen in Figure 5-3. Although net growth increases as tree volume increases at the tree-level, there appears to be factors that occur at the plot-level that may inhibit positive growth, and induce increased mortality and negative growth rates for stands with higher stand volume. This landscape-level dynamic would create a cross-scale negative feedback mechanism that would result in more variability in plot-level net growth as stand volume increases, which is indeed observed in the FIA data (shown in Figure 5-3). Thus, addressing this plot-level disturbance dynamic is important when considering long-term biomass and carbon dynamics, as the impact of disturbances and stressors operating at larger scales (e.g., microscale climatic conditions or insect infestation) may increase as stand volume increases.

This plot-level disturbance dynamic underscores a limitation in projecting increased landscape level growth, biomass, and carbon due to restoration and recovery using only tree-level growth regression models and ignoring larger scale disturbance effects, which ultimately impacts statewide biomass and carbon predictions. For example, ignoring such processes could lead to significantly over estimating long-term biomass and carbon sequestration potential of maturing forest stands, as maturing forest stands become more vulnerable to losing a portion of their biomass due to landscape scale disturbances. Even if tree-level models are calibrated to average growth rates across a large landscape (which would include some disturbance effects), such an approach would not adequately address long-term stand growth and carbon sequestration potential as landscape scale disturbances may increase in frequency and severity as stands mature in the future (such increased rates would not be reflective in the empirical analysis of current growth and disturbance effects). Furthermore, ignoring these types of disturbances could significantly reduce estimated stand level variability estimates across a larger landscape, as the tree-growth models would typically predict net stand growth for all plots, while in actuality 1/5th of the stands in West Virginia lost live biomass and acted as carbon sources due to landscape level disturbances. Although these processes can be modeled through user-defined scenarios in both FVS and PnET-CN, this analysis underscores the importance of addressing these landscape scale disturbances when conducting long-term projections of biomass and carbon sequestration across a large landscape.

Other landscape-level forest research has also shown the importance of addressing large-scale disturbance regimes when estimating long-term biomass and carbon dynamics across a region (USGCRP 2008). The cause and effect of landscape disturbances on forest resources is a complex process that requires detailed analysis of site-specific and landscape-level conditions and processes that are often species and forest-type specific (USGCRP 2008). Anthropogenic disturbances and forest management practices can often alter these relationships, creating new cumulative effects. Studies have shown that significant disturbance events are cyclical and spatially clustered in nature, with many fire and insect related disturbance events increasing in frequency and severity due to increased stand density or age, competition, and adverse climatic conditions (e.g., drought), as well as species composition (e.g., host species) (Alfaro et al. 2001, Bouchard et al. 2008, Chen et al. 2008, Hanson and Weltzin 2000, Harvey et al. 2002, Porte and Bartelink 2002, Yu et al. 2009). Furthermore, USFS stand density related mortality models estimate increased tree mortality rates, when stand density approaches the maximum basal area estimated for a stand (USFS 2010b,c). Drought has also been shown to increase the rate of mortality in tree species, which can also increase the vulnerability of stands to other disturbance regimes (fire and insect infestation) (Bouchard et al. 2008, USGCRP 2008). Stand thinning has also been shown to reduce mortality rates and soil moisture content during drought conditions, indicating that droughts may increase competition for remaining resources and increase mortality rates for stands with higher stand density (Cotillas et al. 2009, Powers et al. 2010). To date, modeling disturbance regimes has been recognized as an important dynamic for more accurately addressing long-term stand biomass and carbon projections, in considering the complex and region-specific disturbance interactions and cyclical characteristics that impact many forest systems (USFS 2010b,c; Schelhaas et al. 2002; Seidl et al. in press; Sturtevant et al. 2004).

5.3.3 Tree-Level Mortality and Regeneration

The results of an ANOVA test indicated that timbering events did not have a statistically significant effect on the volume of mortalities ($p = 0.26$) or regeneration rates ($p = 0.08$) on forest stands across West Virginia. In addition, the results of the multiple regression analyses indicated that timber removal intensity did not significantly impact total mortality rates ($p = 0.26$) or poletimber regeneration rates ($p = 0.17$) at the plot level. Based on these results, status quo timbering methods used in West Virginia do not appear to be having a measurable statistically significant effect on mortality and regeneration rates (either positive or negative).

To estimate tree mortality rates for the integrated model, a heuristic analysis of the FIA data was initially conducted to identify key variables that may impact tree mortality rates. This analysis was also informed by evaluating other tree mortality models and key parameters utilized by USFS for estimating tree-specific mortality probabilities, which are based on tree size classes (USFS 2010b,c). Overall, much higher mortality rates were seen on plots with net negative growth rates; therefore, tree mortality probabilities were developed separately for each tree size class and disturbance regime. For plots that experienced a disturbance, the incidence of tree mortality significantly increased (17 times) for the largest sized trees. For plots that didn't have a net negative growth rate, the incidence of tree mortality was actually lowest for the largest size tree class. The probabilities developed from this heuristic analysis were then used in a Monte Carlo simulation analysis to predict the incidence of these events as seen in the FIA database for the 2000 sampling period.

For tree regeneration, the CFM model tracks only poletimber and sawtimber tree dynamics over time (and not saplings < 5"); therefore, it was necessary to predict the number of new poletimber trees that will be added to a plot in the future from continued growth of saplings. On average, approximately 0.13% of the biomass that is added to the total tree biomass pool for the stand (for all trees above 5" DBH) is the result of annual regeneration (i.e., growth of new poletimber trees added to the stand). This added volume is approximately 30% of the tree volume removed from timbering actions; therefore, it represents a smaller, but still significant dynamic that impacts tree volume and biomass, which was modeled in CFM.

5.3.4 Integrated Model Verification and Validation

The timber models presented in Section 4 were integrated with the models and methods discussed above for estimating volume growth, disturbances, mortality, regeneration in order to simulate net change in live forest volume (m^3/ha) from 2000 to 2050. The models were applied to the plot-level dataset (representing nearly 1,500 forested plots located randomly across West Virginia) and tree-level dataset (representing 60,000 trees) for the 70% sample to predict near-term annual changes in forest volume. Overall, the integrated CFM model estimated average net annual live forest volume growth of 1.33% in 2000 (five year average of 1.34%), which includes positive growth, negative growth, mortalities, timbering, and landscape disturbances, while FIA field measured value was very similar at 1.32% (within 1% of the observed value).

Figure 5-9 presents a graphical comparison of the CFM modeled net growth and the FIA field measured growth by quantile of forest stand density for stands that were not timbered between 1988 and 2000 and experienced positive net growth, which includes over 80 percent of the forest stands. The modeling results indicate that CFM was able to replicate forest plot-level net annual growth rates measured in the field using FIA for each of the quantiles. Currently, forest stands with higher aboveground tree volume continued to grow at a higher rate as compared to stands of lower volume, as shown in Figure 5-9, which is evident of a system that is still in a state of recovery. Figure 5-10 provides the same comparison using the original data, prior to aggregation

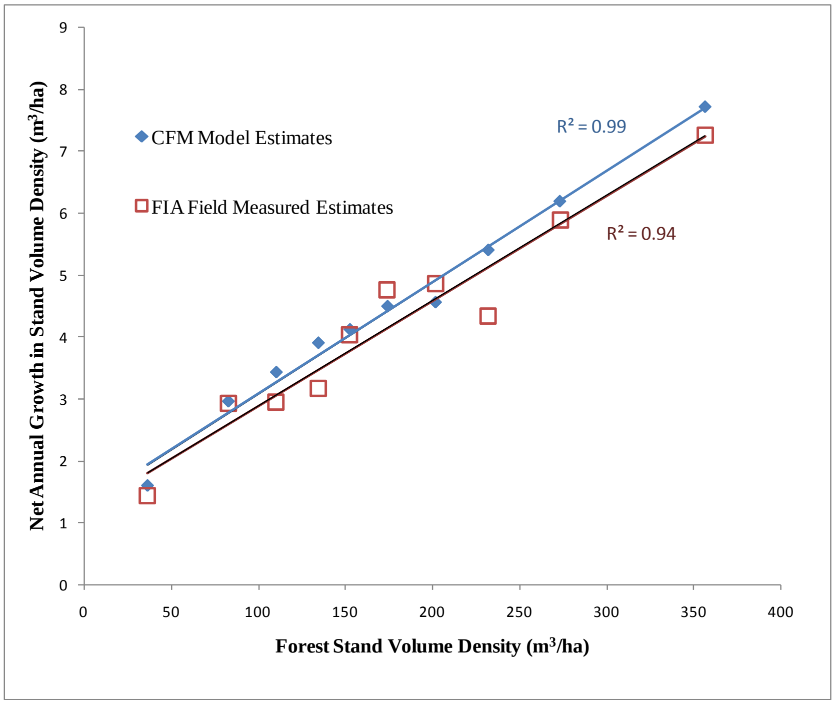

Figure 5-9 Comparison of Plot-Level CFM Modeled Net Growth and FIA Field Measured Net Growth by Forest Stand Density Quantiles

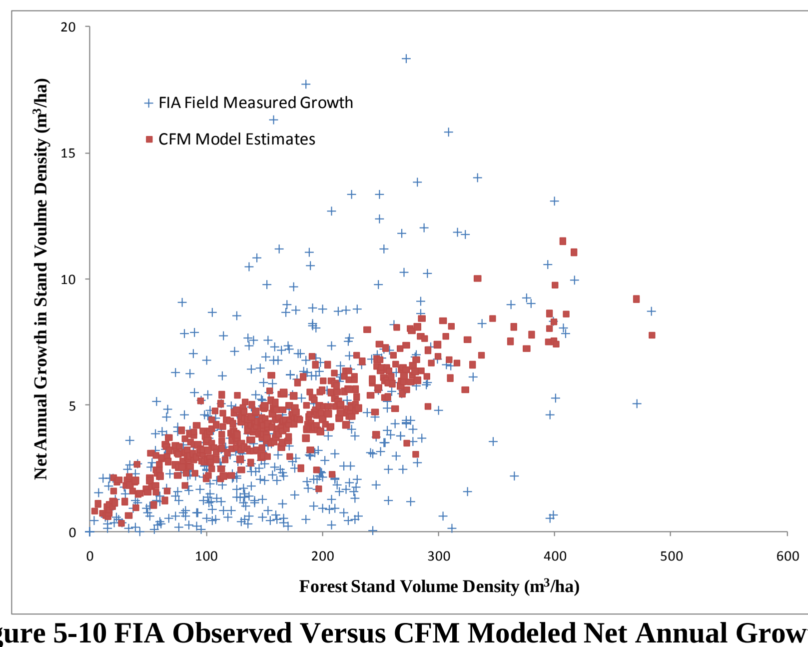

Figure 5-10 FIA Observed Versus CFM Modeled Net Annual Growth (m^3/ha) (without Monte Carlo analysis of natural variation) by Forest Stand Volume Density

into quantiles. Note that the predicted data presented in Figure 5-10 is not based on a Monte Carlo simulation of natural variability in the growth response; thus, there is less variability in the predicted estimates which fall mainly along the average trend line.

For model verification purposes, Figure 5-11 presents FIA field measured net annual growth rates (observed values) versus predicted CFM modeled net annual growth rates for quantile partitions of the data (R^2 = 0.94 for the average quantile values). The results presented in these figures indicate that CFM was able to replicate the magnitude and pattern in growth response for forest stands of different size classes.

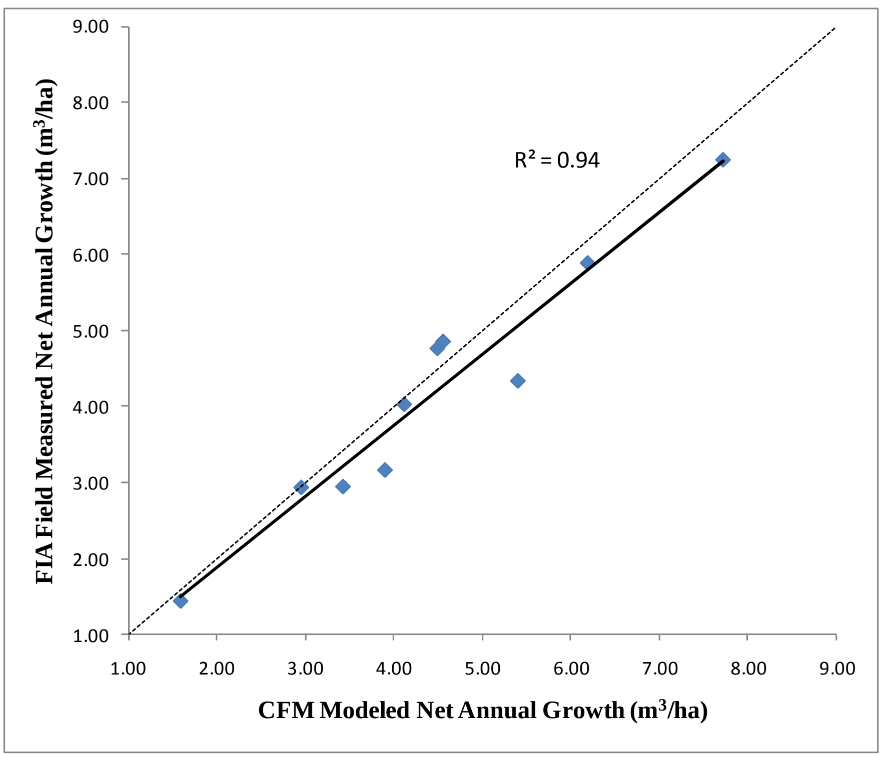

Figure 5-11 FIA Observed Versus CFM Modeled Net Annual Growth (m^3/ha) by Forest Stand Volume Quantiles

An analysis of the annual net growth for the 30% out of sample dataset was also performed for model validation purposes. The average annual net growth for the 30% out of sample dataset based on FIA field measured net annual growth was 1.40%, which includes positive growth, negative growth, mortalities, timbering, and landscape disturbances. CFM modeled average annual net growth for the 30% out of sample dataset was 1.38% in 2000 (5 year average growth of 1.33%), which was within 1% of the observed value. Overall, the results of the verification and validation study indicated that CFM generated reasonable estimates of net growth (factoring in growth, disturbances, and timber removals) that were commensurate with FIA field measured growth and timbering rates for West Virginia.

5.4 Conclusions

Beyond the direct impact of a timbering event, which removes forest biomass and future growth potential, timbering activities did not have a significant indirect effect on net growth rates, landscape level disturbances, regeneration rates, or mortality rates for the trees that remain on the plot. Rather, other plot condition variables were much more important in predicting growth, mortality, and regeneration, including tree volume, stand volume, annual precipitation, and slope.

Forest stands with the highest tree volumes still continued to grow more in volume than stands with lower volumes, but their growth rates appeared to be decelerating commensurate with a sigmoid growth response. This continued growth may be due to the fact that many forest stands in West Virginia are still in a state of recovery (Brown et al. 1997). The cumulative effects of timbering, positive growth, negative growth, mortality, and regeneration simulated using CFM replicated timbering patterns and net growth reasonably well. CFM estimated the net live forest volume growth rate of forests in West Virginia in 2000 to be 1.38% (5 year average was 1.33) (factoring in removals, mortality, positive growth, negative growth, and regeneration) for the 30% out of sample validation dataset, while the estimated FIA observed net live forest volume growth rate in 2000 was 1.40%. Thus, CFM was able to replicate the cumulative effect of these factors on net annual growth rates reasonably well, i.e., within 1% of field measured value.

Stands with large volumes appeared to be more susceptible to landscape level disturbances and exhibited greater variability in terms of annual growth response, than forest stands with smaller volumes. Landscape level disturbances, resulting in net negative growth rates observed on about $1/5^{th}$ of the plots from 1989 to 2000, occurred on plots with lower average annual precipitation, higher slopes, and higher stand volumes. Although forest stands with higher tree volumes had higher growth rates, their apparent increased vulnerability to landscape level disturbances creates a negative cross-scale feedback mechanism that diminishes growth for some plots and creates greater stand growth response variability for higher stocked stands. Timbering events did not increase the frequency of these landscape level disturbances. These landscape disturbances reduced live tree volumes on plots nearly to the same extent as total timbering activities across the state, indicating that disturbance regimes operating at larger scales (e.g., climate shifts resulting in localized droughts) may significantly impact landscape level growth, biomass, and carbon sequestration. The results of this study indicate that ignoring such processes could lead to significantly over estimating long-term biomass and carbon sequestration potential of maturing forest stands, as maturing forest stands become more vulnerable to losing a portion of their biomass due to landscape scale disturbances. This result assumes that climatic conditions and drought potential remains the same for West Virginia over the next half century. If the incidence of severe climatic events increases over time, then this may exacerbate this problem and increase vulnerability of the forest systems to these types of disturbance regimes. Furthermore, ignoring these types of disturbances could significantly reduce estimated stand level variability estimates across a larger landscape, as the tree-growth models would typically predict net stand growth for all plots, while in actuality $1/5^{th}$ of the stands in West Virginia lost live biomass and acted as carbon sources due to landscape level disturbances. Although these processes can be modeled through user-defined scenarios in both FVS and PnET-CN, this analysis underscores the importance of addressing these landscape scale disturbances when conducting long-term projections of biomass and carbon sequestration across a large landscape.

There are limitations with the disturbance modeling approach, which could be further refined through additional research. For example, there are other biophysical characteristics, such as historic disturbance effects, climatic patterns, longitude, micro-scale drought patterns, terrain classification, slope orientation, and other factors that may create spatial patterns and explain some of the variance in disturbance events not captured in this analysis. Evaluation of many of these variables would be difficult to analyze with the FIA dataset, as the exact locations are not publically available. Through working with the USFS, it may be possible to utilize the actual coordinates of the FIA plots and obtain higher resolution drought, terrain classification, and other biophysical data that could refine this analysis. Further studies and research are needed to determine whether some of these other factors are important and whether spatial and regional patterns exist in the data.

Overall, the empirical modeling approach performed better than the process-based modeling approach in estimating forest growth across West Virginia. By adjusting key historic disturbance variables, the PnET-CN/sat model runs were able to replicate estimates of AGBD in the wood pool for baseline conditions that were within 10% of observed values for 85% of the plots in Boone and Tucker Counties. However, several concerns were raised: 1) site-specific data were not available to properly parameterize the model and regional average statistics were not sufficient to fit the model for about 60% of the plots; 2) the model was very sensitive to the agriculture disturbance assumption (1750 to 1850) for which little data were available; and 3) the key area of concern was that the growth response profiles for the AGBD wood pool did not match observed data from FIA regardless of how the disturbance regimes were manipulated. Further research is recommended for parameterizing and validating wood pool fluxes in PnET-CN across a broader array of disturbance regimes and stands for larger geographical areas.

6. Long-Term Effects of Timbering on Forest Resources using an Integrated, Multi-Scale Model

6.1 Introduction

Over the past several decades, forest resources throughout the northeast, including West Virginia, have continued to increase in biomass (USDA 2008, Brown et al. 1997). It is uncertain how recent and future timbering will impact forest biomass and continued recovery of West Virginia forests into the 21st century. Furthermore, increased emphasis on sustainable forestry practices and state sustainable policy development may have benefits to the overall state forest ecosystem, but it is unclear to what degree such measures will improve forest ecosystem indicator metrics and timber resources, as well as alter timbering effects at a landscape scale. To address these issues, this portion of the study analyzes the long-term effects of timbering on forest ecosystem and timber resource indicator metrics at multiple scales across West Virginia from 2000 to 2050 under different timber market and silviculture scenarios.

The overall research question addressed by this portion of the study is: *What long-term effect will status quo and sustainable timbering scenarios, under varying timber market conditions, have on forest ecosystem and timber resource indicator metrics in West Virginia?* To address this question, a status quo scenario and one sustainable timbering scenario were analyzed in this study. Specific forest ecosystem indicator metrics were defined and simulated for each scenario in order to evaluate changes in forest resources over time. In this context, an indicator metric is a specific measured parameter that can be readily analyzed and obtained (e.g., AGBD from FIA) that serves as a surrogate measure of a particular criterion that describes a forest process or issue of interest (e.g., biological diversity conservation) (Montreal Process 2009). For this research, indicator metrics were developed that describe habitat conservation and important elements of sustainable forest management. Forest ecosystem indicator metrics are further defined and discussed in Section 6.2.3. These metrics were estimated for the status quo timbering scenario under varying timber market economic conditions in order to evaluate potential outcomes under status quo timbering conditions (i.e., continuation of current timbering practices as modeled in Section 4), as discussed in Section 6.1.1.

To address the sustainable forestry research question, sustainable forest management requirements were imposed on the system to evaluate potential outcomes as compared to the status quo timbering scenario. These restraints consisted of limiting timber removals to no more than 30% of the timber volume, conserving the largest trees in the stand to improve stand structure, conserving all trees which are important features of old growth forests (> 70 cm in DBH), and ensuring that timber rotations are not less than 20 years (Buehler et al. 2007, Register and Islam 2008, Brown et al. 1997, USFWS 2009, Wood et al. 2005). Using this approach, it was possible to test how this sustainable timbering scenario has the potential to affect system level dynamics, including tree-, stand-, and state-level forest indicator metrics and timbering practices. The specific timbering constraints, methods, and background information pertaining to the sustainable timbering scenario are discussed in Sections 6.2.4 and 6.2.6.

Developing a sustainable timbering policy may involve testing a range of specific regulatory controls and prescriptions, subsidies, certifications, market-based carbon credits, taxes, and other instruments to achieve the desired objective of the policy. The development and testing of specific policy instruments is beyond the scope of this research. To do so would require targeted surveys and participatory modeling techniques to simulate the change in human behavior from implementation of a specific policy (Parker et al. 2003, Bousquet and Le Page 2004). Only with such carefully designed surveys and methods would it be possible to utilize CFM to test the effectiveness of a specific policy instrument. But as a first step in this process, it is important to first understand the theoretical benefits and limitations of implementing a policy if it were put into place. To that end, this analysis is only a visioning exercise to assess certain theoretical outcomes (both potential positive and negative) that may occur by implementing sustainable forest management strategies across the state assuming the goals of the policy were achieved. This analysis makes no prediction of specific policy outcomes or probability of success. The sustainable timbering scenario to be evaluated and hypotheses to be tested are outlined in Section 6.1.2.

6.1.1 Status Quo Timbering Scenario

The status quo timbering scenario assumes that basic timbering practices will continue to occur into the future as modeled in Section 4, i.e., the range of timber practices will occur and the intensity will fluctuate in response to timber prices. CFM was used to simulate the status quo timbering scenario in order to evaluate how, and the degree to which, forest ecosystem indicator metrics would change from 2000 to 2050, assuming current timbering practices occur. These metrics were estimated for the status quo scenario under two different timber market economic conditions: 1) a most-likely timber market scenario, i.e., 0.24% annual increase in timber prices with inflationary effects removed, as projected as the most-likely long-term average growth based on national economic modeling by USDA (2003); and 2) a high timber market scenario, i.e., a 1% annual increase in timber prices with inflationary effects removed, which has occurred over the past 2 decades. Based on recent trends in forest biomass growth in West Virginia reported by USDA (2008) from 1990 to 2005, *it is hypothesized that under most-likely market conditions (i.e., 0.24% long-term average annual increase in timber prices) forest ecosystem indicator metrics and forest stand recovery will continue to improve to 2050.* However, if timber prices continue to increase as they have in the past two decades (~1% per year), then *it is hypothesized that forest ecosystem indicator metrics and forest stand recovery will diminish relative to most-likely scenario market conditions to 2050.* Table 6-1 presents the inferred relationships between these scenarios and the indicator metrics. As these are inferred relationships, the null hypothesis that these market scenarios have no impact on forest ecosystem indicator metrics was also evaluated.

Table 6-1 Hypothesized Long-term Annual Trends in Forest Ecosystem Indicator Metrics Over Time for the Most-Likely and High Timber Market Scenarios

Forest Indicator Metrics	**Most-Likely Timber Market Scenario Relative to 2000**	**High Timber Market Scenario Relative to Most-Likely in 2050**
State Forest AGB (tg)	+	—
Average AGBD (g/m^2)	+	—
Average % of State Timber Harvest to Net Growth in AGB	—	+
State Commercial Timber Volume (10^6 m^3)	+	—
State Forest AGB (tg) of Black Cherry and Red Oak AGB (tg)	+	—
Average State Frequency of Low Intensity Timbering Events	+	+
Average State Frequency of Medium/High Intensity Timbering Events (> 30% AGBD removals)	+	+
% of Biomass in Large Trees (>70 cm)	+	—
% of Advanced Recovery Plots (AGBD > 15,000 g/m^2)	+	—
% of Old Growth Plots	+	—
"+" = Increase in metric from the previous year; "—" = decrease in metric from the previous year; "blank" = no major change in metric		

6.1.2 Sustainable Timbering Scenario

Currently, many timber removals are not conducted in a manner that would be considered sustainable. As discussed in Section 4, only 13% of timber removals across West Virginia were considered low intensity timber removals (i.e., below 30% biomass removal), while over 87% of the timber removals were medium or high intensity removals, with 6% consisting of clear cuts. In some cases, forest plots have been over-harvested. Also, removal of the largest and commercially valuable trees (e.g., diameter limited cuts) reduces stand structure and complexity, which are important for biodiversity. Implementing sustainable timbering measures discussed previously (i.e., restricting removals to < 30% of stand volume, conserving the largest trees, and lengthening rotation cycles to > 20 years) would constrain the amount of biomass and short-term economic return that can be harvested from a forest stand, thereby conserving much of the trees for future growth and production of ecological services (including forest resources for future timber removals). However, the end result of constraining timber removals may be that more plots are timbered across the state in a given year in order to meet annual market demand for timber, due to a shifting of timber removal activity. As such, the cumulative effect of implementing sustainability practices at a state level will be addressed, including shifts in timber impact and potential increases in low intensity disturbances that may result. For this scenario it is assumed that any timber removal would occur in accordance with sustainable timbering practices and such removals may occur at any location across the state; therefore, the principal adverse effect that is evaluated in this analysis is the potential increase in timber frequency across forest stands of the state to make up for the loss of timber revenue due to the sustainable timbering restriction.

Using CFM it was possible to test how various sustainable forestry silviculture techniques affect forest ecosystem indicator metrics and timber resources relative to status quo timbering methods.

Overall, *it is hypothesized that if sustainable silviculture practices are applied across West Virginia (while still achieving the same annual total timber production across the state), then forest ecosystem indicator metrics and forest stand recovery will be significantly enhanced.* Table 6-2 presents the inferred relationships between the sustainable timbering scenario and indicator metrics relative to status quo conditions. As the relationships presented in Table 6-2 are inferred, the null hypothesis that the sustainability timbering scenario has no impact on forest ecosystem indicator metrics was also evaluated.

Table 6-2 Hypothesized Annual Trend in Forest Ecosystem Indicator Metrics Over Time for the Sustainability Scenario Relative to the Status Quo Timbering Scenario (under Most-Likely Timber Market Conditions)

Forest Indicator Metrics	Change in Metric for the Sustainability Scenario Relative to Status Quo Timbering
State Forest AGB (tg)	+
Average AGBD (g/m^2)	+
Average % of State Timber Harvest to Net Growth in AGB	—
Average State Frequency of Low Intensity Timbering Events	+
Average State Frequency of Medium/High Intensity Timbering Events	—
% of Biomass in Large Trees (>70 cm)	+
% of Advanced Recovery Plots (AGBD > 15,000 g/m^2)	+
% of Old Growth Plots	+
"+" = Increase in metric from the previous year; "—" = decrease in metric from the previous year; "blank" = no major change in metric	

6.2 Methods

6.2.1 Modeling Approach

To simulate changes in forest ecosystem and timber resource indicator metrics, a multi-scale integrated model, CFM, was developed and tested as part of this study (see Section 3.1 and Figure 3-2 for a description of the conceptual model). The models developed in Sections 4 and 5 were combined with a timber price model (discussed in Section 6.2.5) to simulate indicator metrics of ecological services under different timber scenarios and market conditions. To address fine-scale effects, CFM was used to conduct future simulations of timbering events and forest growth for each tree (60,000 trees across West Virginia) and plot (1,500 plots forested plots randomly located across West Virginia) on an annual time step, for a 50 year duration (2000 to 2050). For each annual iteration, the model estimated endogenous variables using Monte Carlo simulation and randomization of estimates using the models discussed in Sections 4 and 5 and exogenous variables presented in Table 6-3. CFM was initialized based on field measured tree and plot data (see Table 6-3) from 70% of the FIA plots located randomly across West Virginia for the 2000 sampling period.

To model AGBD at the tree-, plot-, and state-level, the logistic and multiple regression equations discussed in Section 5 were used to estimate changes in the central stem volume for each tree and plot on an annual time step in CFM based on the multiple factors impacting live tree volume including growth, mortality, regeneration, and landscape disturbances. Total tree biomass was then estimated for each poletimber and sawtimber tree using simple regression models, which relate estimated central stem volume to the total biomass of the tree (which includes the roots,

Table 6-3   CFM Endogenous and Exogenous Variables

Model Parameter	Units	Field Data Source/Derivation
ENDOGENOUS VARIABLES		
State-Level Indicator Metrics	Forest ecosystem and timber resource metrics are discussed in Tables 6-1 and 6-2.	
Regional-Level Timber Prices in 2006 to 2050	\$/MBF	Simulated timber prices based on trends analysis of market price fluctuations and USDA 2003.
Plot-Level Disturbance that Impacts Growth and Mortality Rates	boolean	Probability based on logistic regression analysis (Section 5) that relates stand volume, annual precipitation, latitude, elevation, and slope to the probability of a landscape level disturbance.
Plot-Level Tree and BF Volume	m^3/ha	Derived by compiling tree-level volumes and growth, which are derived on an annual basis.
Plot-Level Tree and BF Volume for RO and BC	m^3/ha	Derived by compiling RO and BC tree-level volumes and growth, which are derived on an annual basis.
Plot-Level AGBD for Live Trees > 5" DBH	g/m^2	Derived by compiling tree-level biomass values, derived using models presented in Section 6.2.2.
Plot-Level Timber Value	\$/ha	Total tree-level values derived on an annual basis.
Plot-Level Removals of Timber (BF) and Biomass	g/m^2 m^3/ha	Removals derived by compiling tree-level volumes and biomass removed during timbering events.
Plot-Level Timbering Disturbance	unitless	The frequency and intensity of removals are tracked at for each plot.
Tree-Level +/- Growth for Gross Volume and BF	m^3	Derived growth using regression models from Section 5 and landscape level disturbance probabilities.
Tree-Level Mortality	boolean	Derived tree mortality event probability
Tree-Level Regeneration of a Poletimber Trees	m^3	Derived using probabilities based on forest stand total volume. Tree species assigned randomly based on relative volume of different species for the forest type.
Tree-Level tree biomass	kg	Derived using regression models in Figure 6-1.
Tree-Level value	\$	Derived using BF and regional stumpage prices (\$/BF).
Tree-Level removals	unitless	Derived probability of tree removal based on value, stand value density, and ownership regime.
EXOGENOUS VARIABLES		
Plot-Level Initial Timber Stand Stump Value	Total \$ value/ha	Based on FIA 2000 Plot Data providing BF and Regional Species-Specific Stumpage Prices in WV using 2000 regional price data obtained from http://ahc.caf.wvu.edu/
Plot-level Forest Type	Unitless	FIA 2000 Plot Data
Tree-Level AGB and total tree biomass in 2000	kg	FIA 2000 Plot Data
Tree-Level Volume (Gross and BF) in 2000	kg	FIA 2000 Plot Data
Tree Species Category	Unitless	FIA 2000 Plot Data http://www.fia.fs.fed.us/. Tree species categories are presented in Table 3-1.

stump, central stem, and tree tops). These regression models, presented in Figure 6-1, were derived using FIA data which includes data on the estimated central stem volume of each tree and the estimated total tree biomass for the tree (USFS 2010a). Excellent model fits were obtained for these simple regression equations with R^2 ranging from 0.89 to 0.99 for each of the species categories. Other non-linear regression methods also may be appropriate for certain species, as some of the relationships shown in Figure 6-1 indicate a slight curvature for certain data points. For example, a non-linear polynomial model was applied for white oak, which yielded an excellent model fit (R^2 =0.985), although these results were not substantially different from the linear model (i.e., R^2 = 0.982). Thus, the linear regression model fits were considered to be sufficient for converting tree volume to biomass for the purposes of this study.

6.2.2 Sensitivity and Uncertainty Analysis Using Monte Carlo Simulation

CFM underwent both a sensitivity analysis and uncertainty analysis using Monte Carlo simulation to assess the range of possible outcomes given the complexity of the integrated, multi-scale model. The purpose of the sensitivity analysis was only to evaluate the relative sensitivity of the integrated model output to different input model parameter values, as well as the relative importance of these variable values in predicting biomass estimates. As integrating several models and variables may compound model errors, the sensitivity analysis was important to identify the specific model variables that had the largest impact on long-term model estimates of biomass in 2050. The sensitivity analysis, however, was not used for predicting long-term biomass estimates, which was the focus of the uncertainty analysis discussed further below.

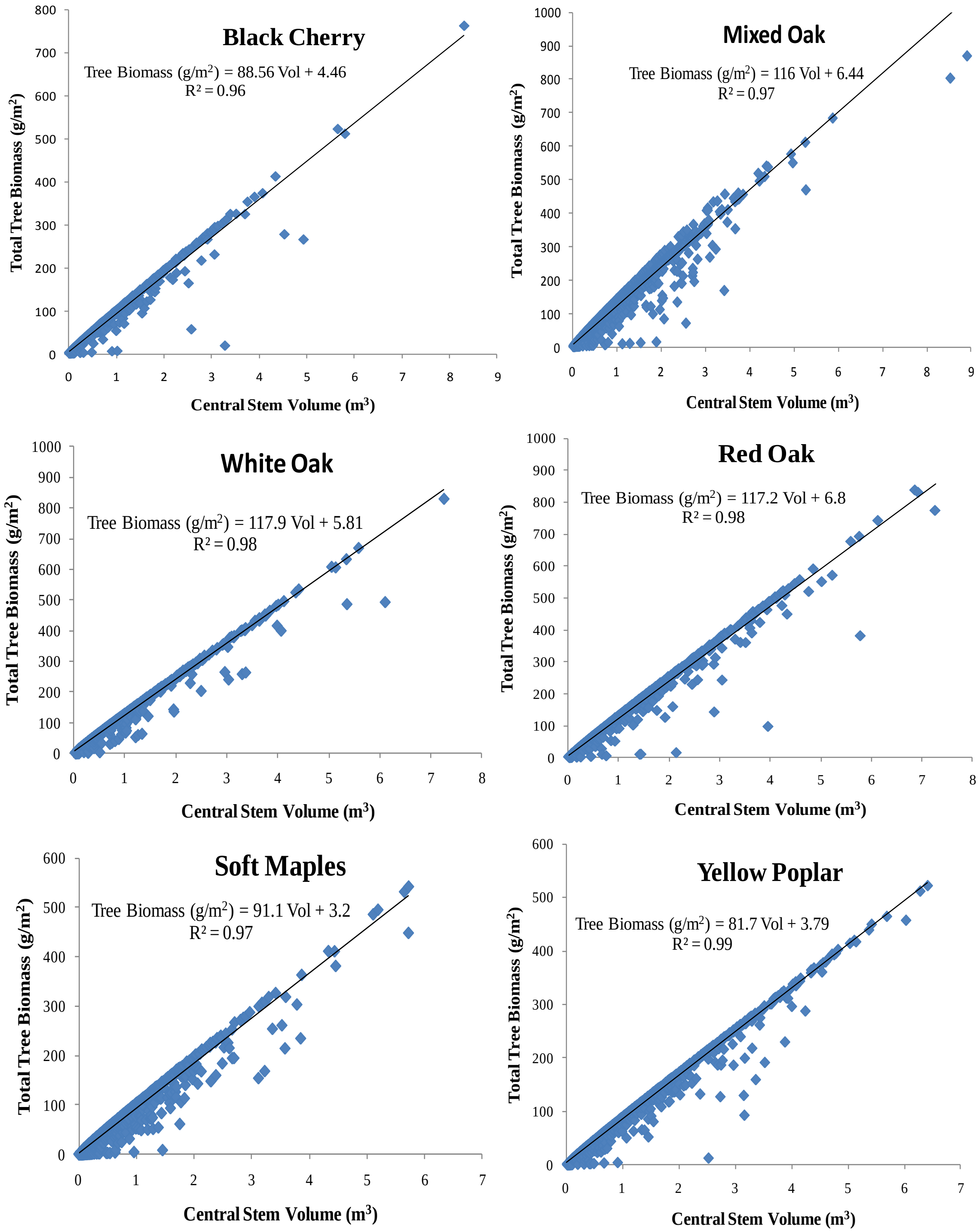

Figure 6-1 Models for Predicting Total Tree Biomass Based on Central Stem Volume for Key Species (BC, MO, RO, SM, WO, and YP)

The sensitivity analysis involved varying the principal variables that drive forest biomass, growth, and timber frequencies and intensity by +/-25% of their most-likely value. The same value was applied for all variables included in the sensitivity analysis in order to compare their impact on forest biomass estimates over time. The magnitude of this variation was chosen because of the high variability of some of the input parameters which could potentially mask the effect of the change, if a smaller factor was applied. For example, the average percent change in annual prices was 12% (with a standard deviation of 9%); therefore, it was more appropriate to use a larger sensitivity factor [well above 5 or 10%] to assess the impact of price changes on biomass. The following variables were included in the sensitivity analysis: probability of timber removal, timber prices, mortality rates, landscape disturbance rates, negative growth rates, positive growth rates, and generation of new poletimber tree rates. Key model output metrics that were tested in the sensitivity analysis were average AGBD (g/m^2) removed by timbering from 2000 to 2050 and average plot AGBD (g/m^2) in 2050.

In addition to the sensitivity analysis, a stochastic uncertainty analysis using Monte Carlo simulation was conducted for all key variables in CFM. The uncertainty analysis utilized Monte Carlo simulation techniques to estimate forest biomass from 2000 to 2050. This Monte Carlo simulation included a full randomization of parameter distributions for input variables in order to evaluate the long-term variation in scenario outcomes to 2050. The results of the uncertainty analysis were used to derive confidence intervals around long-term estimates generated by the integrated model. When distribution statistics were available for these variables, then the values were generated by selecting randomly from these distributions. When ranges and most-likely values were only available, then a triangular probability distribution was used to generate values used in the analysis. When the range was unknown, then the value was varied by a reasonable degree using a triangular distribution (e.g., +/-25%). For regression models, the most-likely estimated value and the mean square error were used to generate probable values for individual calculations. Many variables and modeling processes were included in the Monte Carlo simulation, with up to 3 tiers of nested simulations. The metrics that describe these distributions for these variables are presented in Table 6-4.

6.2.3 Forest Ecosystem and Timber Resource Indicator Metrics

This section describes specific forest ecosystem indicator metrics that were used as indicators of forest resource condition and recovery for the entire state. For this research, indicator metrics were developed that describe habitat conservation and important elements of sustainable forest management. In this context, sustainable forest management refers to the ability of the forest system to produce ecological services for the environment (e.g., wildlife habitat, food), as well as consumptive and non-consumptive services for human use (e.g., timbering, recreational use) that do not compromise the needs of future generations (USFS 2000). Although there are many factors (e.g., health metrics for disease, infestation, fire hazards) that can affect the ability of the forest system to produce ecological services, the context of the anthropogenic effects being considered in this research project (i.e., timber removals) focuses on elements of forest resource condition that pertain to conservation, restoration, and biodiversity (USFS 2000).

Table 6-4 Monte Carlo Simulation Distribution Metrics and Processes Modeled in the Uncertainty Analysis

Type	Key Variables	Distribution Metrics and Probabilities
Regional Timber Market Prices	Long-term Annual Change in Timber Prices	Triangular Distribution: Range: 0 to 1%, Midpoint: 2.4% (Sources: USDA 2003 for most-likely long-term average, analysis of 20 year trends for range [AHC 2010], See Section 6.2.4 for further discussion).
	Timber Price Market Oscillation Cycles	Market cycle duration in years when prices are either continuously above or below predicted average price trends: 1 year (43%), 2 years (32%), 3 years (20%), 4 years (3%), 5 years (2%), and 6 years (1%) (Sources: AHC 2010).
	Tree-specific Market Price Fluctuations	Modeled tree-specific amplitude fluctuations around the long-term predicted average price. Normal Distribution: Mean: 9% Standard Deviation: 11% (Source: AHC 2010).
	Consistency Between Tree and WV Market Trends	Probability that a tree-specific price fluctuation trend modeled above coincides with the overall average national market trend in a given year: 68% (Source: AHC 2010).
Multi-Level Timbering	Plot-Level Timber Stand Selection	Monte Carlo analysis of plot-level data using probability model (see Section 4). For the uncertainty analysis, the annual probability was adjusted using a triangular distribution with a range of +/-25%.
	Multi-Level Tree Selection for Timbering Events	Monte Carlo analysis of plot-level and tree-level data using probability model derived using multi-level logistic regression analysis discussed in Section 4.
Tree-Level Regeneration	Poletimber Regeneration Rate	Monte Carlo analysis of probability estimates that a new poletimber tree regenerates in a year, based on 9 plot level stand density classes (Source: analysis of FIA data [USFS 2010a]). For the uncertainty analysis, the annual probability was adjusted using a triangular distribution with a range of +/-25%. Species type was assigned based on a Monte Carlo simulation of relative species abundance for the specific forest type (USFS 2010a).
	Commercial Tree Regeneration of BF	When poletimber grows are large enough to become commercial sawtimber (> 11"), then BF is estimated for the new commercial sized tree based on the distribution of BF for trees of that size. All BF are based on a normal distribution with the means and standard deviations by species group. (Source: analysis of FIA data [USFS 2010a])
Plot-Level Disturbance	Plot-level Disturbance	Monte Carlo analysis of disturbance events using plot-level data and probability model, and a triangular distribution with a range of +/-25%.
Tree-Level Negative Growth	Tree Negative Growth Probability Rates	Probability that a tree on a plot will experience negative growth, based on tree volume and stand disturbance condition (Source: heuristic analysis of FIA data [USDA 2010a]).
	Tree-Level Annual Negative Growth Rates	A Monte Carlo analysis was performed for simulating annual negative growth rates for trees identified as having negative growth in the 12 year growth cycle (based on the West Virginia sampling cycle) by tree volume (Source: heuristic analysis of FIA data [USFS 2010a]):
Tree-Level Mortality	Tree-Level Mortality Probability Rates	A Monte Carlo analysis of tree mortality was performed using derived annual probabilities that a tree on a plot will die, based on tree volume and stand disturbance condition (Source: statistical analysis of FIA data [USDA 2010]). For the uncertainty analysis, the annual probability was adjusted using a triangular distribution with a range of +/-25%.
Tree-Level Positive Growth	Tree-Level Annual Positive Growth Rates	Incremental BAG for each live tree was estimated using the methods outlined in Section 5. BAG was then converted to annual central stem volume growth and BF growth using regression equations and root mean square error for each species group which were presented in Section 5.

Forest ecosystem indicator metrics used for this research were developed in consideration of international and national forest sustainability initiatives that apply to temperate forests in the northeast (Buehler et al. 2007, Brown et al. 1997, Montreal Process 2007, Register and Islam 2008, USFS 2000, USFWS 2009, Wood et al. 2005). In 2007, the United States participated in the development of a set of criteria and measurement indicators for the conservation and sustainable management of temperate forests as part of the Montreal Process (2007). This effort was initiated in 1994, when 12 countries that manage 90 percent of the worlds temperate forests agreed to work in cooperation to develop sustainable management indicators in response to the Rio Forest Principals initiated by the United Nations Conference on Environment and Development in 1992. As the lead Federal agency for ensuring adherence to the Montreal Process, the USFS has co-developed and adopted these forest indicators and applied them to forest systems in the northeastern United States as part of their USDA Forest Service Strategic Plan (USFS 2000). Key indicator metrics from the 2007 Montreal Process include: forest ecosystem diversity metrics (1.1) (e.g., ecosystem type, age class, size class, biomass, structure, stocking, ownership), species diversity (1.2), growing stock and incremental growth (2.b), annual harvests as a percent of net growth (2.d), and net change in forest and wood products pools and fluxes (5.a and 5.b).

These and other forest metrics were considered for the purpose of tracking and evaluating forest resources and sustainability. Since the focus of this research is on the effect of timbering on forest biomass, it was important to evaluate sustainability in terms of the ability of the forest system to sustain future timber removals (i.e., annual harvests as a percent of net annual growth, changes in timbering intensity) and the impact of timber removals on AGBD and BF resources over time, including impacts to specific commercially important species (e.g., AGBD and BF metrics for black cherry and red oak). Thus, indicator metrics that measure these aspects of sustainability were selected and defined as "forest ecosystem indicator metrics" for use in this research, including: distribution of forest stand AGBD, distribution of tree biomass by size class, the ratio of AGB harvested to net growth in AGB, net annual change in ABGD and BF pools (including black cherry and red oak), and frequency and intensity of timber disturbances across forest stands in the state.

With respect to forest system recovery metrics, Brown et al. (1997) conducted research on the distribution of AGBD and old growth forest metrics for the eastern United States deciduous forest systems (Brown et al. 1997). This research tested and validated methods for categorizing eastern deciduous forest stands as to their recovery stage based on AGBD and large tree metrics (portion of AGBD in large trees > 70 cm) and several studies of old growth forest conditions. Using metrics presented in Brown et al. (1997), forest stands dominated by larger commercial sawtimber (majority of AGBD in sawtimber trees with DBH >11", with AGBD > 15,000 g/m^2) were considered to be in an advanced stage of recovery, while forest stands dominated by poletimber (majority of AGBD in trees with DBH between 5" to 11" DBH, which are not commercially used as sawtimber) were classified as young secondary growth stands (Brown et al. 1997). Forest stands classified as being in advanced stages of recovery generally had AGBD above 15,000 g/m^2 or higher, while young secondary growth stands had AGBD between 5,000 and 15,000 g/m^2. Seedling/sapling stands (dominated by trees less than 5" DBH) had AGBD generally below 5,000 g/m^2. Old growth forests were defined as stands with AGBD over 25,000 g/m^2, and with over 30% of this biomass in trees that exceeded 70 cm DBH (Brown et al. 1997). These old growth forest metrics presented in Brown et al. (1997) were based on commensurate hardwood forests of the eastern United States, and may not be representative of old growth conditions in other forest systems.

These AGBD thresholds and large tree criteria for old growth forests were used to classify and track West Virginia forest stand recovery for each timber and market scenario from 2000 to 2050. Although old growth forests can be characterized by additional stand metrics (e.g., distribution of biomass among different tree age cohorts, indicating regeneration potential), for this state-level study, the classification criteria follows definitions provided in Brown et al. (1997), which provides a reasonable indicator of forest stand recovery in the northeastern United States. Additional analysis of tree size cohorts was also conducted for advanced recovery and old growth stands, to assess the distribution and change of forest stand structure across the state from 2000 to 2050.

In consideration of competing goals and interests for forest management, the USFS and USFWS have moved to restore more forest habitat to conditions that more closely resemble mature forest stands, with greater stand complexity, and old growth characteristics that favor forest species that once thrived in pre-colonial, old growth forest systems. The USFS and USFWS have selected a small number of species of interest for the purpose of developing detailed indicator metrics for specific forest ecosystems across the country as part of the national forest sustainability initiative (USFS 2000). In addition to the temperate forest sustainability measures discussed in the paragraph above, the USFS is developing detailed forest sustainability metrics, prescriptions, management recommendations, and indicator metrics for the northeast temperate forest system based on the habitat requirements of their selected indicator species. For mature deciduous forests found throughout West Virginia, as well as in many states in the northeast, the USFS selected the cerulean warbler (*Dendroica ceruleaas*) (CERW) as a key management indicator species (MIS) on which to base the development of detailed forest sustainable metrics (USFS 2000). The USFS selected the CERW due to its dependence on mature intact temperate forests, vulnerability, loss of habitat, declining population, and species of concern listing status. As such, forest indicator metrics that directly benefit CERW recovery are being researched and integrated into regional forest management plans in the northeast by Federal agencies.

The USFS believes that restoring forest habitat conditions for MIS will benefit most forest species that prefer intact, mature forests and help restore the entire system (USFS 2000). Thus, the approach is not focused on benefiting a single species, but rather a group of species that have been most adversely impacted by post-colonial anthropogenic activity within the eastern deciduous forest ecosystem. In many cases, the loss of the original habitat has resulted in serious population declines for forest species that were found in these locations, including CERW (a listed SOC). Therefore, certain adverse impacts that would occur from the MIS management approach are considered reasonable trade-offs that seek to restore habitats to a condition that more closely resembles their natural pre-colonial settlement state. To that end, CERW habitat requirements that favor restoration of fully mature forest systems, with a much greater percentage of forest biomass in larger trees would support that goal.

Although enhancement of forest recovery metrics defined above may indicate a higher percentage of forest stands in advanced stages of recovery, this does not necessarily indicate that biodiversity and resilience to disturbance regimes are improved. As discussed later, higher biomass may actually increase a forest stands vulnerability to disturbance regimes. Changes in forest systems, even to more natural pristine conditions, will result in both positive and negative effects to forest species depending on their unique habitat requirements, which will either be enhanced or diminished through landscape manipulation. Ultimately such a strategy, may reduce habitat diversity across the landscape, and reduce habitat that may be more favorable to other species that do not prefer mature, intact forest systems. Such a strategy may ultimately lower certain metrics of biodiversity as measured by the number of species inhabiting the landscape per unit area, as well as potential vulnerability of the system to certain disturbance regimes. The preferred strategy for forest management would ultimately depend on the priorities and value system of policymakers, to either restore habitat that is threatened and lost, or maintain greater habitat variability across the landscape for a greater variety of species. Establishing such goals is principally a question of personal value and policy, rather than a scientific question. For this assessment, management approaches and policies that seek to restore habitat most severely impacted by anthropogenic activities over the past two centuries (i.e., loss of mature, old growth forests) and to restore conditions to more closely resemble their natural state, was selected as the preferred approach for this project from a conservation standpoint.

As it pertains to this research, key forest habitat indicator metrics that could be measured from the FIA data that relate to the habitat preferences of CERW and other species that prefer mature forest systems include: increased percentage of forest biomass in the larger trees, stand diversity (range of tree size classes), and increased percentage of stands in advanced stages of recovery (as defined above) (Buehler et al. 2007, Brown et al. 1997, Register and Islam 2008, USFWS 2009, Wood et al. 2005). In addition, research has shown that low intensity timbering events that slightly opened up the canopy (e.g., thinning, select tree cuts) had higher CERW population densities than untreated plots (Buehler et al. 2007, USFWS 2009). Therefore, low intensity select cuts that remove a smaller volume of trees with varying age class, while preserving the largest stand trees, may provide the best habitat for CERWs, and also allow for low intensity sustainable timber harvests. Also, population studies have been done that indicate that plots with high biomass to tree count ratios (indicating a higher percentage of biomass in larger trees) provide better habitat than plots with larger numbers of smaller trees (regardless of biomass) (USFWS 2009). To address these factors, the distribution of biomass in different tree size classes will be tracked. Overall, specific metrics that will be evaluated in this study that relate to improving habitat for CERWs and other species that prefer mature forest systems, consist of: increased percentage of forest stands in advanced stages of recovery and old growth status (Brown et al 1997); increased percentage of biomass in larger tree size classes; and distribution of biomass in a range of tree size classes.

In summary, the specific forest ecosystem indicator metrics to be evaluated as part of this dissertation for evaluating timber resources, forest sustainability, and forest ecosystem habitat restoration for MIS, include:

- Annual distribution of forest stand AGBD over time to 2050;
- Annual percentage of forest plots that are classified as advanced recovery plots or old growth forests over time to 2050;
- Distribution of the percent of stand AGBD classes in 2000 versus 2050;
- Distribution of stand classifications (i.e., seedling/sapling stands, young secondary growth stands, advanced recovery stands, or old growth stands) across West Virginia in 2000 versus 2050;
- Net annual change in ABGD and BF pools to 2050;

- Annual ratio of AGB harvested to net growth in AGB to 2050;
- Annual change in red oak and black cherry biomass over time to 2050;
- Distribution of tree biomass by size classes in 2000 versus 2050;
- Percent of stand AGB in large trees (>70 cm DBH) over time to 2050; and
- Annual frequency and intensity of timber disturbances across forest stands in the state (annual frequency of low intensity [<= 30%] and higher intensity removals [>= 30%]) to 2050.

During the CFM model simulation, forest ecosystem indicator metrics were derived for each plot and up-scaled to estimate state-level impacts for each year using expansion factors provided in FIA. These metrics were estimated for average plot conditions and for West Virginia for each scenario. The metrics for status quo conditions and sustainable forest management scenarios were then plotted over time.

6.2.4 Timber Market Scenarios

To simulate timbering activity to 2050 using CFM, it is necessary to estimate how stumpage prices will change over time. The USDA/USFS conducted a detailed economic study and analysis of timber stumpage prices from 1950 to 2050 and forecasted the timber price changes in the northeast for hardwoods (USDA 2003). Due to increased availability of hardwoods to 2050 (due to continued re-growth of these forests above removal rates, as seen in West Virginia), timber prices are not expected to increase significantly to 2050. USDA/USFS utilized an integrated economic forecasting model (TAMN/NAPAP/ATLAS [USDA 2003]) to simulate prices and timber markets from 2000 to 2050 in consideration of national and international market forces, regional timber product prices, and timber production supply. The results of this modeling effort indicated that timber stumpage prices are expected to only increase at an average annual rate of 0.24% (with inflationary effects removed) to 2050 for the northeastern hardwoods market (USDA 2003).

A statistical analysis of West Virginia stumpage prices as surveyed and tracked by the AHC indicated that West Virginia prices are highly correlated (r = 0.92) with U.S. hardwood prices. Therefore, the national and regional results obtained from the USDA/FS model are reasonable measures of how average timber prices will likely change in the future to 2050 in West Virginia.

To evaluate the uncertainty and variability in timber prices, a trends analysis was conducted on average state prices in West Virginia by species group over the past 20 years from 1989 to 2009. The results of this analysis indicated that average West Virginia prices increased at a rate of approximately 1% annually (with inflationary effects removed). Although this rate of increase is comparable to the national average, USDA/FS model results indicate that such a rate of increase will not be sustained to 2050. Rather, prices would only increase at an average annual rate of 0.24% from 2000 to 2050, as previously discussed. The USDA/FS model results are supported by more recent trends since 2000, which have shown significant declines in West Virginia stumpage prices due in part to the economy, imports, and reduced demand for woods with highly visible grains such as red oak, which is one of the primary wood products of West Virginia. It is possible that decreased demand for red oak could change in the future, as grain preference could be a transient preference. In any event, stumpage prices have dropped by approximately 25% from 2000 to 2009. Thus, the significant growth in timber prices and production that occurred from 1989 to 2000 is unlikely to continue to 2050, as evident by the recent downturn in the timber market after 2000, which is in keeping with the USDA/USFS model results. Therefore, a 1% increase in stumpage prices is considered a reasonable upper-bound market scenario for the purposes of model simulation, which is defined as the *high timber market scenario*. The 0.24% increase in stumpage prices, which the USDA/USFS projects as the most likely long-term change in hardwood prices in the northeast to 2050 was defined as the *most-likely timber market scenario*.

The trends analysis also revealed that there were significant fluctuations in timber prices from year to year, with particular cyclical patterns that were evident in long-term changes in U.S. prices from the 1950s to the present. An analysis of West Virginia market fluctuations from 1989 to 2009 were used to develop market cycle probabilities and durations, as well as species-specific variations around that average market cycle to simulate reasonable fluctuations in prices that replicated patterns over the past two decades (see specific results presented in Table 6-4). For this analysis, a distribution of the amplitude and period of market cycles (averages and standard deviations) around the overall average long-term trend were derived over the past two decades. These statistics were used in a Monte Carlo simulation to estimate similar fluctuation patterns around the average mean price trend, which was based on national/international market price projections for northeast hardwoods (TAMN/NAPAP/ATLAS integrated timber market and price model) (USDA 2003). The Monte Carlo analysis was designed to allow prices to fluctuate, but to ensure that the long-term average price increase would be maintained over the 2000 to 2050 time period for each model iteration.

The trends analysis also indicated that there were definite patterns and shifts in prices for specific species groups. For example, even though average West Virginia market prices were increasing, certain species increased at a much greater rate, e.g., black cherry and hard maple prices, while other species actually declined, e.g., red oak prices have significantly declined since 2000. Given the results presented in Section 4, these price trends will have a significant impact on tree selection and potential sustainability of micro-scale resources in a given year. For example, significant increases in black cherry prices may increase removal rates, and black cherry availability and sustainability for both future timbering and ecosystem services across West Virginia. Therefore, to simulate price changes, species-specific prices were simulated, in consideration of species-specific trends, micro-scale market fluctuations, and long-term macro-scale increases. The approach allowed for estimating individual species prices that demonstrated a collective long-term average increase commensurate with the overall timber market scenario under investigation (i.e., 0.24% or 1% increase), species specific growth trends (relative to other species), and micro-scale market trends (both national market fluctuations, and species specific variation around the national market trend). The variability in prices and market fluctuations were built into multiple Monte Carlo simulations that allowed for the calculation of distribution bands for long-term projections of timbering, AGBD, and other forest ecosystem metric indicators.

6.2.5 Sustainable Forestry Scenario Constraints

The status quo and sustainable timbering scenarios were simulated using the same methods outlined in the previous sections with the exception that for the sustainable timbering scenario, specific limitations to timbering activity were artificially imposed on the system to test the impact of this change relative to status quo conditions. Specifically, the sustainable timbering scenario constrains timbering activities on selected plots with respect to the percent of forest biomass that can be removed, timber rotation cycles, and removal of the largest trees. As discussed in Section

6.2.3, these constraints are important for ensuring high quality habitat for MIS species (low intensity removals, e.g., < 30%), maintaining stand structure and diversity, mixed-age stands, and retention of biomass to support ecological services (Buehler et al. 2007, Brown et al. 1997, Register and Islam 2008, USFWS 2009, Wood et al. 2005). Furthermore, these silviculture practices may conserve mature forest habitat and may enhance metrics indicative of old growth forest stand conditions, as previously defined.

Based on an analysis of several sustainability research studies and MIS forest metrics discussed in Section 6.2.3, the following specific constraints were placed on timber removals to replicate a "sustainable forest management" approach to timber removals, as outlined below:

- No more than 30% of the AGBD can be removed from a plot (Buehler et al. 2007, USFWS 2009);
- Timber rotations cannot be less than 20 years (Register and Islam 2008);
- The largest tree on a 0.1 ha area grid must be preserved (i.e., the largest tree on the FIA plot) (Buehler et al. 2007, Register and Islam 2008, Brown et al. 1997, USFWS 2009); and
- Trees larger than 70 cm in diameter must be preserved (Brown et al. 1997).

These measures will significantly constrain the amount of biomass and short-term economic return from a given forest stand that may have been timbered more extensively under status quo conditions (as the average biomass removal was over 60% under status quo timbering conditions, rather than under 30%). To make up for the loss in opportunity for removals from a given forest stand, it was assumed that timber firms will shift the unrealized portion of this timbering activity to additional lands in West Virginia in order to meet annual market demand for timber. In reality, such a restriction may reduce timbering in state, with a portion of the timbering activity shifted out of state. For example, adoption of ecological sustainable timbering practices on public lands over the past two decades has resulted in a shift of timber burden to private lands and Canada, according the former Assistant Director of Forest Management for USFS (MacCleery 1999), as per capita demand for forest products rose during this same period. Since the purpose of this analysis is to demonstrate the potential effect of sustainable timbering practices, it was necessary to assume that there would not be any policy leakage or shifting of timber burden outside of the system. Otherwise benefits realized from the sustainable timbering scenario may only be attributed to the scale of the analysis, due to shifting of timber burden outside of the system. So to control for such leakage effects, it was assumed that the same total value of timber would be removed at the state level under the sustainable timbering scenario as was calculated for the status quo timbering scenario, in order to ensure that the differences that are seen are solely due to differences in silviculture practices, and stand and tree selection patterns.

This requirement was achieved by monitoring total state timber removals for the sustainable timbering scenario and ensuring that the timber stand selection Monte Carlo analysis was repeated until simulated status quo statewide totals were achieved (i.e., plots were re-evaluated for selection using the same models previously discussed). Essentially, this model algorithm simulated the potential shift in timber burden to more plots that may occur if removals on any plot were restricted to the point that timber firms could not extract timber volumes that the market would typically generate in that year (as measured by the status quo scenario at the state-level). Beyond these measures, all other aspects of the CFM model were the same for the status quo and sustainable timbering scenarios. The increased costs associated with removing timber from additional plots; however, was not factored into the model. Overall, the purpose of this simulation is a first step in testing potential solutions that attempt to reconcile human and environmental problems, which consider both the direct and indirect consequences (positive and negative) of forest management decisions at multiple scales.

6.3 Results and Discussion

6.3.1 Sensitivity Analysis

The results of the sensitivity analysis are presented in Table 6-5. Of the key variables that impact timber removals, tree stumpage price and positive growth rates had the most significant impact on CFM predictions of timber removals. When these variables were varied by +/- 25%, the average timber removal across West Virginia changed by +/- 16 to 21%. Changes in tree regeneration rates had a negligible effect on removals within this 50 year simulation (as most regenerated trees were still too small for harvesting by 2050) , while other disturbance measures (i.e., plot level disturbance rates, tree mortality rates, and negative growth rates) had minor to moderate effects (2 to 13%) on timber removal rates. Overall, the results indicate that the model's estimation of timber removals appear to be most sensitive to changes in timber price and positive tree growth, followed by changes in plot-level disturbance rates.

With respect to long-term predictions of AGBD, the model was most sensitive to changes in positive tree growth rates (+/- 9 to 11%), which was similar to the finding above. However, timber prices had far less impact on standing timber AGBD, as compared to timber removal rates, as might be expected. Changes in disturbance rates, tree mortality rates, and tree regeneration rates also had an impact on standing timber AGBD. Overall, the results indicated that positive growth and landscape-scale disturbance regimes are the most important dynamics to be modeled accurately when estimating ABGD and ultimately carbon sequestration.

Table 6-5 CFM Sensitivity Analysis Results

Parameter	% Change Based on +/-25% Change in Parameter	
Average AGBD Removed by Timbering (g/m^2)		
Regional Timber Prices	-16%	19%
Plot Level Disturbance Rates	12%	-13%
Tree Mortality Rates	5%	-7%
Tree Negative Growth Rates	2%	-3%
Tree Positive Growth Rates	-19%	21%
Tree Regeneration	negligible	negligible
Average Plot AGBD (g/m^2)		
Regional Timber Prices	5%	-5%
Plot Level Timber Rates	6%	-5%
Plot Level Disturbance Rates	8%	-6%
Tree Mortality Rates	5%	-4%
Tree Negative Growth Rates	negligible	negligible
Tree Positive Growth Rates	-11%	9%
Tree Regeneration Rates	-4%	2%

6.3.2 Timber Removal and Disturbance Metrics under Status Quo Timbering

Under status quo timbering, annual removal of forest biomass is projected to nearly double from 2.9 tg/year in 2000 to 5.4 tg/year by 2050 based on CFM model results (see Figure 6-2). This projected increase in removals was mainly due to projected growth in forest biomass, rather than timber price changes (as discussed further in Section 6.3.3). Timber removals were projected to increase in frequency and intensity as shown in Figures 6-2 and 6-3, which is consistent with the hypothesized trends shown in Table 6-1. The frequency of annual commercial timbering events for a forest stand increased from about 0.5% to 0.7%, which was due to an increase in forest stand value, resulting from continued growth of timber resources and to a lesser extent price.

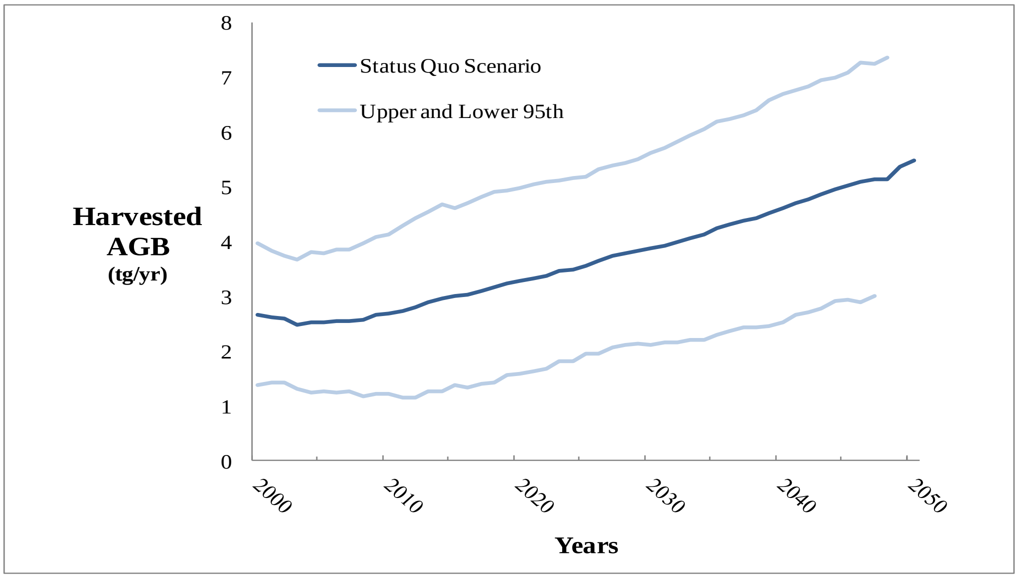

Figure 6-2 Annual Statewide Harvest of AGB from West Virginia Forests (tg/yr) (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

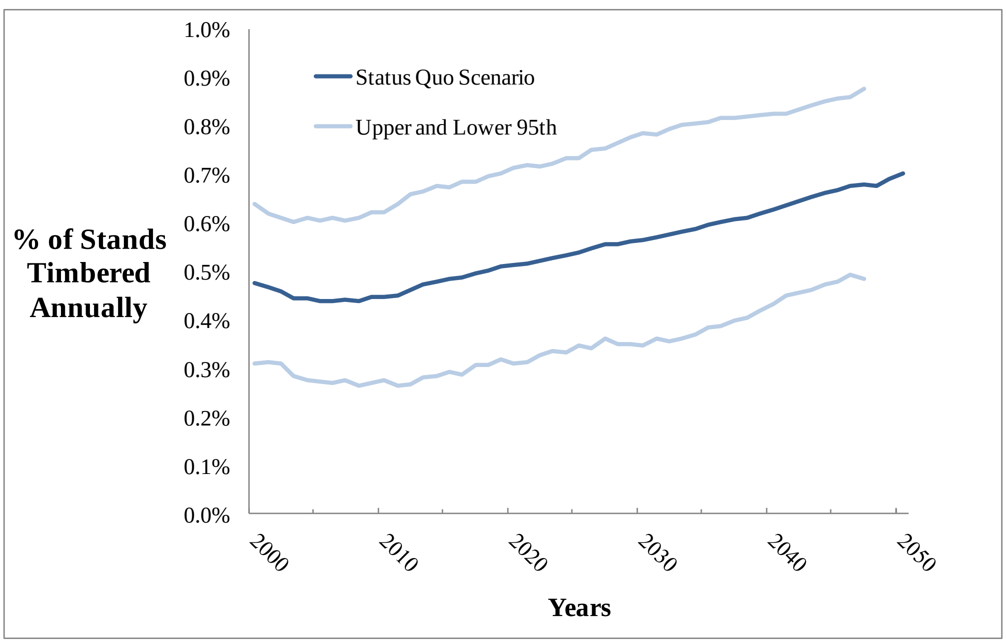

Figure 6-3 Percent of Stands Commercially Harvested Annually (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

As a measure of forest sustainability, forest removals consisted of only 33% of the annual net growth in forest resources in 2000, indicating that timbering events were removing far less biomass than was generated in a given year (as shown in Figure 6-4). However, due to increases in the amount of commercial BF volume and timber stumpage prices, as well as reduced annual growth rates (due to increased stand density), over 60% of the net growth will likely be removed annually by timbering in 2050. Furthermore, under higher timber market conditions, the percentage may exceed 100% of the net annual growing capacity of the forest system after 2040 during certain years. Note that this trend line in Figure 6-4 is influenced by annual fluctuations in the market and harvesting rates. Overall, these results indicate that the West Virginia forest system may be nearing its carrying capacity for timber removals by mid-century. Under these market conditions, unsustainable removals of timber that exceed annual net growth beyond 2040 would result in future declines in forest resources and ecosystem metrics, as well as creation of a carbon source (rather than a sink) in West Virginia after mid-century (as further discussed in Section 7).

6.3.3 AGBD Metrics under Status Quo Timbering

Trends in AGB growth in West Virginia are projected to continue to 2050 under the most-likely timber market scenario (Table 6-6), consistent with hypothesized trends presented in Table 6-1. AGB of West Virginia's forests is projected to grow from just over 500 tg in 2000 to over 680 tg in 2050 (see Figure 6-5). Similarly, the average AGBD on forest stands is projected to increase from 11,600 gC/m2 to over 15,000 gC/m2 (see Figure 6-6), which is above the threshold of forest stands that are considered in a state of advanced recovery (Brown et al. 1997). As shown in

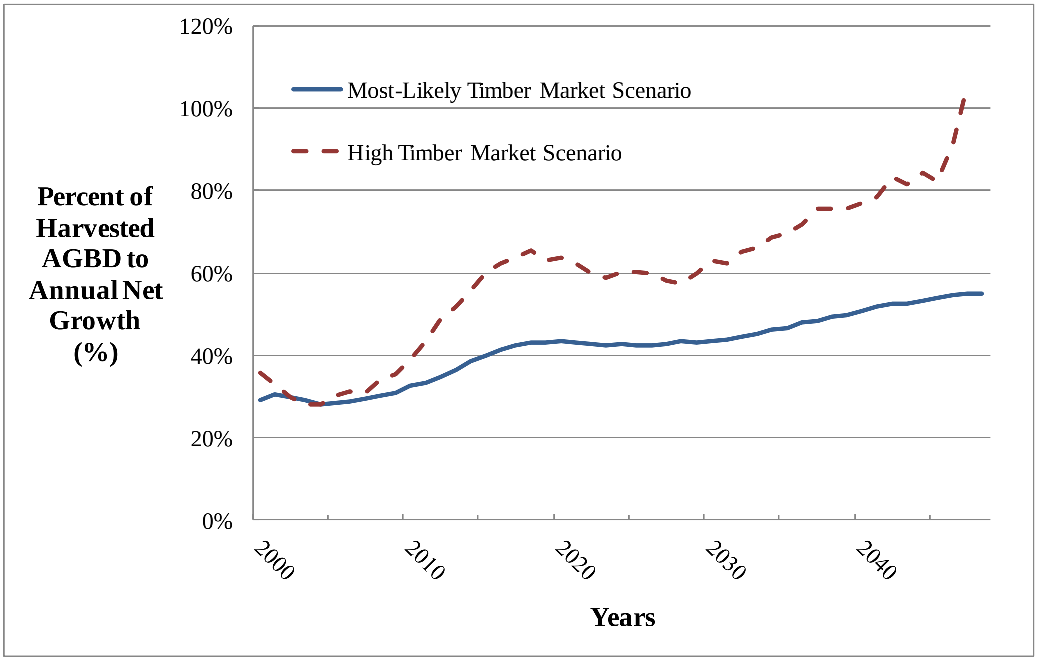

Figure 6-4 Percent of Harvested AGBD to Net Annual Growth under Most-Likely and High Timber Market Conditions for the Status Quo Scenario

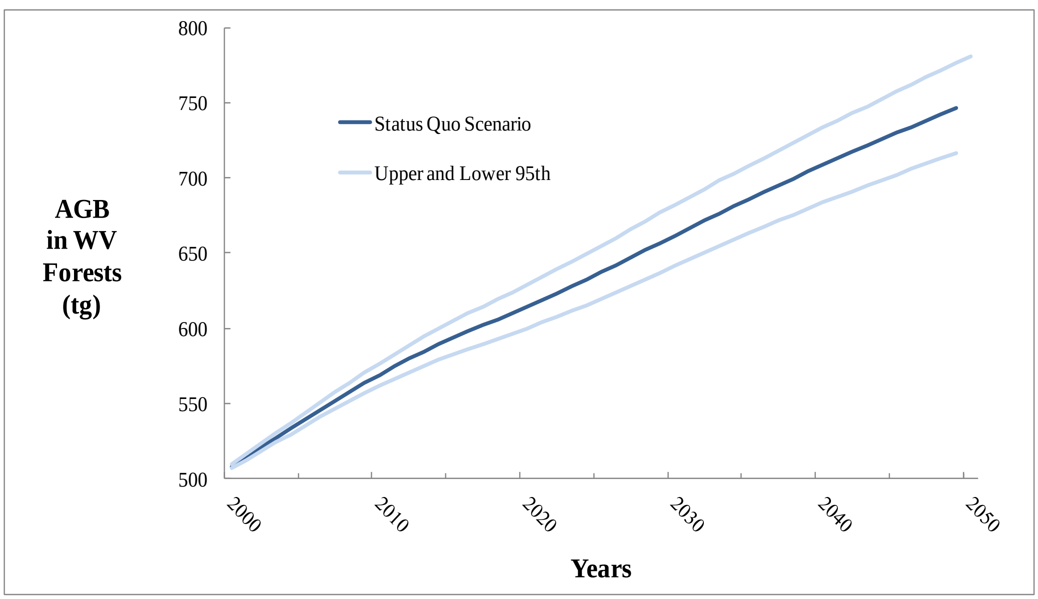

Figure 6-5 Statewide Forest AGB (tg) (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

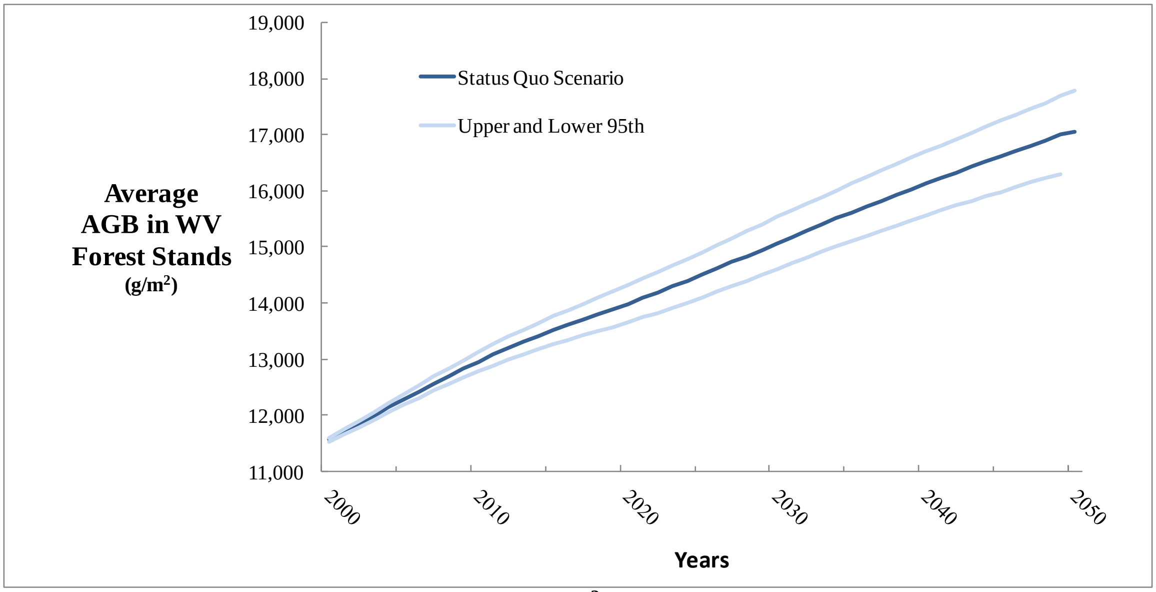

Figure 6-6 Average Forest Stand AGBD (g/m^2) (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

Table 6-6 Predicted Long-term Forest Ecosystem Indicator Metrics for the Status Quo and High Timber Market Scenario under Status Quo Timbering Conditions

Forest Indicator Metrics	Current Conditions (2000)	Most Likely Timber Market Conditions in 2050	High Timber Market Conditions in 2050
State Forest AGB (tg) in 2050	511	688	658
Average AGBD (g/m^2) in 2050	11,600	15,700	15,000
Average % of State Timber Harvest to Net Growth in AGB from 2040 to 2050	33%	61%	102%
State Commercial Timber BF Volume (10^6 m^3 BF) in 2050	144	224	210
State Forest AGB (tg) of Black Cherry and Red Oak AGB (tg) in 2050	BC: 16 RO: 42	BC: 19 RO: 50	BC: 17 RO: 44
Average State Frequency of Low Intensity Timbering Events (< 30% AGBD removals)	< 0.02%	< 0.02%	< 0.02%
Average State Frequency of Medium/High Intensity Timbering Events (> 30% AGBD removals)	0.5%	0.7%	0.8%
% of Biomass in Large Trees (>70 cm) in 2050	5%	12%	11%
% of Advanced Recovery Plots (AGBD > 15,000 g/m^2) in 2050	28%	49%	45%
% of Old Growth Plots (AGBD > 25,000 g/m^2, 30% of AGBD in Large Trees > 70 cm) in 2050	0.7%	4.5%	3.6%

Figures 6-5 and 6-6, AGB and AGBD continue to increase to 2050, but the rate of annual increase decelerates to 2050. This deceleration is due to increased timber removal rates, increases in landscape scale disturbances, and decreased annual growth rates. These, in turn, are all due in part to increased stand density, which represents a negative cross-scale feedback mechanism.

The results of the simulation analysis indicated that landscape-scale disturbances are projected to increase by approximately 50% from 2000 to 2050, as forest stands continue to increase in biomass. By 2050, approximately 1/4th of the state forest acreage is projected to experience landscape scale disturbances (as opposed to 17% in 2000) due to increased forest stand density (resulting in increased competition), resulting in net negative growth, particularly for locations with higher forest biomass, lower annual precipitation, and greater slopes. Additional research is needed to better understand and predict these landscape disturbance events. If drought and other disturbance events increase in frequency, then the frequency and severity of these events could increase beyond the estimates projected using CFM.

To better adapt to these disturbances, it may be possible to use monitoring and predictive tools to identify the locations that are most vulnerable to these disturbances and apply sustainable silviculture techniques to preempt these events, reduce stand vulnerability to these events, and shift timber production burden to locations that are likely to have mass tree mortalities. This approach would improve the overall health of the forest system across the entire state, in part because timber burden would be shifted away from healthy stands. Similar concepts have been suggested for adapting to cyclical and large-scale disturbance events in forests of Canada (Bouchard et al. 2008, Cotillas et al. 2009, Powers et al. 2010). By mimicking larger-scale disturbance events, it may be possible to reduce the incidence and impact of climatic disturbance events on the West Virginia forest system, while increasing growth potential, accelerate recovery, and increase the carrying capacity of the forests for timber production and improve ecological services relative to status quo conditions. Further research is needed to study the potential merits of this type of forest management technique for adapting to climate and other disturbance regimes, in order to increase system carrying capacity and recovery potential of the entire system across the landscape.

As shown in Figure 6-7, AGBD on forest stands in 2050 will significantly increase, with approximately half of the forests in a stage of advanced recovery, and approximately 16% of the forests achieving total AGBD commensurate with old-growth forests (i.e., > 25,000 g/m^2). However, these plots lack the large percentage of biomass in very large trees (> 30% in trees > 70cm); and therefore would not be classified as “old growth forests” based on this definition. The percentage of AGB in larger trees (see Figures 6-8 and 6-9) would also significantly increase by 2050, with over 10% of West Virginia forest AGB in the largest trees (> 70 cm). Furthermore, the percentage of forest stands that can be classified as old growth forests, as defined as having AGBD greater than 25,000 g/m^2 and greater than 30% of forest AGBD in large trees (> 70 cm), will increase from 0.7% in 2000 to nearly 5% in 2050 under status quo timbering.

As shown in Figures 6-8 and 6-9, the distribution of trees size classes in 2050 on advanced recovery and old growth forest stands indicates the potential for multiple size classes and developed understory, with a well developed large tree size class upper canopy. The recovery of tree stands at the plot-level (Figure 6-7) and the tree size class distributions indicate significantly improved stand conditions, which will likely favor forest species (such as CERW) that rely on mature forests with well developed stand structure (Buehler et al. 2007, Brown et al. 1997, Register and Islam 2008, USFWS 2009, Wood et al. 2005). These results are consistent with the hypothesized trends of increased percentage of forest stands in advanced stages of recovery and increases in stands classified as old growth forests (as shown in Table 6-6) for the status quo scenario. However, forest biomass in large trees (>70 cm) was similar for both timber market scenarios.

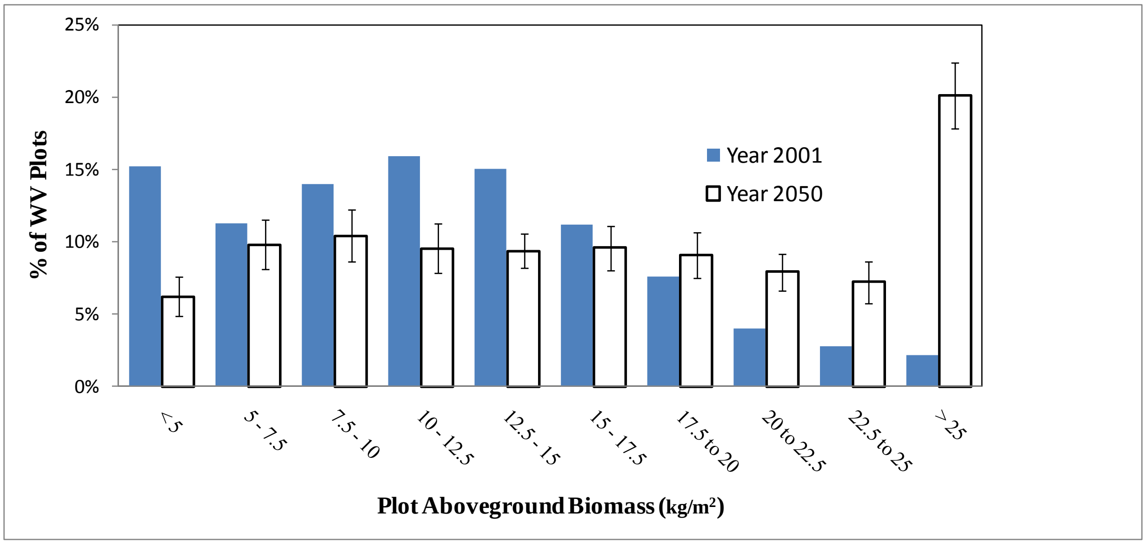

Figure 6-7 Distribution of Plot AGBD under Status Quo Timbering in 2000 and 2050

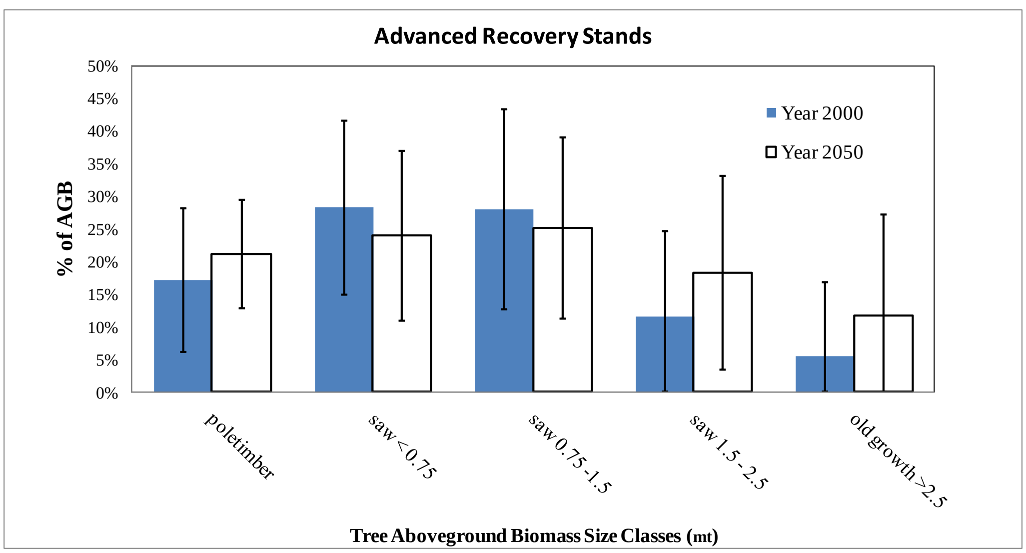

Figure 6-8 Distribution of Tree Biomass by Tree Size Class for Advanced Recovery Stands under Status Quo Timbering in 2000 and 2050

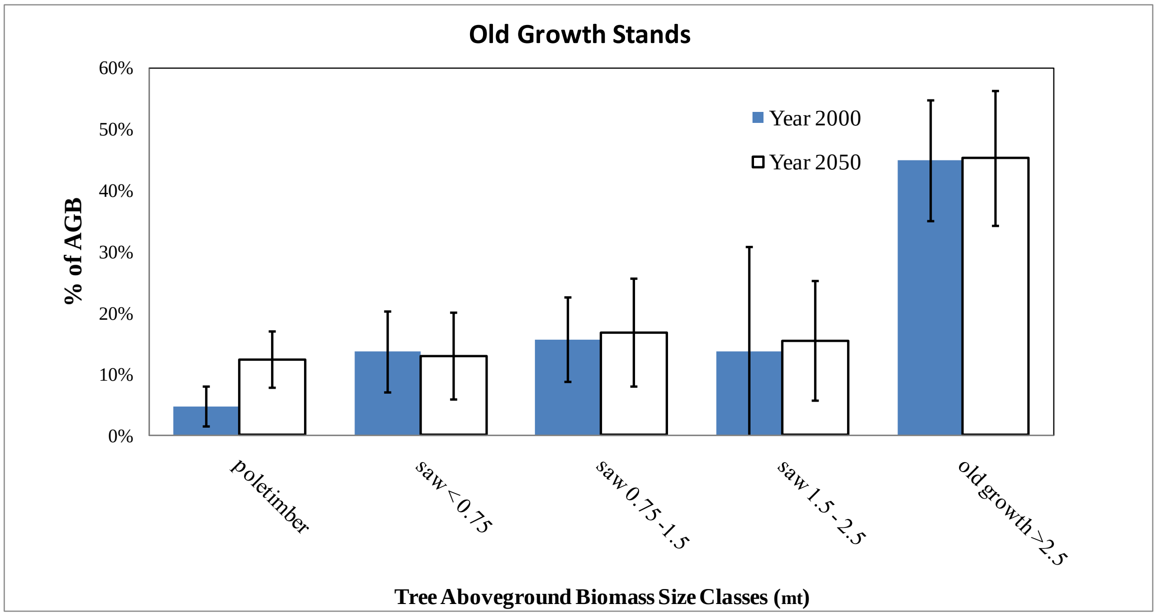

Figure 6-9 Distribution of Tree Biomass by Tree Size Class for Old Growth Stands under Status Quo Timbering in 2000 and 2050

With the West Virginia forests continuing to mature and grow, the value of this timber will significantly increase, as previously discussed. If market growth conditions experienced over the past 20 years were to continue, resulting in a long-term average annual market increases in stumpage prices of 1%, then the projected increase in timbering activity would result in a leveling off and eventual decline in forest AGB after 2050, as shown in Figure 6-10. The increase in timbering intensity and frequency and reductions in statewide AGB, AGBD, and commercial timber volumes are consistent with hypothesized trends presented in Table 6-1 (and summarized in Table 6-6). The decrease in statewide AGB also reduced other biomass ecosystem indicator metrics relative to most-likely market conditions, including: percentage of forests in advanced stages of recovery, percent of biomass in large trees (> 70 cm), and forest stands classified as old growth forests (as shown in Table 6-6).

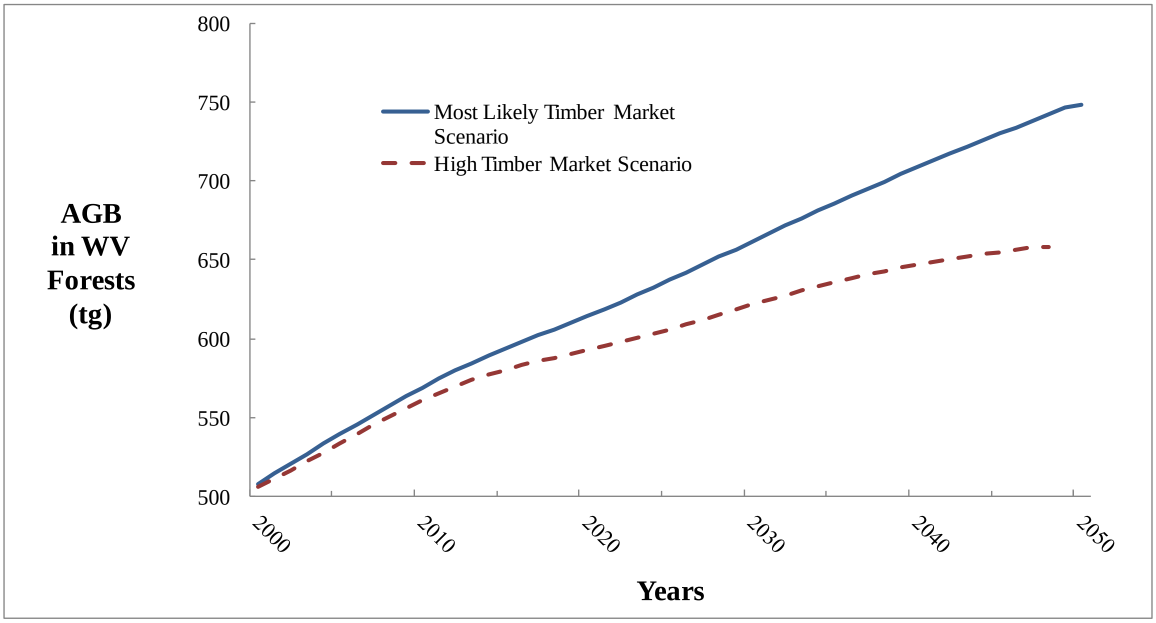

Figure 6-10 Statewide AGB (tg) under the Most-Likely and High Timber Market Scenarios (1% annual growth in timber prices) (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

6.3.4 Timber Resource Metrics under Status Quo Timbering

Just as with AGBD, commercial timber resources (i.e., BF volume [m^3]) in West Virginia are projected to continue to increase in the coming decades under most-likely market conditions, as shown in Table 6-6 and Figure 6-11, consistent with hypothesized trends presented in Table 6-1. Commercial timber volume is projected to grow from just over 140 million m^3 in 2000 to over 220 million m^3 in 2050. Similarly, the average commercial timber volume density on forest stands is projected to increase from over 30 m^3/ha to over 50 m^3/ha in 2050. However, for both metrics the rate of growth is projected to significantly decline due to increased projected timbering intensity, increased disturbances, and reduced annual growth, as these stands mature and increase in value. If a 1% average annual growth in timber prices occurs, then the projected increase in timbering activity would result in long-term leveling off of commercial timber resources, which would eventually decline after 2050, as shown in Figure 6-12. This increased market pressure would ultimately result in declines in commercial BF available for future timbering, which would not be sustainable in the long-term.

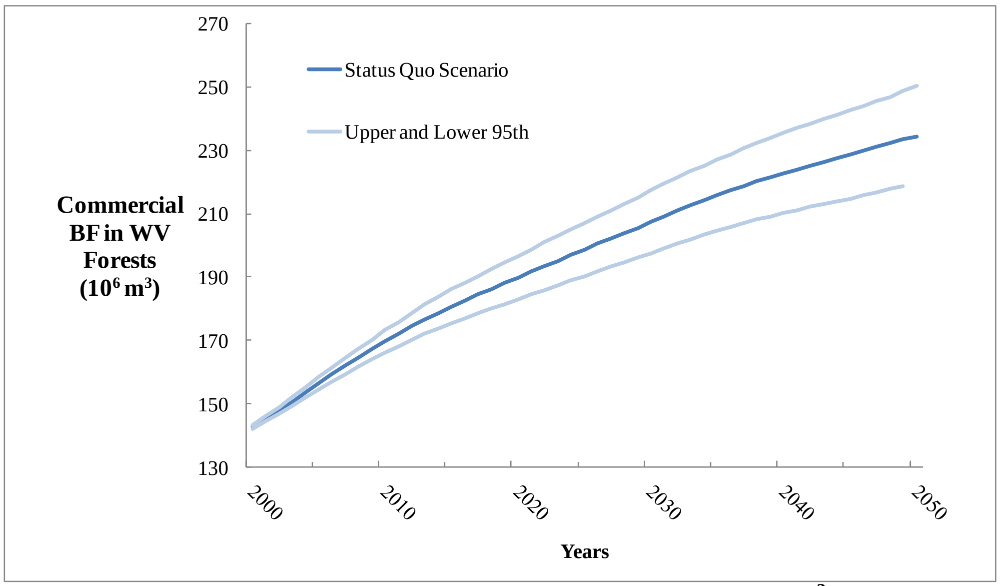

Figure 6-11 Statewide Commercial BF (International scale, million m^3) under Status Quo Timbering (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

Based on trends in market prices, it was evident that black cherry prices were increasing at a higher rate than other commercial species. In addition, black cherry is significantly more valuable than all other commercial species (see Table 3-1 and Figure 4-2). In 2000, the stumpage price for black cherry was the highest of all species in West Virginia of over $700 MBF, and nearly twice as valuable as the next highest priced timber species (i.e., northern red oak). Given that tree species selection for timbering events is significantly driven by price, it was important to

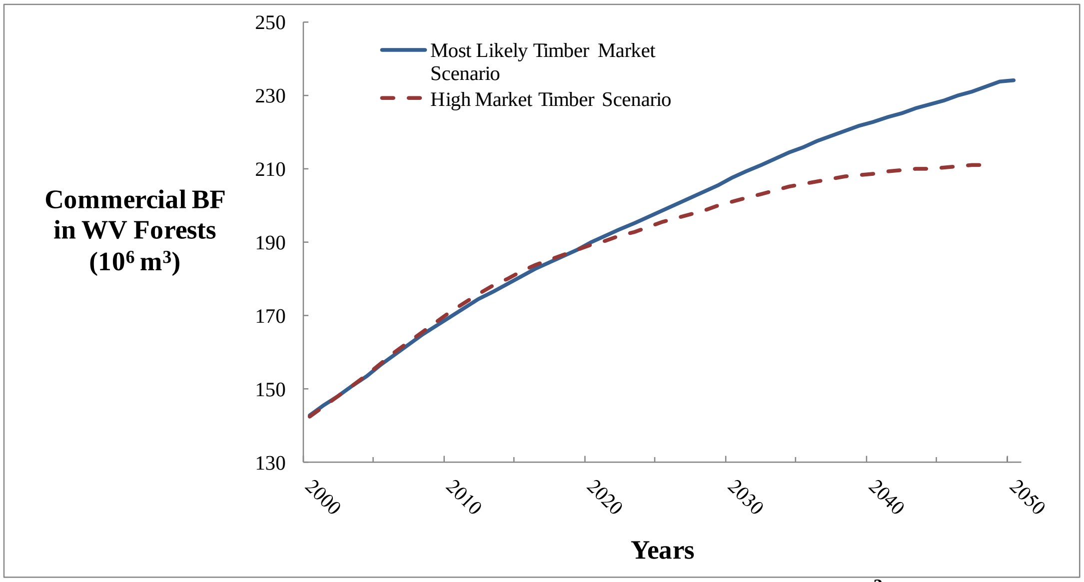

Figure 6-12 Statewide Commercial BF (International scale, million m^3) under the Most-Likely and High Timber Market Scenarios (1% annual growth in timber prices) (smooth trend lines based on Monte Carlo analysis)

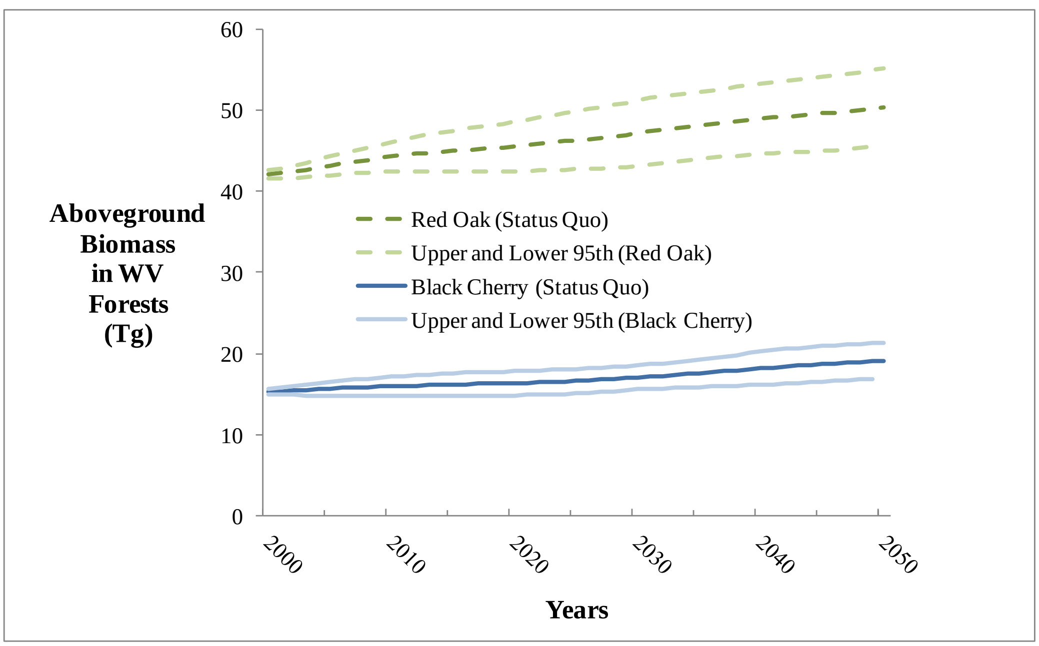

Figure 6-13 Red Oak and Black Cherry AGB under Status Quo Timbering Conditions

evaluate how market changes and timbering events may also impact the availability of black cherry for future timbering, along with red oak. As shown in Figure 6-13, despite the increase in market prices, both black cherry and red oak biomass were projected to most-likely increase, albeit at a much slower rate, to 2050. Although black cherry is highly sought after, the resilience of this species to increased timber pressure may be due in part to its higher relative growth rate. Even when the long-term average annual timber prices increased at higher rates, the long-term biomass levels of black cherry and red oak did not decline as compared to current conditions (see Table 6-6). However, the relative percentage of black cherry biomass to other tree species did drop from 3.1% in 2000 to 2.5% in 2050, while red oak declined from 8.2% in 2000 to 6.7% in 2050 relative to other tree species. Thus, the relative decline in black cherry and red oak biomass to other tree species indicates a shift in species abundance at the stand level.

6.3.5 Comparative Analysis of Status Quo and Sustainable Timbering Scenario Ecosystem Metrics

A comparison of long-term forest ecosystem indicator metrics for the status quo timbering scenario and the sustainability timbering scenario are presented in Table 6-7. With respect to AGB, the sustainable timbering scenario enhanced forest biomass by approximately 5.4% over the status quo timbering scenario, which is consistent with hypothesized trends presented in Table 6-2. This difference is fairly significant as this projected increase in biomass is approximately equal to over 10 years of statewide total timber removals conducted at current timber removal rates. In addition, this sustainable timbering approach increased statewide carrying capacity for timbering, and enhanced long-term sustainability of the system. As shown in Figure 6-14, AGB growth appeared to continue at relatively the same pace through 2050 under the sustainability scenario, while net annual growth began to clearly decelerate at a higher rate under the status quo timbering scenario. Similar results were found for trends in commercial timber volume (m^3) to 2050, as shown in Figure 6-15. In fact, the increase in commercial timber volume for the sustainable timbering scenario resulted in a net increase in economic value of standing timber in West Virginia forests of $0.8B in 2050, above the value under status quo conditions, even though the value of timber removed was the same for both scenarios.

Table 6-7 Predicted Long-term Forest Ecosystem Indicator Metrics for the Status Quo and Sustainable Timbering Scenarios

Forest Indicator Metrics	Current Conditions (2000)	Status Quo Timbering	Sustainable Timbering
State Forest AGB (tg) in 2050	511	688	724
Average AGBD (g/m^2) in 2050	11,600	15,700	16,500
Average % of State Timber Harvest to Net Growth in AGB from 2040 to 2050	33%	61%	56%
State Commercial Timber BF Volume (10^9 BF) in 2050	144	224	239
State Forest AGB (tg) of Black Cherry and Red Oak AGB (tg) in 2050	BC: 16 RO: 42	BC: 19 RO: 50	BC: 20 RO: 48
Average State Frequency of Low Intensity Timbering Events (< 30% AGBD removals)	< 0.02%	< 0.02%	2.0%
Average State Frequency of Medium/High Intensity Timbering Events (> 30% AGBD removals)	0.5%	0.7%	0%
% of Biomass in Large Trees (>70 cm) in 2050	5%	12%	12%
% of Advanced Recovery Plots (AGBD > 15,000 g/m^2) in 2050	28%	49%	56%
% of Old Growth Plots (AGBD > 25,000 g/m^2, 30% of AGBD in Large Trees > 70 cm) in 2050	0.7%	4.5%	2.9%

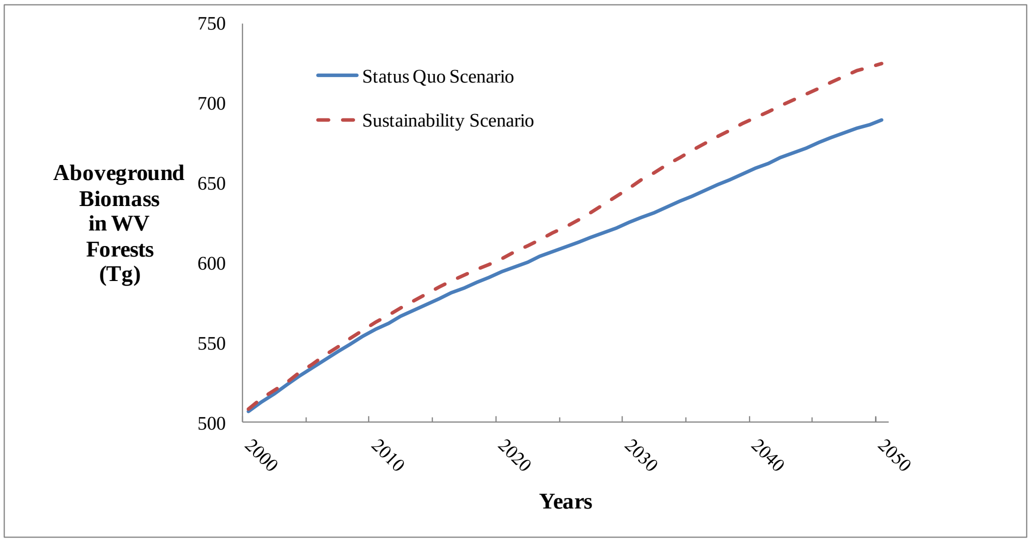

Figure 6-14 Statewide Forest AGB for the Status Quo and Sustainable Timbering Scenarios

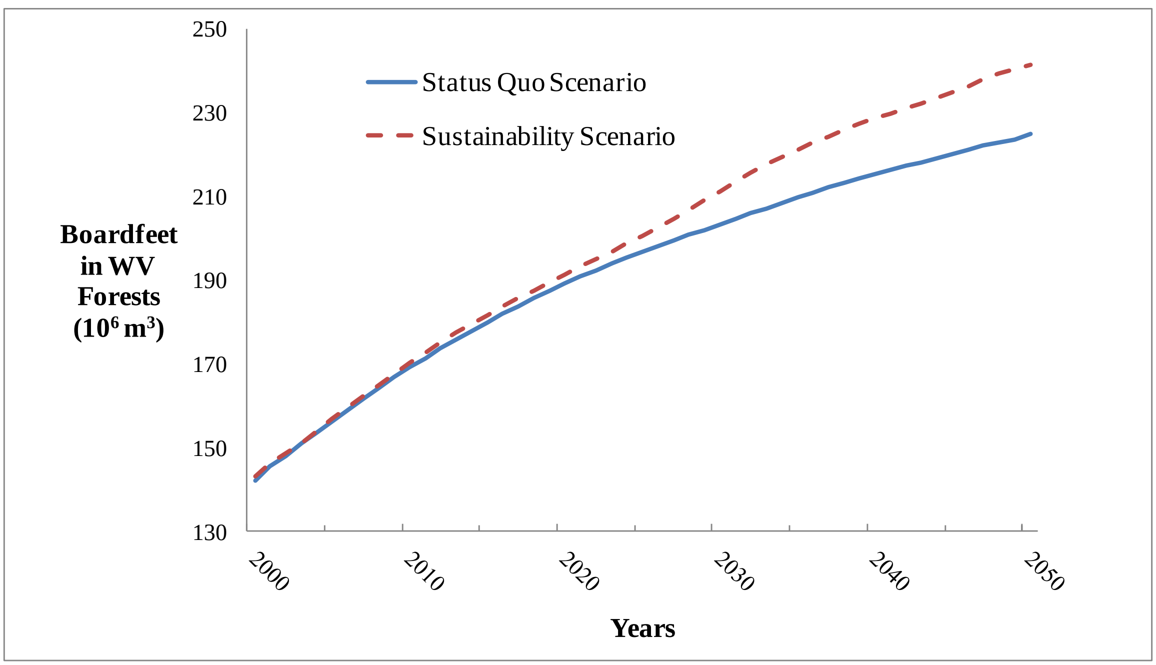

Figure 6-15 Statewide Commercial BF Resources for the Status Quo and Sustainable Timbering Scenarios (million m^3)

Although the total value of timber being extracted from the state is the same for both scenarios, the total AGB extracted is significantly lower for the sustainability scenario. Under this scenario, 6% less biomass is removed statewide principally due to the manner in which trees and plots are selected across the state. Of the 30% of AGBD that firms may remove under the sustainability constraint, tree selection would be driven by economic value and as a result removals would be focused on the most valuable species that could be extracted from each plot. As a result, smaller less valuable trees and low value trees are left on the plot under the sustainability scenario, which reserves more of the 30% biomass restriction to higher value commercially important species.

Another indirect effect of a sustainable timbering requirement is that timber firms are projected to remove a smaller amount of timber per unit area, but over a much larger area across the state. In fact, it was simulated that twice the area of forestland would be timbered under the sustainability scenario, albeit at a significantly reduced intensity, than under the status quo timbering scenario. As timber firms will access more land for removal events, they will be able to select from a larger number of trees on which to conduct removals. Essentially, the logistic regression models derived for stand and tree selection are "cherry picking" algorithms that select the best stands and trees for removal. By restraining removals on individual forest stands, firms applied their cherry picking selection criteria to a much larger area, which has the indirect effect of enhancing the average value of volume removed. As such, timbering firms may select from a much greater sample of forest stands and remove much more valuable timber, such as red oak and black cherry that they find on twice the number of stands timbered each year. This would indirectly cause greater timber pressure on higher value stands and species, like red oak and black cherry.

Sustainable timbering was also shown to enhance long-term forest biomass and net annual growth rates across the state, which was a significant finding. Overall, the statewide average annual net growth rate for all forest stands under the sustainable timbering scenario was 50% higher than for the status quo timbering scenario in 2050. This significant difference in net annual growth rate in 2050 across the state was due to several processes, including: the effect of low intensity removals and thinning on more mature stands (where growth was decelerating), which increased stand growth relative to status quo conditions; elimination of medium and high intensity timber pressure (including clear cuts) on recovering stands; longer rotation cycles that allowed stands to recover; and reduced biomass removals due to the extraction of higher value timber across more stands (i.e., cherry picking effect across more acreage of forest stands), as previously discussed. Therefore, the sustainable timbering scenario provided an opportunity for the entire system to more fully recover, while at the same time producing the same value of timber for the entire state.

Although access to individual trees may result in some collateral damage to less desirable trees, studies have shown that sustainable timbering and low intensity removals (< 30%) are feasible (FAO 2001) and have limited impact on CERW (Buehler et al. 2007, USFWS 2009). For example, extensive research has been done on the benefits of low impact or reduced impact logging (RIL) (FAO 2001, Putz et al. 2008), which has indicated that significant increases in forests yields can be achieved while maintaining carrying capacity, including reduced collateral damage from timbering. Reduced impacts can be achieved through several improved silviculture practices, which include carefully planning tree selection and removals, and utilizing smaller-scale extraction techniques to surgically remove the selected trees to minimize stand damage. Some studies indicate that RIL increase operational costs, while other research has shown lower operational costs to timber firms over conventional logging practices. The reduced costs were achieved in part from lower operational and equipment costs, and lower infrastructure (e.g., roads) and maintenance costs (FAO 2001, Putz et al. 2008).

With the 20 year rotation cycle restriction for the sustainable timbering scenario, timber firms would need to seek out additional areas for timbering. Over the long-term, CFM model predicts that the sustainability scenario would result in timbering about 40% of all forestland across the state within a 20 year rotational cycle (on average from 2000 to 2050) in order to meet most-likely timber market demand, while only about 15% of the forestland would be timbered within the same 20 year period under the status quo timbering scenario. From 2000 to 2050, CFM predicted that the sustainability scenario would result in timbering on approximately 60% of forestland across the state, while only about 30% of the forestland would be timbered within this same period under the status quo timbering scenario. Within the 20 year rotation cycle restriction, it is uncertain whether timber firms would be able to gain access to over 40% of forestland across West Virginia to conduct low intensity removals as this frequency is more than double current conditions. Furthermore, nearly 80% of the forestlands are privately held and over 70% of those lands are owned by NIPFs, who may not be willing to participate in a sustainable forest management effort. Some surveys of NIPFs have been conducted to determine their willingness to allow timbering on their lands, although not specifically regarding long-term participation in a sustainable forest management program. NWOS, conducted by USFS, indicates that 19% of NIPFs in West Virginia would be willing to sell commercial timber on their lands in the next five years (USFS 2009b). In another survey, researchers demonstrated that 24% of NIPFs in one county in West Virginia would also be willing to enter into long-term timbering contracts (McGill et al. 2008). Therefore, there is evidence to suggest a large-scale sustainable forest management policy would be plausible.

Figures 6-16 through 6-21 compare stand and tree-level distribution metrics for the sustainability and status quo timbering scenarios. With respect to AGB distributions across the state, the sustainable timbering scenario enhanced the conservation of long-term forest stand recovery metrics in 2050 over the status quo timbering scenario, which was consistent with hypothesized trends (see Tables 6-2 and 6-7), as shown in Figure 6-16. By 2050, a higher percentage (56%) of forest stands was classified as being in an advanced recovery stage under the sustainable timbering scenario, as compared to the status quo scenario (49%).

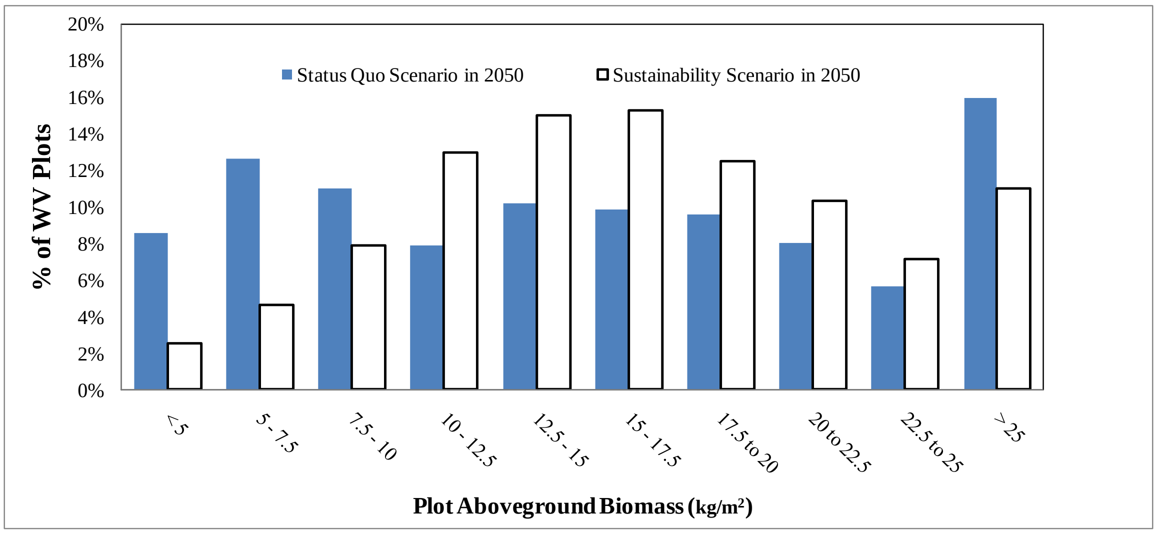

Figure 6-16 Distribution of Forest Stand AGBD across West Virginia in 2050 for the Status Quo and Sustainable Timbering Scenarios

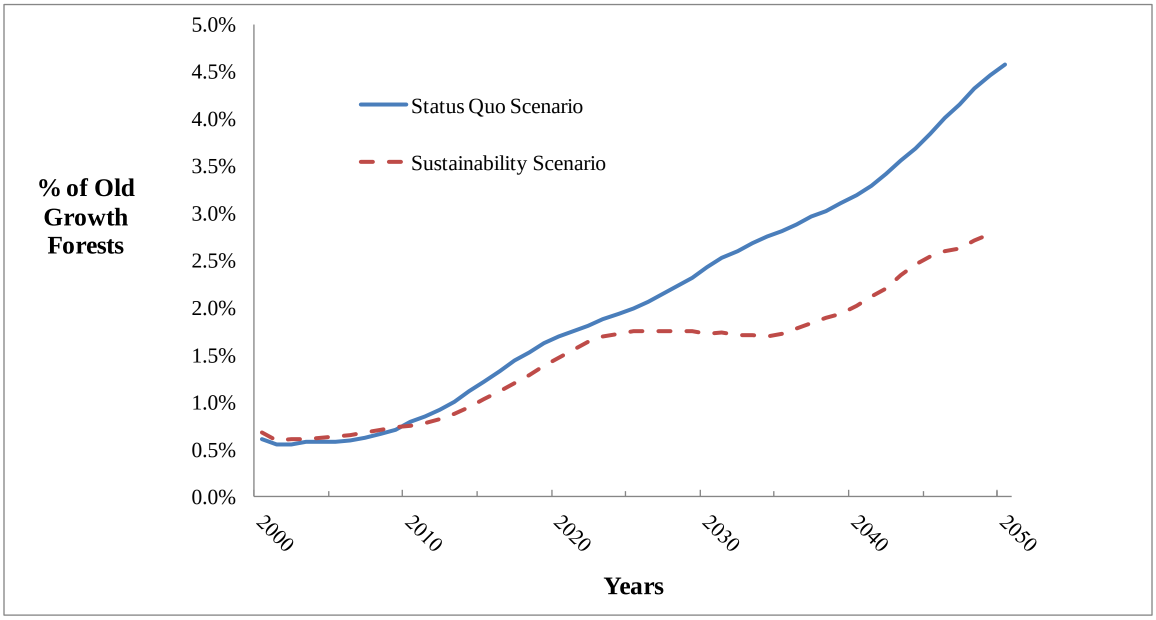

Figure 6-17 Percent of Forest Stands Exhibiting Old Growth Characteristics

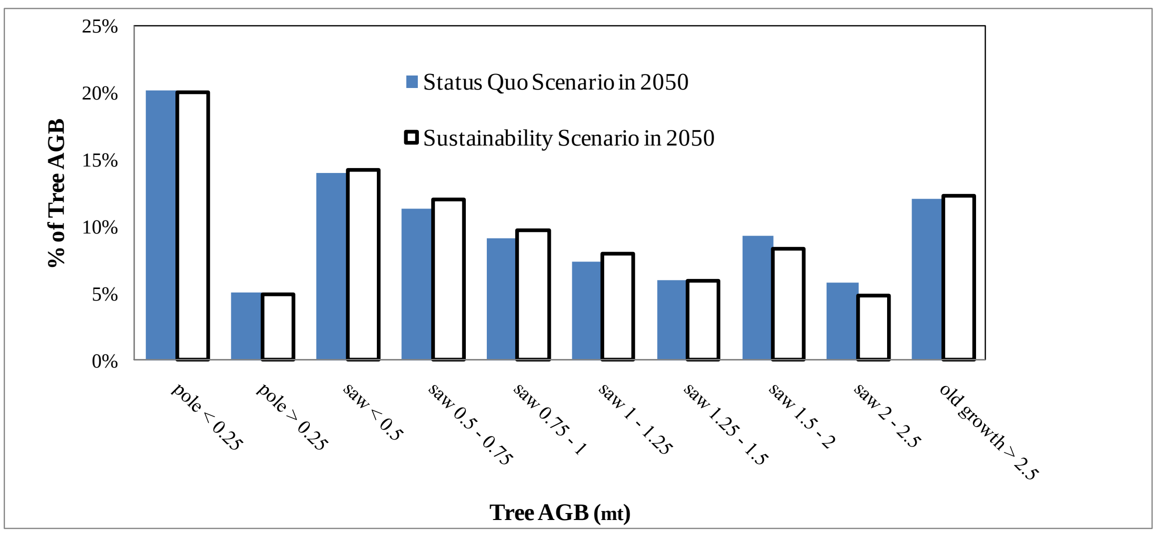

Figure 6-18 Distribution of Tree Biomass by Size Class across West Virginia in 2050 for the Status Quo and Sustainable Timbering Scenarios

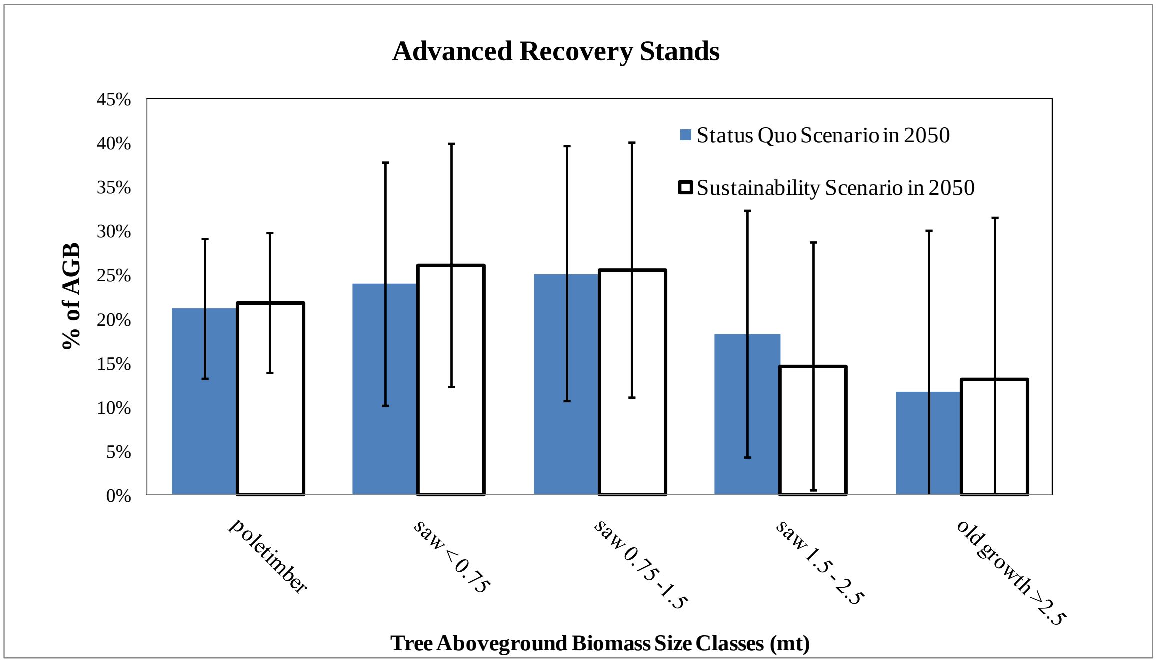

Figure 6-19 Distribution of Tree Biomass by Size Classes for Advanced Recovery Stands under Status Quo and Sustainable Timbering Scenarios in 2050

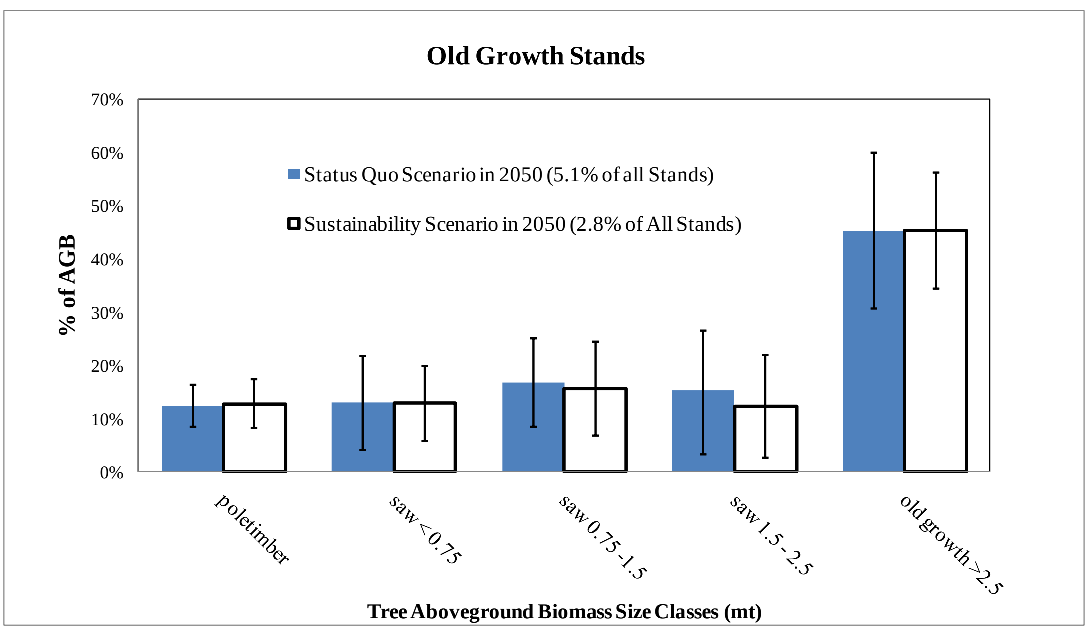

Figure 6-20 Distribution of Tree Biomass by Size Classes for Old Growth Stands under Status Quo and Sustainable Timbering Scenarios in 2050

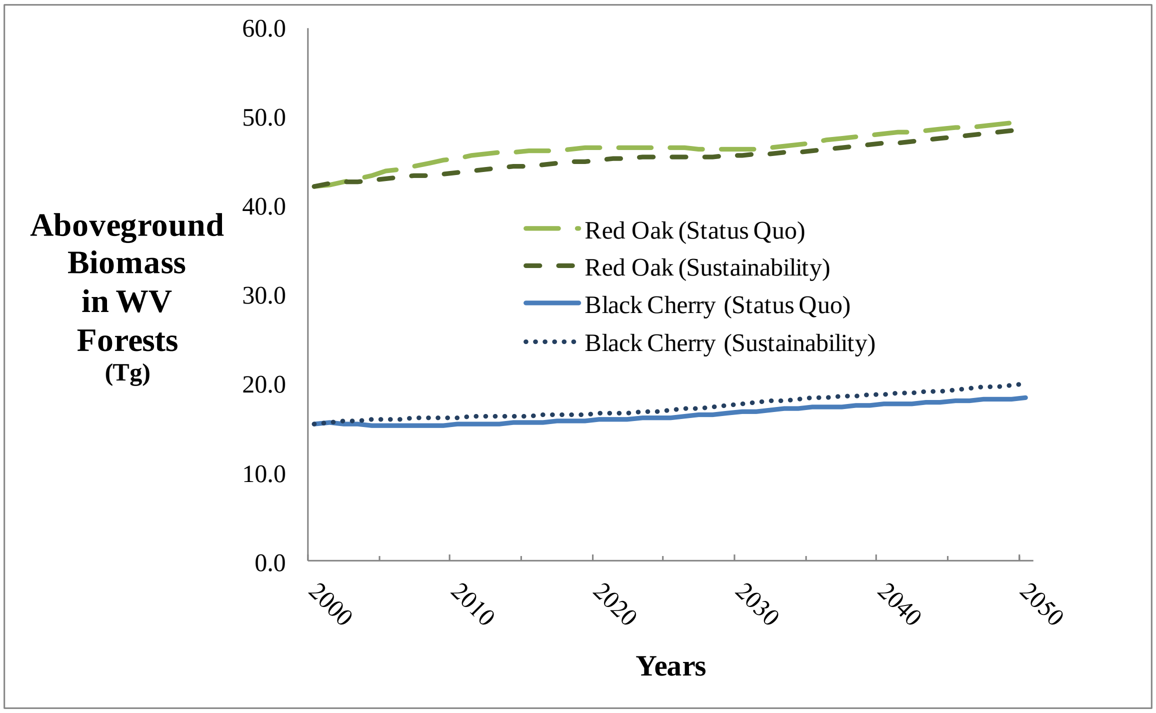

Figure 6-21 Red Oak and Black Cherry AGB under Status Quo and Sustainable Timbering

Although most aspects of sustainability and recovery were enhanced under the sustainability scenario, there were certain forest ecosystem indicator metrics that were actually more improved or similar under the status quo scenario at the landscape scale. Although it is clear that a low intensity sustainable timber removal would improve forest stand metrics as opposed to an unsustainable timber removal (e.g., 80% removal of all timber) on the same plot (plot-scale), differences are seen when comparing the benefits and effects at the landscape scale, as outlined below:

- Under the sustainability scenario the frequency of timber removal events doubled as compared to the status quo scenario, due to the shift in timber burden.

- The status quo scenario yielded a higher percentage of stands that would achieve “old growth forests” conditions. The status quo scenario yielded 4.5% of plots classified as old growth forests versus 2.9% for the sustainability scenario, as shown in Figure 6-17. Similarly, the status quo scenario generated a higher percentage (16%) of acreage across the state with AGBD above 25,000 g/m^2 (see Figure 6-16) (commensurate with old growth forests, but many lacking higher biomass in large trees above 70 cm) as compared to the sustainability scenario (11%). These results were due to a higher frequency of timbering (albeit at a lower intensity level) on plots with higher biomass under the sustainability scenario, resulting in fewer plots achieving the highest biomass levels.
- The status quo scenario yielded a similar percentage of biomass in trees greater than 70 cm across the state (12% for both scenarios) (see Figure 6-18). Although there was a restriction to preserve trees greater than 70 cm under the sustainability scenario, the increased “cherry picking” effect on twice the acreage being timbered across the state resulted in timbering of more valuable large trees that were just below 70 cm (and therefore would not grow into future trees above 70 cm). Thus, there was little difference in the conservation of large trees between both scenarios (see Table 6-7 and Figures 6-19 and 6-20).

For the status quo scenario, the same economic drivers were generating stand and tree selection, but the lower acreage of forest resources being timbered each year, and the ability to re-timber plots, allowed many high value trees and plots to go untouched and/or unnoticed under the status quo scenario. Although higher value plots and trees are more likely to be timbered in a given year, the logistic regression models for stand and tree selection (used for both timbering scenarios) do not select the highest valued plots and trees for timbering in any given year, rather it simply increases their probability of selection. As discussed in Section 4, the results of the statistical analysis indicated that some of the variability in plot and tree selection for timbering events could not be explained by economic and other variables. For example, in any given year, many of the highest valued forest stands and the highest valued trees are not selected for removal. Thus, there appears to be other factors that prevent purely profit-based decision-making for ranking and selecting stands and trees, which allows some high valued plots to go untouched or unnoticed for a half century. These factors may include imperfect knowledge of timber resources across the state (due to lack of access and surveys on private property), inability for timber firms to obtain timbering contracts on more valuable forest stands due to private ownership controls, physical access limitations, and/or self imposed sustainable timbering procedures.

As a result of the processes occurring at multiple scales, i.e., the net timbering effects at a forest stand scale versus net effects at the landscape scale, sustainable and status quo timbering scenarios appear to create very different forest habit quality distributions across the landscape. In very general terms, status quo timbering tends to create greater differences and polarization of habitat quality across the state, including increased habitat fragmentation due to some clear cutting and large scale removals (although specific spatial fragmentation metrics were not tracked in this study). For example, higher intensity removals create significant disturbances to individual forest stands, but at a larger landscape scale there are unintended, indirect effects in that certain plots may remain undisturbed for a greater period of time. On the other hand, the sustainable timbering scenario created more of an averaging effect that reduced the polarization of habitat quality across the landscape, which also reduced the occurrence of the extremes of habitat quality across a landscape (i.e., reducing both the lowest and highest quality stands across the state). This would reduce overall habitat variability across the state, but also an increase in the percentage of stands in advanced stages of recovery (approximately 7% more than status quo by 2050) (see Table 6-7). With respect to the distribution of tree size classes on advanced recovery stands and old growth stands, little difference was seen between the results of the status quo and sustainable timbering scenarios (as shown in Figures 6-19 and 20) at the state scale. Thus, the results were mixed between the two scenarios relative to the forest indicator metrics tested at the state scale.

At the plot-level, sustainable timbering generates many benefits to a forest stand in that less biomass would be removed, large trees would be preserved, and the stand could recover over a longer rotational cycle. At the state-level, sustainable timbering significantly increased the growth potential of forest system, increased the carrying capacity for future timbering, and significantly increased the acreage of forests that will reach an advanced stage of recovery by 2050. On the other hand, the sustainable timbering scenario was less effective at creating old growth forest stands and conserving large-trees important for re-establishing old growth forests, even when a specific policy was imposed on the system to create such habitat. Certainly, more plots achieved higher biomass under the sustainable timbering scenario, but there were some positive and negative, indirect and unintended consequences of both status quo and sustainable timbering that were only seen when evaluating conditions at the landscape scale. As such, the results underscore the importance of addressing both the positive and negative implications of forest management policy at multiple scales for the entire system.

6.4 Conclusions

AGB and AGBD are projected to continue to grow from just over 500 tg in 2000 to over 680 tg in 2050, with nearly half of the state acreage being classified as being in advanced stages of recovery by 2050 (> 15,000 gC/m2). Although, biomass will continue to increase to 2050, the rate of annual increase decelerates. This deceleration is due to a projected doubling of the timber removal rates toward mid-century, increases in landscape scale disturbances, and decelerating net annual growth rates, which are all due in part to increases in stand density.

The results of the logistic regression analysis indicated that landscape-scale disturbances are projected to increase by approximately 50% from 2000 to 2050, as forest stands continue to increase in biomass. By 2050, approximately $1/4^{th}$ of the state forest acreage is projected to experience landscape scale disturbances (as opposed to 17% in 2000), resulting in net negative growth, particularly for locations with higher forest biomass, lower annual precipitation, and greater slopes.

Overall, the results of this study indicated that under status quo timbering and most-likely timber market conditions, forest ecosystem indicator metrics and forest stand recovery will continue to improve to 2050. However, if timber prices increase as they did in the past two decades (~1% / year), then forest ecosystem indicator metrics and forest stand recovery will level off and begin to decline by mid-century. Sustainable timbering techniques enhanced certain forest ecosystem indicator metrics, particularly AGB (increased by 5%), the percentage of forest stands that achieve an advanced recovery stage across the state, and the economic value of standing timber ($0.8B in 2050). However, it had little effect on large tree conservation at the landscape scale, statewide tree stand structure diversity, and achievement of old growth forest conditions at the landscape scale. The doubling of low intensity timbering events across the state under the sustainable timbering scenario reduced the number of forest stands predicted to achieve very high AGBD exceeding 25,000 g/m^2 and AGB in the largest trees (> 70 cm) at the landscape scale. Although the frequency of timbering events increased under the sustainable timbering scenario, it does not follow that the cumulative effect of more low intensity timber removals is greater than lower frequency, high intensity removals. On the contrary, studies have shown that timber removals less than 30% have enhanced habitat for certain species (e.g., the cerulean warbler, which is the MIS for northeastern forests systems [USFS 2000]). In any event, the results of this study point to one of many trade-offs that should be considered in the development of state-level sustainable forestry plans and finer-scale plans. In addition, this study demonstrates the importance of modeling anthropogenic and natural disturbance agents at multiple scales, in order to evaluate conservation habitat scenarios and strategies. Further research would be required using participatory methods (Parker et al. 2003, Bousquet and Le Page 2004) and targeted surveys to determine whether sufficient landowners would be willing to participate in a sustainable forestry management program that would involve low intensity removals. Such participatory modeling techniques are also recommended for properly modeling, designing, and testing the acceptance and potential success of such a program if it were to be considered.

7. Long-Term Effects of Timbering on Carbon Sequestration using an Integrated, Multi-Scale Model

7.1 Introduction

Over the past century, forest resources in West Virginia have continued to significantly increase in carbon content, acting as a sink to offset West Virginia anthropogenic carbon emissions. Natural growth and regeneration of forest stocks in West Virginia are estimated to have resulted in an average annual carbon flux of 13.1 teragrams (tg) CO_2 eq/year from 1989 to 2000 (USFS 2010a), which factors in the total annual loss in forest biomass from timbering and land use conversions and growth from all live growing stock trees. It is uncertain how future timbering will impact continued carbon sequestration and whether West Virginia's forests will continue to act as a sink or potentially a source throughout this century. Towards the end of the 20th century the restoration of forest resources in the state, along with increased timber market prices, gave rise to significantly higher timber removals. Using CFM, this portion of the study evaluates the long-term implication of timbering on carbon sequestration for two timbering scenarios under varying timber market conditions from 2000 to 2050.

Using forest systems as carbon sinks has been put forward as one of many viable policy solutions for mitigating climate change and achieving carbon sequestration goals (USFS 2006). Economic research conducted by the Pew Research Center finds that forest-based carbon sinks are one viable approach for creating carbon credits (Stavins and Richards 2005).

In parallel to the consideration of climate change legislation, forest systems are simultaneously undergoing land use conversion, active forest management, natural and anthropogenic-related disturbances, as well as system-wide climate change. The cumulative effect of these forces can create synergistic and antagonistic effects, which can potentially eclipse the benefits gained through natural regeneration, as well as more costly certifiable carbon credits created through afforestation/reforestation projects and easements. As such, it is important that a more holistic systems approach be used to evaluate the net cumulative effect of all the principal forest and carbon processes that occur in the entire system.

The overall research question addressed by this portion of the study is: *What long-term effect will status quo and sustainable timbering scenarios, under varying timber market conditions, have on forest carbon sequestration in West Virginia?* Table 7-1 presents the specific hypothesized relationships between the timbering scenarios and market conditions on carbon sequestration. Based on current carbon sequestration rates and market conditions, it is hypothesized that *West Virginia forests will continue to operate as a carbon sink through 2050, with a reduction in the carbon sink under the High Timber Market Scenario (1% annual increase in timber prices)*. It is further hypothesized that *sustainable timbering practices will increase carbon sequestration relative to status quo timbering practices under most-likely timber market conditions*. As these are inferred relationships, the null hypotheses that these scenarios have no impact on carbon sequestration were also evaluated.

To address these hypotheses, the same timbering and market scenarios previously discussed in Section 6 were imposed on the system in order to assess changes in carbon sequestration. Estimates of carbon sequestration include not only the increase in aboveground portion of trees, but also estimates of carbon in various pools of above- and belowground biomass to include carbon in soil, roots, litter, understory brush, saplings, standing deadwood, and down deadwood, and the wood products pool. Available carbon models were added to CFM and the methods are discussed in Section 7.2.

Table 7-1 Hypothesized Net Change in Carbon Sequestration for West Virginia Over Time Under Timbering and Market Condition Scenarios

Timbering and Market Scenarios	Carbon Sequestration	
	Short-Term	Long-Term (2050)
Most-Likely Timber Market Conditions [1]	+ [2]	+ [2]
High Timber Market Conditions	— [3]	— [3]
Sustainable Timbering Practices [5]	+ [4]	+ [4]

[1] Assuming status quo timbering practices
[2] Relative to conditions in 2000
[3] Relative to most-likely timber market conditions
[4] Relative to status quo timbering practices
[5] Assuming most-likely timber market conditions

7.2 Methods

7.2.1 Modeling Approach

The CFM model, discussed in detail in Section 6.2, was enhanced with several carbon models to simulate carbon dynamics at the tree-, plot-, and state-scale (see Section 4.1 and Figure 3-2, and Section 6.2.1 and Figure 6-1 for a description of the conceptual model). CFM was used to conduct future simulations of timbering events, forest growth, and carbon mass for each tree and plot on an annual time step from 2000 to 2050. For each annual iteration, the model estimated endogenous variables discussed in Section 6.2, based on initial tree and plot conditions in 2000, which are based on FIA field sampling data and estimates (including estimates of DBH, volume, biomass, and carbon). Additional endogenous and exogenous variables added to CFM that pertain to carbon dynamics are presented in Table 7-2. CFM was used to simulate carbon dynamics and fluxes at the tree-, plot-, and state-level for status quo timbering and sustainable timbering scenarios, under a range of timber price market conditions. During the model simulation, carbon densities (gC/m^2) were derived for each tree and plot, and up-scaled to estimate state-level carbon fluxes. USEPA published total carbon emissions for West Virginia (which includes estimates of anthropogenic point and mobile source emissions) were also compared to modeled carbon fluxes to determine the potential offsets associated with the forest sink in West Virginia (USEPA 2010).

As discussed in Section 5.3.5 and 6.2.1, CFM estimated the total tree biomass (root, stump, central stem, tree tops) for each tree with a DBH > 5” on an annual time step. For estimating carbon, the total tree biomass estimates were multiplied by the fraction of carbon mass in dry weight biomass of 0.5 (Smith et al. 2006, USEPA 2009, Aber and Federer 1992), which is the

Table 7-2 CFM Endogenous and Exogenous Variables

Model Parameter	Units	Field Data Source/Derivation
ENDOGENOUS VARIABLES		
State-Level Offset of State Carbon Emissions	%	Ratio of total annual flux in carbon for forestland divided by the total carbon emission for the state.
State-Level Annual Carbon Sequestration Flux of State Forest Sink	tg CO2 eq/year	Total annual flux in carbon per year.
State-Level Carbon in Forestland	tg CO2 eq	Derived by compiling carbon from plots and expansion factors to estimate state level carbon for all forestland.
Plot-Level Carbon Density in Understory	gC/m^2	Derived using 8 forest type-specific regression models presented in USEPA (2009), based on total live large tree carbon density on the plot on an annual basis.
Plot-Level Carbon Density in Standing Dead and Down Dead Trees	gC/m^2	Derived using 16 forest type-specific regression models presented in USEPA (2009), based on total live large tree carbon density on the plot on an annual basis.
Plot-Level Carbon Density	gC/m^2	Derived by compiling carbon in trees [root, stump, stem, tree tops], soil carbon, litter, understory, saplings, down dead trees, and standing dead trees on an annual basis.
Tree-Level Carbon (mt)	mt	Derived using 11 species specific regression models discussed in Section 6 (Figure 6-1) that convert gross volume of the central stem for trees > 5" DBH to total tree mass using specifies specific data from FIA 2000. Regression models R^2 ranged from 0.89 to 0.99.
EXOGENOUS VARIABLES		
State-wide Carbon Emissions (All Sources)	38.8 tg/year	West Virginia state emission estimate for 1999 (USEPA 2010).
State-wide Carbon Emission Growth Rate (All Sources)	1%	Annual CO_2 emissions were assumed to grow at an annual rate of 1%/year, which is the estimated state gross domestic product (GDP) growth. To predict future emissions, the average growth in state GDP was applied to emissions in 2005 as an indicator of anthropogenic growth. To be conservative, no discounts were applied for potential future conversion to energy efficient systems. http://www.epa.gov/climatechange/emissions/downloads/WVInventorySummary_11-16b.pdf
Plot-Level Forest Stand Forest Type	Unitless	FIA 2000 Plot Data (USFS 2010a). Assumed to be unchanged through the model simulation to 2050
Plot-Level Soil Carbon	gC/m^2	FIA 2000 Plot Data (USFS 2010a)
Plot-Level Sapling Carbon Density	gC/m^2	FIA 2000 Plot Data (USFS 2010a)
Tree-Level AGB and Tree Biomass in 2000	kg	FIA 2000 Plot Data (USFS 2010a)
Tree-Level Species Category	n/a	FIA 2000 Plot Data (USFS 2010a). Tree species categories are presented in Table 3-1.
Tree-Level Portion of Biomass that is Carbon	0.5	Smith et al. 2006, USEPA 2009

approach typically used by the USFS, USEPA, and internationally for estimating carbon based on biomass of the tree (IPCC 1997a). Although no studies were found on the variability or error in the 0.5 conversion factor that would apply to the study area or region, it was confirmed that this same factor was applied in PnET for the wood carbon pool (while 0.45 was applied for estimating carbon in the fine roots and leaves), and by USFS and USEPA for estimating carbon in forestlands in West Virginia.

Recently released USFS carbon data and regression models used for predicting regional and forest-type specific carbon pools for deadwood, soil, litter, and understory were incorporated into CFM for estimating carbon stocks in other carbon pools (USEPA 2009, USFS 2010a) (presented in Table 7-3). These models were developed by USFS to estimate carbon pools that are not already included in the FIA database. Aboveground carbon in the tree tops, central stem, stumps, and roots for large trees is already provided in the FIA database for all trees located on study plots based on estimated biomass. The total carbon in the live large tree pool was modeled for each tree on an annual time step using the models discussed in Section 6 and the 0.5 conversion factor. Carbon in down deadwood, standing deadwood, and understory were modeled annually as endogenous variables by forest type for each forest stand in the CFM model using regression models developed by USFS and applied by USEPA for estimating regional carbon stocks for the United States (USEPA 2009) (see Table 7-3).

For soil organic carbon, USFS estimates of SOC for the 1,500 FIA sampling plots in West Virginia were used in CFM for estimating carbon in this pool. This data were recently released as part of the Version 4 FIA database (USFS 2010a). The SOC estimates are based on geostatistical analysis of SOC field data collected from throughout the U.S. and compiled in the STATSGO

Table 7-3 Forest Carbon Pool Equations Developed by USFS (USEPA 2009, USFS 2010a)

Forest Type	Carbon Pool Equation[1]
White, Red, Jackpine Group	Understory (gC/m2) = ((Tree_Carbon) * $e^{(1 - 1.116 * \ln(Tree\_Carbon/100))}$
	Standing Deadwood (gC/m2) = (2.841 * $(Tree\_Carbon/100)^{0.134}$)*100
	Down Deadwood (gC/m2) = 0.055 * Tree_Carbon
Spruce, Fir Group	Understory (gC/m2) = ((Tree_Carbon) * $e^{(0.825 - 1.21 * \ln(Tree\_Carbon/100))}$
	Standing Deadwood (gC/m2) = (5.89 * $(Tree\_Carbon/100)^{0.191}$)*100
	Down Deadwood (gC/m2) = 0.092 * Total Tree Carbon
Oak, Pine Group	Understory (gC/m2) = ((Tree_Carbon) * $e^{(2.149 - 1.268 * \ln(Tree\_Carbon/100))}$
	Standing Deadwood (gC/m2) = (1.725 * $(Tree\_Carbon/100)^{0.311}$) * 100
	Down Deadwood (gC/m2) = 0.061 * Total Tree Carbon
Oak, Hickory Group	Understory (gC/m2) = ((Tree_Carbon) * $e^{(0.842 - 1.053 * \ln(Tree\_Carbon/100))}$
	Standing Deadwood (gC/m2) = (3.332 * $(Tree\_Carbon/100)^{0.191}$) * 100
	Down Deadwood (gC/m2) = 0.068 * Total Tree Carbon
Elm, Ash, Cottonwood Group	Understory (gC/m2) = ((Tree_Carbon) * $e^{(0.892 - 1.079 * \ln(Tree\_Carbon/100))}$
	Standing Deadwood (gC/m2) = (4.992 * $(Tree\_Carbon/100)^{0.134}$) * 100
	Down Deadwood (gC/m2) = 0.071 * Total Tree Carbon
Maple, Beech, Birch Group	Understory (gC/m2) = ((Tree_Carbon) * $e^{(0.892 - 1.079 * \ln(Tree\_Carbon/100))}$
	Standing Deadwood (gC/m2) = (3.041 * $(Tree\_Carbon/100)^{0.306}$) * 100
	Down Deadwood (gC/m2) = 0.071 * Total Tree Carbon

[1] Tree_Carbon = Total tree carbon density for growing stock trees greater than 5” DBH (gC/m2) (which includes aboveground and belowground live carbon)

database, with data gaps filled using comparable soil types. The USFS linked this data to the FIA databases based on location and forest type group (USEPA 2010). SOC estimated for each plot by USFS was exogenous to the model and was assumed to remain constant for each plot throughout the model duration and the potential effects of this assumption are discussed in Section 7.3. Although SOC may change over time, there was insufficient data to model SOC in West Virginia and how it would potentially change over time due to changes in AGBD. These results were simply added to the plot level estimates in order to estimate stand- and state-level carbon pool density for forest resources for comparison purposes, as SOC is often included with AGBD for national reporting of carbon stocks (USEPA 2009, USDA 2008). In these national reports, SOC was also assumed to remain constant within areas that remained forestlands, while the changes in forest carbon stock were driven only by measured growth in tree volume and biomass (USEPA 2009, USDA 2008), as assumed in CFM. The lack of soil carbon data was identified as an area of uncertainty in these national studies, which may significantly impact national and state-specific carbon budget estimates (USDA 2008).

For saplings (non-growing stock trees < 5” DBH) and leaf litter, FIA data were used to estimate the total carbon content of all saplings and leaf litter on each of the plots in 2000. No statistical relationships were observed between sapling carbon pools and total AGBD, timbering history, or other site parameters; therefore, it was not practical to simulate saplings as an endogenous pool in the CFM model. The sapling pool represents less than 5% of the carbon stocks of a plot; therefore, leaving the sapling pool as a site-specific measured exogenous variable (which remains constant) was considered reasonable for predicting total carbon density of plots. The litter pool is also relatively small; therefore, plot specific litter estimates reported for each plot by USFS were included as an exogenous variable in the model (USFS 2010a).

With respect to the wood products pool, state-level estimates of current fluxes in this pool indicate that it is currently a sink and contributes less than 10% to the overall forest system sink for the state. To properly address wood product pool dynamics in a given year, it is necessary to not only consider the fluxes associated with timber removals in a given year, but also the release of carbon in the same year for wood products harvested over the previous century and beyond, as well as the near-term lifecycle of wood products that were removed in that year (e.g., burning of waste products in the same year, burning of slash, fuel, etc.). This is a significant historical research effort which has been done at the national level, with state-level wood product pools estimated based on a weighted average approach using historical state production estimates (i.e., a West Virginia specific wood products pool has not been modeled using the methodology applied at the national level). To replicate this national effort and methodology at the state level, and integrate these results with future projected production activity, would have required a great deal of effort. Furthermore, the wood products pool for West Virginia is estimated to be less than 10% of the total forest carbon pool annual flux. Therefore, the effort necessary to only fine tune a very small part of the carbon cycle for the state, was not considered practical for this dissertation project, particularly given the focus of this project. In any event, if long-term average removals continue to increase, as predicted (see Section 6), then it is possible that the wood products sink may continue to grow slightly in the future. However, the contribution of the wood products pool and this possible growth is relatively small (less than 10%) compared to the other carbon dynamics being modeled to estimate statewide fluxes, as previously discussed. Therefore, it was conservatively assumed that the current carbon flux in the wood products pool for West Virginia of 1.2 tg/year at the state-level would remain constant to 2050. Increases in future timber removals were assumed not to add to the overall size of the wood products pool sink to 2050. Since the status quo and sustainable timbering scenarios generate similar quantities of timber removed, this approach for addressing the wood products pool sink should not significantly change the comparative analysis of these scenarios. However, the total estimates of carbon sequestration may be underestimated using this approach, which could conceivably impact perceived outcomes with potential policy implications.

7.2.2 Sensitivity and Uncertainty Analysis

CFM underwent both a sensitivity analysis and uncertainty analysis using Monte Carlo simulation using the same methods discussed in Section 6.2.2. The key metrics tested in this sensitivity analysis were the estimated total statewide sequestered carbon in 2050 (tg CO2 eq) and the average plot aboveground carbon density (gC/m^2) in 2050.

7.3 Results and Discussion

7.3.1 Sensitivity and Uncertainty Analysis

An analysis was conducted to evaluate the sensitivity of the model estimates of carbon to changes in key input variables in CFM. For aboveground carbon density (gC/m^2), the results are identical to those discussed previously in Section 6.3.2 for AGBD, because approximately half of the AGBD is carbon. For estimating statewide carbon pool estimates, the results of the sensitivity analysis are presented in Table 7-4. The impact of variable changes to statewide forest carbon estimates is lower than estimated change to AGBD (discussed in Section 6.3) because soil carbon, which makes up a large percentage of the forest carbon, was assumed to remain constant over time.

Overall, changes in tree positive growth rates (+/- 25%) had the most significant impact on total statewide carbon predictions in 2050 (+/- 5 to 6%). Positive growth directly impacts carbon sequestration rates and was also the key driver in forest biomass estimates, as discussed in Section 6.3. Changes in landscape-scale disturbances also had a significant impact on carbon estimates (+/- 3 to 4%). These results support other studies, which indicate that large-scale disturbance regimes (e.g., extreme weather events including climate change, regional fire, pest infestation) are important dynamics that need to be evaluated when estimating annual carbon fluxes (USGCRP 2008). Timber removal rates, regional timber prices, tree mortality, and tree regeneration rates also had similar impacts on carbon estimates (+/- 1 to 3%), while negative tree growth rates had a negligible effect on carbon.

Table 7-4 CFM Carbon Prediction Sensitivity Analysis Results

Parameter	% Change Based on +/-25% Change in Parameter	
Average Plot Aboveground Carbon Density (gC/m^2) in 2050		
Regional Timber Prices	5%	-5%
Plot Level Timber Rates	6%	-5%
Plot Level Disturbance Rates	8%	-6%
Tree Mortality Rates	5%	-4%
Tree Negative Growth Rates	negligible	negligible
Tree Positive Growth Rates	-11%	9%
Tree Regeneration Rates	-4%	2%
Total Statewide Forest Carbon in 2050 (tg CO^2eq)		
Regional Timber Prices	3%	-3%
Plot Level Timber Rates	3%	-3%
Plot Level Disturbance Rates	4%	-3%
Tree Mortality Rates	3%	-2%
Tree Negative Growth Rates	negligible	negligible
Tree Positive Tree Growth Rates	-6%	5%
Tree Regeneration Rates	-2%	1%

7.3.2 Long-Term Timbering and Carbon Sequestration Dynamics

Based on FIA, natural growth and recovery of forest stocks in West Virginia are estimated to have generated an average annual carbon flux of 13.1 tg CO_2 eq/year from 1989 to 2000 (USFS 2010a), which factors in the total annual loss in forest biomass from timbering and land use conversions and growth from all live growing stock trees greater than 5" DBH. The annual carbon flux in 2000 estimated using CFM is ten percent higher at 14.4 tg CO_2 eq/year of sequestered carbon for the entire forest system, which includes not only growing stock trees but estimated growth in other carbon pools including understory, saplings, standing deadwood, and down deadwood. The CFM estimates also include the most recent soil carbon data and carbon models used for estimating forest carbon pools (USFS 2010a, USEPA 2009), including models that estimate increases in carbon pools for deadwood (standing and down), litter, and understory pools, which are derived from equations based on increases in live stock tree carbon density (USFS 2010a, USEPA 2009). Thus, the CFM results would be slightly higher than the total carbon flux estimated using the 2000 FIA data alone, which did not include fluxes from these smaller carbon pools. Furthermore, the carbon flux estimated from FIA data of 13 tg CO_2 eq/year is based on an average annual flux rate between a 12 year interval (1989 to 2000), which is not directly comparable to the CFM flux rate estimated for the last year, 2000. Since the forest system grew significantly between these time periods, the average annual flux rate estimated using FIA between 1989 and 2000 would be smaller than the flux that occurs in the very last year (2000), which also explains why the CFM model estimate is slightly higher.

Overall, CFM estimates that carbon stocks in West Virginia forests are projected to continue to increase to 2050 under most-likely timber market conditions. Carbon stocks are projected to grow from just over 2,500 tg CO2 eq in 2000 to just over 3,000 tg in 2050 (see Figure 7-1). Similarly, the average carbon in forest stands is projected to increase from over 15,000 gC/m^2 to over 19,000 gC/m^2 (see Figure 7-2). Thus, the forest system is projected to continue to remain a carbon sink to 2050, although the rate of growth is projected to decelerate. As shown in Figure 7-3, the net flux in carbon sequestration is projected to decline from over 15 tg/year (which includes 1.2 tg/year for the wood products pool) to around 6 tg/year by 2050. During this period of time, forest resources in West Virginia will offset approximately 40% of the state's estimated annual emission of carbon in 2000, which will decline to 10% in 2050 (see Figure 7-4). This projected decline is due to increases in timber removals brought on by increased commercial volume and stumpage prices, reduced net annual growth rates due to increased stand density,

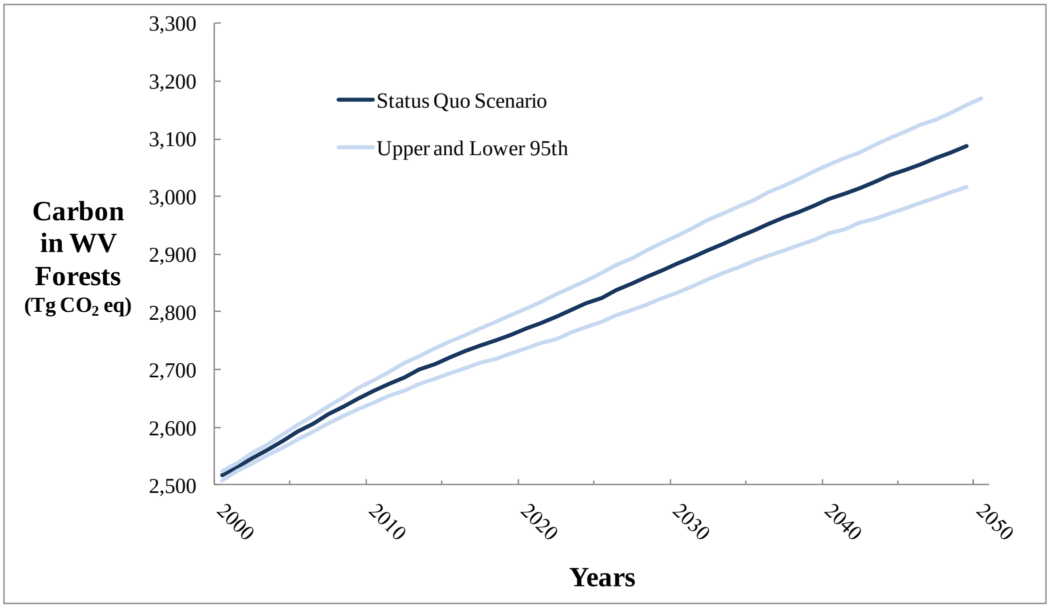

Figure 7-1 Statewide Forest Carbon (tg CO2/eq) for the Status Quo Timbering Scenario (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

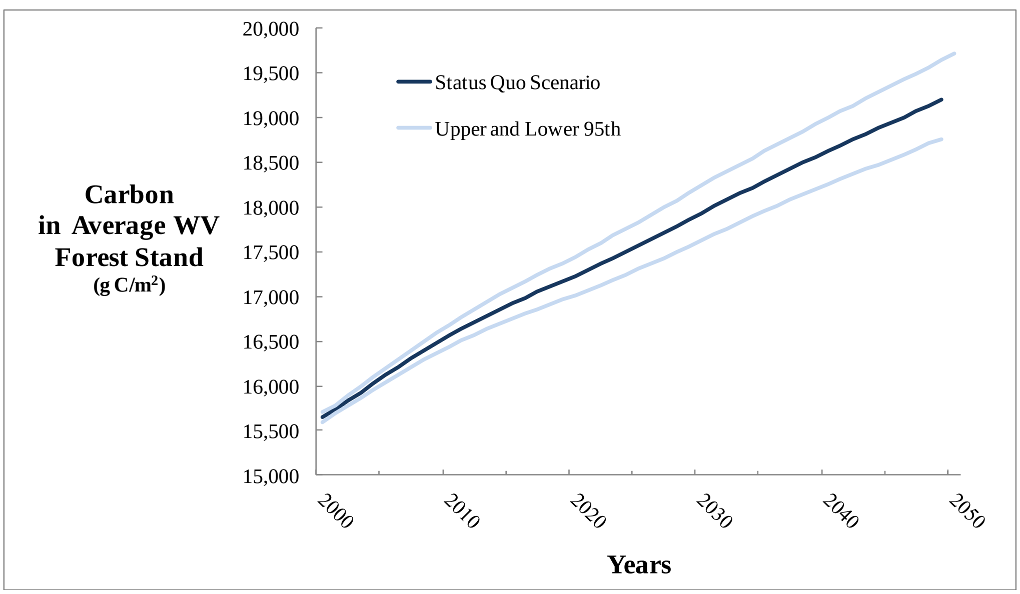

Figure 7-2 Average Forest Stand Carbon Density (gC/m2) for the Status Quo Timbering Scenario (smooth trend lines based on Monte Carlo analysis depicting typical and 95th upper and lower bounds)

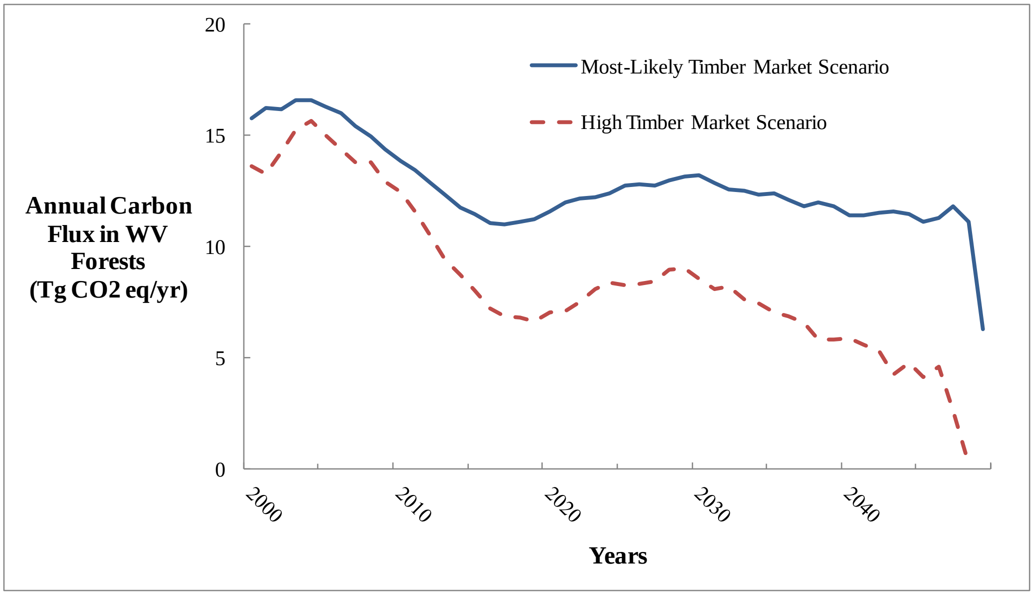

Figure 7-3 Annual Net Carbon Sequestration of West Virginia Forests (Tg CO_2 eq/yr) for the Most-Likely and High Timber Market Scenarios (trend line fluctuation due to oscillation in the timber market)

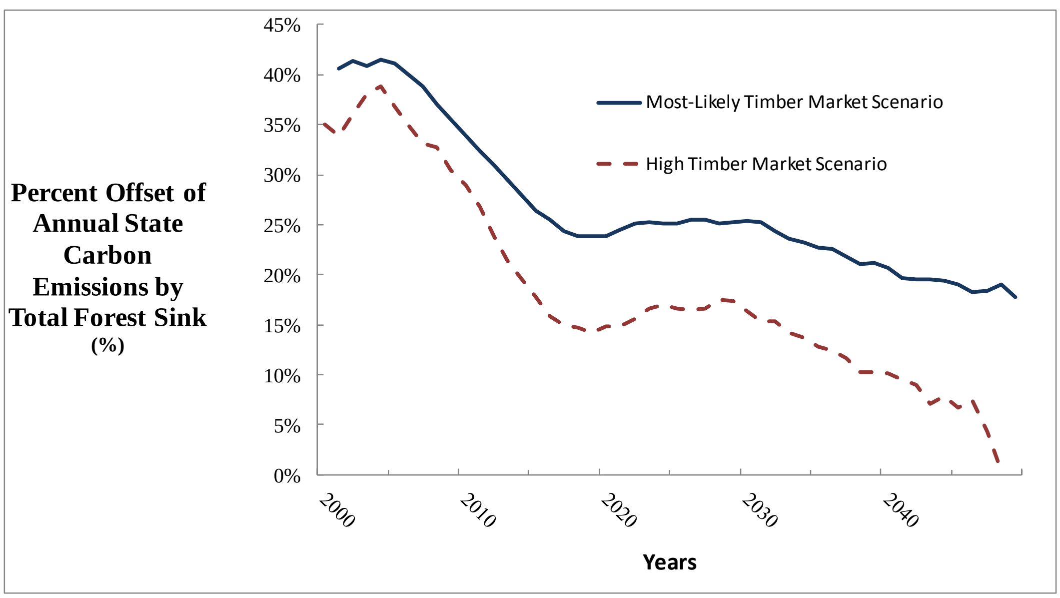

Figure 7-4 Percent Offset of West Virginia Total Carbon Emissions by Total Forest Sink under Most-Likely and High Timber Market Scenarios (trend line fluctuation due to oscillation in the timber market)

increased incidence of landscape scale disturbances toward mid-century (also due to increased stand density), and increased anthropogenic emissions. Overall, the results of the logistic regression analysis indicated that landscape scale disturbances are projected to increase by approximately 50% from 2000 to 2050, as forest stands continue to increase in biomass. By 2050, approximately 1/4th of the state forest acreage is projected to experience landscape scale disturbances, resulting in net negative growth, particularly for locations with higher stand density, lower annual precipitation, and greater slopes.

With respect to timber prices, if market growth conditions experienced over the past 20 years were to continue, resulting in a long-term average annual market increase in stumpage prices of 1%, then the projected increase in timbering activity would result in a very significant decline in the carbon sink, ultimately resulting in the forest system nearly becoming a carbon source by 2050, as shown in Figure 7-4.

7.3.3 Comparative Analysis of the Effect of Status Quo and Sustainable Timbering Scenarios on Forest Carbon Sequestration

The sustainable timbering scenario slightly enhanced forest carbon stocks by approximately 3% over the status quo timbering scenario (see Figure 7-5). Similar results were observed at the plot level (see Figure 7-6). More importantly, under the sustainable timbering scenario, carbon stock growth appeared to continue at the same pace through 2050, while growth decelerated slightly under the status quo timbering scenario in the last decade. As discussed in Section 6.3, the difference in carbon stocks and fluxes between the two scenarios is likely due to the decrease in AGBD that was removed during sustainable timbering events and differences in average stand growth rates (as net annual growth for the sustainable scenario was 50% higher than the status quo scenario in 2050). Essentially, the sustainability restrictions resulted in timber removals with higher average value, as compared to the status quo timbering scenario, which resulted in less biomass being removed. Under the sustainable timbering scenario, 6% less carbon was removed statewide during timbering events, principally due to the manner in which trees and plots are selected across the state (as discussed in Section 6.3). When comparing the annual fluxes in carbon sequestration between the two timbering scenarios, the sustainability scenario also maintained a larger carbon pool to 2050 than the status quo scenario, as shown in Figure 7-7. In any event, the overall size of the forest carbon pool declined for both timbering scenarios, as stand growth rates decelerated and landscape level disturbances increased under both scenarios due to increasing stand density.

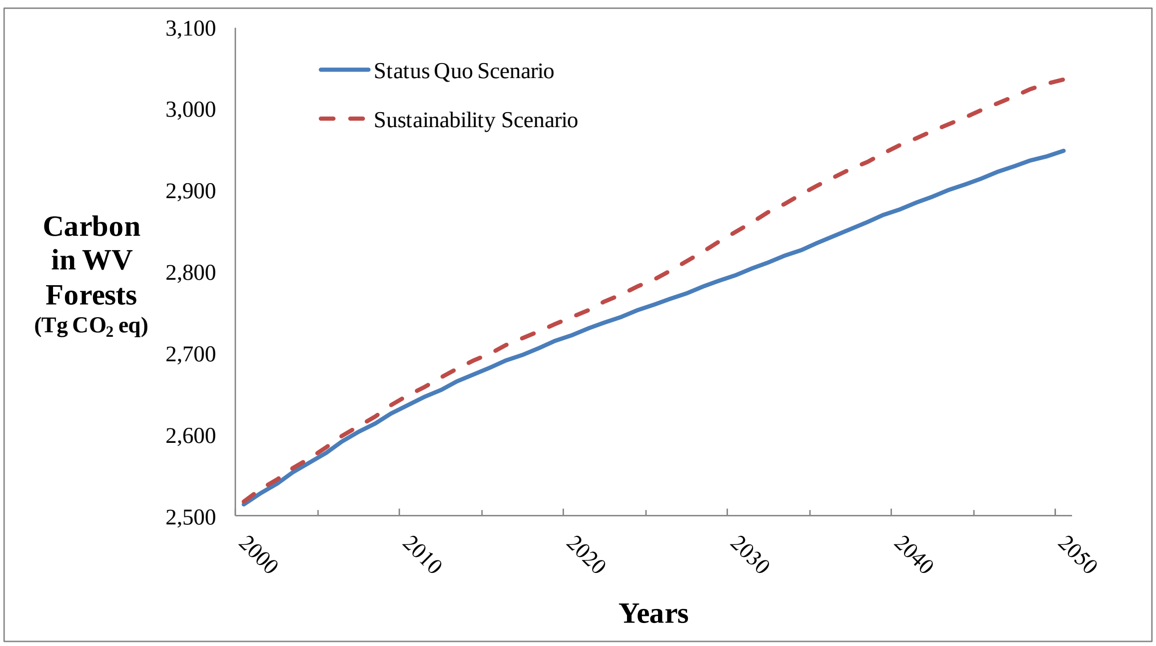

Figure 7-5 Statewide Forest Carbon Sequestration (tg CO2 eq) for the Status Quo and Sustainable Timbering Scenarios

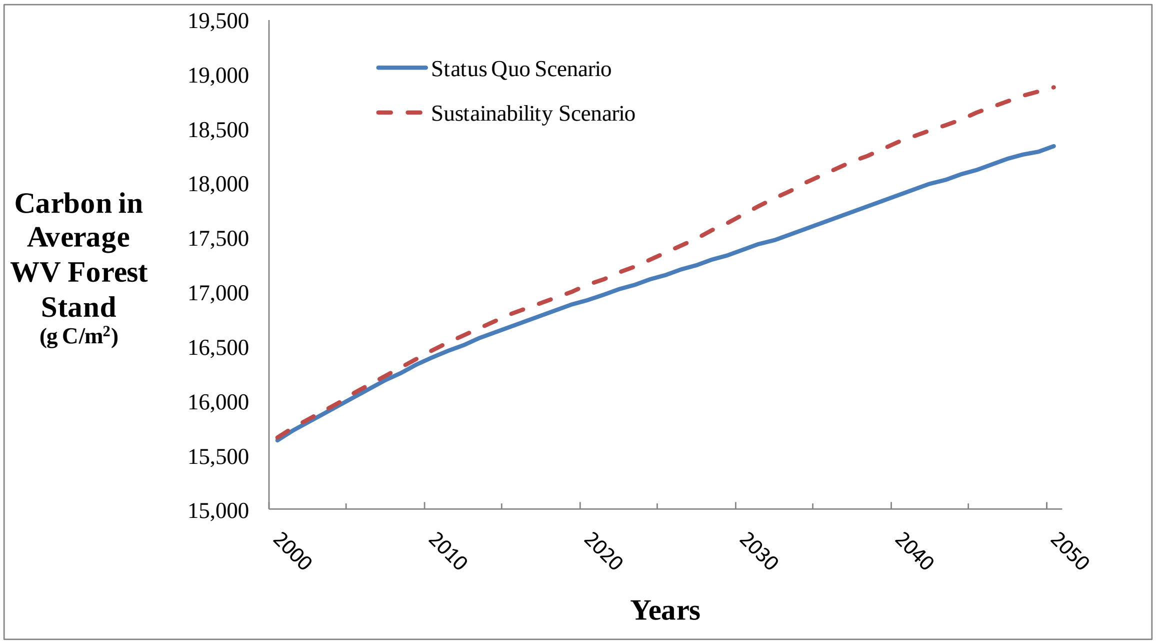

Figure 7-6 Average Forest Stand Carbon Density (gC/m2) for the Status Quo and Sustainable Timbering Scenarios

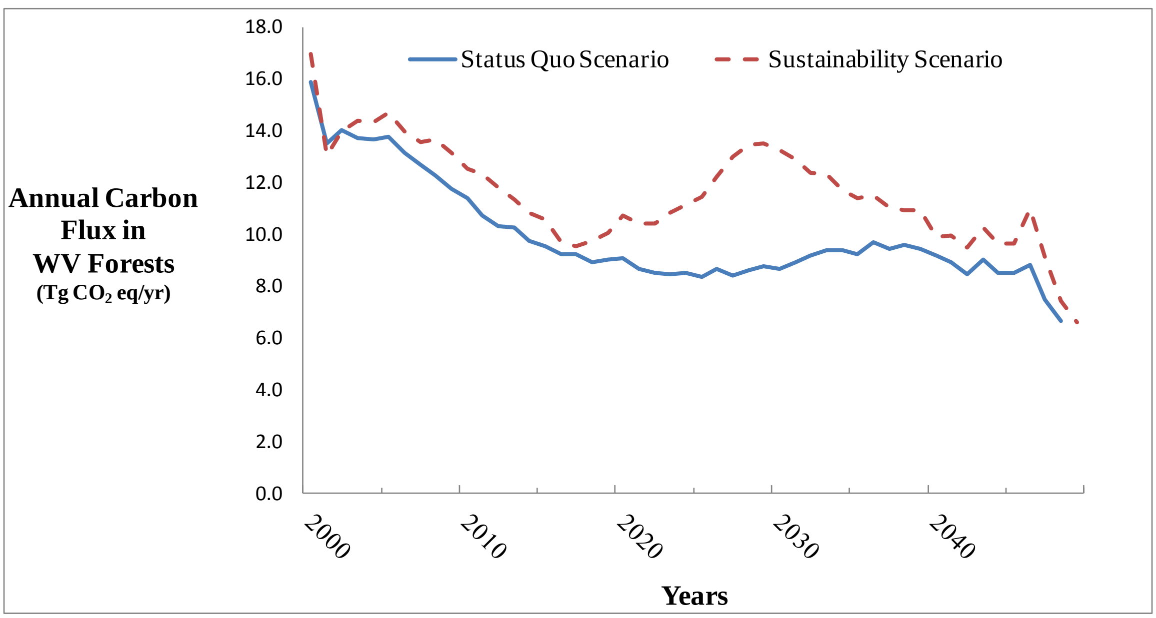

Figure 7-7 Annual Statewide Net Carbon Sequestration (tg CO2 eq/yr) for the Status Quo and Sustainable Timbering Scenarios (trend line fluctuation due to oscillation in the timber market)

7.4 Conclusions

The results of this study indicated that forest carbon stocks in West Virginia will continue to increase to 2050 under status quo timbering and most-likely timber market conditions to about 3,000 tg CO_2 eq. Under carbon accounting rules being considered internationally, this increase in carbon stocks is unlikely to have direct monetary value on the open market, as baseline forest growth can't be used for creating carbon credits, particularly from developed countries. In any event, the increase in forest carbon stocks of 380 tg CO_2 eq, worth over $7B if it could be sold at current carbon prices, would offset carbon emissions reported by the State of West Virginia and the United States over the next 50 years using USEPA accounting methods (USEPA 2009). In the future, if carbon legislation were established that required offset of anthropogenic emissions in the United States and there were provisions to offset these emissions with baseline growth of forest resources (as currently applied by USEPA [2009]), then this growth would have monetary benefits, even if the carbon credits could not be sold in the international market.

If timber prices increase as they did in the past two decades (~1% / year), then annual carbon fluxes may significantly decline after 2040 and the forest system is projected to become a carbon source after 2050. This change is principally due to reduced forest stand growth and increased disturbances due to increased stand density, and projected long-term increases in timber prices and commercial timber volume and associated stand value. This outcome was projected to be the same for both status quo and sustainable timbering scenarios, although the effect was significantly diminished for the sustainability scenario. Variability in annual carbon fluxes was due principally to market fluctuations in timber prices.

In the long-term, implementing statewide sustainable timbering would increase carbon stocks above status quo timbering conditions, due to less AGB being extracted and higher net annual growth rates achieved for the sustainability scenario. If future carbon accounting rules allowed for the establishment and sale of certifiable carbon credits on the open market from implementing sustainable timber management plans (which is currently be considered for undeveloped countries), then the net increase in carbon stocks from implementing the plan could be sold as carbon credits (growth in carbon stocks under status quo conditions would likely be ineligible for carbon credits, as previously discussed). At recent carbon prices of \$16/Mt CO_2 eq (World Bank 2010), the increase in carbon stocks from 2000 to 2050 from implementing statewide sustainable timbering management are estimated to be worth \$1.5B (without adjustments for inflation or market growth) relative to projected status quo conditions, with an annual average rate of \$30M/year. If carbon prices increase commensurate with modeled projections for establishing category III stabilization of CO_2 levels at 550 ppm (i.e., \$24 Mt CO_2 eq [IPCC 2007b]), then the value of carbon credits may be 1.5 times higher than these projections, or \$2B with an annual average rate of about \$50M/year. These projected annual returns from carbon credits (\$30M/year to \$50M/year) from increased forest growth were projected to be approximately 1/3rd of the total value of all timber removed annually from West Virginia during this period (average of \$130M/year between 2000 and 2050). Therefore, the economic return from carbon credits from establishing a statewide sustainable forest management plan could significantly contribute to the revenue from forestry services in West Virginia. As suggested by the IPCC, carbon prices in the \$20 to \$50 Mt CO_2 eq range could achieve substantial cuts in carbon emissions as a result of the viability of alternative energy technologies and other market forces (IPCC 2007b). If carbon prices increased to \$50 Mt CO_2 eq, then this would potentially triple the economic return to West Virginia (i.e., \$5B from 2000 to 2050, \$90M/year in 2050) (IPCC 1997b, World Bank 2010). It is unclear whether international and/or national policy initiatives will create market conditions that would generate such increases in carbon prices.

Given the economic returns from increasing forest carrying capacity for sustaining future timbering levels (which increases standing timber value by $0.8B by 2050) and potential carbon credit sales from implementing sustainable timbering policy at the state-level, it may be possible to design policy instruments that could actually increase economic opportunities for West Virginia. Furthermore, it may be possible to design policy instruments that could be self-funded from partial use of carbon credit funds generated by the policy. It should be noted that such results would require the implementation of new carbon accounting policy that would allow for the sale of carbon credits associated with implementing sustainable forest management in the United States, which currently does not exist. In any event, the increase in carbon stocks could be used to offset carbon emissions reported by the State of West Virginia and the United States, using USEPA (2009) accounting rules.

Some of the limitations of the carbon modeling approach used to project long-term carbon stocks were the treatment of SOC and the wood products pool as exogenous processes in the analysis. Given the potential increase in forest biomass, timber removals, and disturbance events that are projected from this analysis, it is likely the SOC and wood products pools will increase over time, thereby resulting in a larger carbon sink than what is projected from this analysis. Further research is needed to evaluate the integration of PnET-CN, or other process-based models, to more accurately evaluate carbon cycling and dynamics for estimating SOC and the implications of these cycling processes on long-term growth of the system, and for evaluating the effects of climate change. Furthermore, additional research and analysis is needed to more accurately and efficiently estimate changes in the wood products pool at a state-level. Currently, estimating changes in wood product pool fluxes is very labor intensive, as it requires simulating wood product usage and carbon releases not only for new timber production products into the future, but also all historic removals that occurred over the past century and beyond (Skog 2008).

8. Conclusions

The logistic and multilevel models developed in this research demonstrate an important and novel way of simulating micro-scale timbering events as an endogenous process when conducting forest management planning and carbon modeling. This approach allows for evaluating important cross-scale feedbacks and other processes for estimating the long-term impact of timbering and market scenarios on forest stand metrics, biomass, and carbon at multiple scales. Since the statistically significant independent variables for simulating timbering events are all currently available in the FIA database, it suggests that this modeling approach could readily be applied for other states and regions for simulating timber and tree selection events as an endogenous process. This approach is particularly important for addressing timbering and long-term forest carbon stocks at a national, regional, and state-scale, when a significant portion of the timbering events are driven by timber market conditions involving private land holdings, which are typically not governed or restrained by a forest management plan (as in the case of public lands, where modeling timbering events as an exogenous process may be appropriate).

The results of the timber stand and tree selection analysis indicated that timber stand value density, tree prices, and plot ownership were key drivers in predicting timber stand and tree selection for removal events. The models predicted timbering practices and tree selection patterns reflective of observed data. Increased tree stumpage prices, which increased overall stand value, significantly increased the probability of a stand being selected, on both private and public lands. Private lands were much more likely to be selected for timbering than public lands, as expected.

At the tree-level, increased value of the commercial tree (based on stumpage price and BF) significantly increased the probability of the tree being selected. The model also indicated that forest stand variables also impacted individual tree selection probabilities, as tree selection probabilities increased on public lands, and stands of higher value decreased individual tree selection probabilities (presumably due to increased competition for selection when conducting select cuts). The increase in tree selection probabilities on public lands was an unexpected result, which could be the subject of further research. Participatory modeling and survey techniques could be used to better understand differences in tree selection and removal techniques on both public and private lands. Modeling changes in ownership regime over time would also provide more insights on differences in timbering practices and plot selection probabilities when industrial timber firms own fee title to the land they timber, versus obtaining timber rights from non-industrial private land owners. Using the results of participating modeling and simulating ownership regime changes using finer-scale spatial agent-based modeling techniques, may provide even further insights into the processes of stand and tree selection.

Beyond the direct effect of timbering on tree and biomass removal, timbering events did not have a statistically significant effect on net annual forest stand growth rates, landscape level disturbances, regeneration rates, or mortality rates. Rather, other stand condition variables were much more important in predicting growth, mortality, and regeneration, including tree volume, stand volume, annual precipitation, and slope. Forest stands with the highest tree volumes still continued to grow more in volume than stands with lower volumes, but their growth rates appeared to be decelerating commensurate with a sigmoid growth response. This continued growth may be due to the fact that many forest stands in West Virginia are still in a state of recovery (Brown et al. 1997), as the prevalence of advanced recovery and old growth forest stands in West Virginia is low. Overall, stands with large volumes appeared to be more susceptible to landscape level disturbances and exhibited greater variability in terms of annual growth response, than forest stands with smaller volumes. These landscape disturbances reduced live tree volumes on plots nearly to the same extent as total timbering activities across the state, which underscores the need to address such disturbances in detail when modeling long-term changes in forest biomass and carbon.

Overall, the cumulative effects of timbering, positive growth, disturbance events, negative growth, mortality, and regeneration simulated using the integrated model developed for this research (i.e., CFM) replicated timbering patterns and net growth reasonably well. Model validation indicated that CFM estimated the average net live forest volume growth rate in West Virginia in 2000 of 1.38% (5 year average: 1.33%) to be within 1% of the observed growth rate of 1.40% for the 30% out of sample validation dataset (factoring in removals, mortality, positive growth, negative growth, and regeneration). Thus, CFM was able to replicate the cumulative effect of these factors on net annual growth rates reasonably well.

Using the integrated model, AGB, AGBD, and carbon stocks in West Virginia forests are projected to continue to increase despite increased timbering activity to 2050, with nearly half of the state acreage being classified in an advanced stage of recovery by 2050 (> 15,000 gC/m^2). Although, biomass and carbon density will continue to increase to 2050, the rate of annual increase decelerates. This deceleration is due to a projected doubling of the timber removal rates toward mid-century (due to increases in timber prices and stand volume), increases in landscape scale disturbances, and declining stand net annual growth due to stand maturation. However, if timber prices increase as they did in the past two decades (~1% / year), then forest biomass and carbon leveled off and began to decline around 2050 and the forest system was predicted to become a net carbon source in West Virginia after 2050.

To improve the estimation of carbon stocks, further research and analysis is needed for more accurately assessing long-term impacts to SOC and the wood products pool, as these were evaluated as exogenous processes in the model. Given the potential increase in forest biomass, timber removals, and disturbance events that are projected from this analysis, it is likely that SOC and the wood products pool will increase over time, thereby resulting in a larger carbon sink than what is projected from this analysis. Further research is needed to evaluate the integration of PnET-CN, or other process-based models, to more accurately evaluate carbon cycling and dynamics for estimating SOC and the implications of these cycling processes on long-term growth of the forest system, and for evaluating the effects of climate change. By calibrating PnET-CN over a larger areas, it would be possible to more accurately capture SOC fluxes, which are very important for accurately estimating forest carbon stocks (USDA 2008; Aber and Federer 1992; Aber et al. 1995, 1996, 1997).

Additional research and analysis is also needed to more accurately and efficiently estimate changes in the wood products pool (i.e., lifecycle analysis of carbon releases from wood removed from forest stands) at a state-level, given the complexity and significant data demands of such an analysis. Accurately estimating carbon fluxes from this pool requires simulating wood product usage and carbon releases not only for new timber products into the future, but also all historic removals and releases that occurred over the past century and beyond at a state or large-scale (Skog 2008). By developing tools that automate or downscale existing wood products pool analysis at the state level, it would be possible to more accurately and efficiently evaluate and test the impact of policy changes and forest management scenarios on carbon fluxes at the state level.

As previously discussed, landscape-scale disturbances had a significant impact on future projections of biomass and carbon. Such events are projected to increase in frequency by approximately 50% from 2000 to 2050, as forest stands increase in stand density. By 2050, approximately 1/4th of the state forest acreage is projected to experience landscape scale disturbances (as opposed to 17% in 2000), resulting in net negative growth, particularly for locations with higher forest biomass density, lower annual precipitation, and greater slopes. These results suggest that forest growth projections and landscape level disturbance dynamics should be carefully considered and modeled when making long-term projections of biomass and carbon, which is consistent with the findings of other landscape-scale studies (as cited in USGCRP 2008). These findings also underscore the need to consider the impact of long-term climate change on key drivers of forest growth, such as annual precipitation and temperature, as well as the indirect effects associated with climate change on disturbance regimes (e.g., higher incidence of extreme weather events, drought, pest infestation, fire), which may adversely impact live forest biomass and carbon fluxes over the long-term.

Additional research is needed to better understand and predict landscape disturbance events given their impact on forest biomass and carbon dynamics. If drought and other disturbance events increase in frequency, then the frequency and severity of these events could increase beyond the estimates projected using CFM. In any event, to better adapt to these disturbances, it may be possible to use monitoring and predictive tools to identify the locations that are most vulnerable to these disturbances and apply sustainable silviculture techniques to preempt these events, reduce stand vulnerability to these events, and shift timber production burden to locations that are more likely to have mass tree mortalities. Such adaptive measures would improve the overall health of the forest system across the state, due in part to a shift in timber burden intensity away from healthy stands. Similar concepts have been suggested for adapting to cyclical and large-scale disturbance events in forests of Canada, as well as potential for increased drought frequency due to climate change (Bouchard et al. 2008, Cotillas et al. 2009, Hanson and Weltzin 2000, Powers et al. 2010).

Modeling disturbance events also requires additional research and refinement. For example, there are other biophysical characteristics, such as historic disturbance effects, climatic patterns, longitude, micro-scale drought patterns, terrain classification, slope orientation, and other factors that may create spatial patterns and explain some of the variance in disturbance events not captured in this analysis. Working with the USFS, it may be possible to utilize the actual coordinates of the FIA plots and obtain higher resolution drought, terrain classification, and other biophysical data that could refine this analysis. In addition, geospatial and regression tree analysis techniques may be helpful in conducting further analysis of disturbance events and spatial patterns.

With respect to sustainable timbering, broad application of sustainable timbering techniques across the entire state significantly enhanced several forest ecosystem indicator metrics relative to status quo conditions, including biomass, carbon, annual growth, and carrying capacity. In particular, broad application of sustainable timbering across West Virginia enabled net annual average forest growth for the state to remain much higher (50% higher than the average under the status quo scenario), even though the same value of timber was being extracted at the state level to satisfy market demand each year to 2050. Thus, the sustainable timbering approach will significantly enhance long-term sustainable use of the forests for timbering and production of ecological services through the 21st century, while still supplying needed timber market demand on an annual basis. Furthermore, the sustainable timbering scenario increased standing timber value by $0.8B in 2050 above the status quo scenario, even though the same value of timber was being extracted each year between 2000 and 2050.

The sustainable timbering scenario had little effect on large tree conservation and achievement of old growth forest conditions at the state scale, which was unexpected. This effect was due to the doubling of the annual rate of low intensity sustainable timbering events across the state (relative to status quo timber event frequencies in order for timber firms to satisfy market demand), which removed more larger trees (just below the regulatory threshold) across the state than the status quo scenario. The results of this study points to one of many trade-offs that should be considered in the development of state-level sustainable forestry plans and finer-scale plans, as well as the need to evaluate the positive and negative effect of policy at multiple scales.

Overall, implementation of a state-level sustainable timbering program could significantly increase the carrying capacity of the forest systems for future timbering, which would preserve commercial timber industry opportunities for future generations, increase the value of carbon stocks ($1.5B to $5B depending on carbon price in 2050), and increase overall forest recovery. The difficulty of implementing such a plan from a policy perspective would be how to design a policy that would gain a high level of participation, without restraining the property rights and flexibility that private landowners in West Virginia are accustomed to. Given that the program would likely increase the value of commercial standing timber ($0.8B in 2050) and carbon stocks ($1.5B to $5B from 2000 to 2050, with annual average revenue of $30M to $90M/year at the state-level), it may be possible to design a voluntary cooperative program that would enable management of statewide forest resources on private land in exchange for revenue sharing. In certain respects, timber firms may resist adding restraints to their timbering activity and there would likely be additional operating and travel costs associated with lower intensity timber removals. On the other hand, anecdotal evidence suggests that timber firms have difficulty finding timber contracts, so such a cooperative program could reduce certain costs associated with identifying, marketing, and procuring timber rights. Further research would be needed to test the viability of such a policy approach, and the potential for broader application in other forested states and regions.

Overall, this study demonstrates the importance of modeling both anthropogenic and natural disturbance agents at multiple scales, when evaluating future forest resource conditions and alternative habitat conservation strategies. Further research would be required using participatory methods (Parker et al. 2003, Bousquet and Le Page 2004) and targeted surveys to determine the viability of specific sustainable and conservation forest management policies, including willingness to participate in a statewide sustainable forestry management program. Such participatory modeling techniques are also recommended for properly modeling, designing, and testing the acceptance and potential success of such a program if it were to be considered.

Appendix A: PnET-CN Model Runs

PnET-CN Model

Detailed results of the PnET-CN modeling analysis are presented below. Plot-level AGBD and net growth (which does not include timber removals, but includes tree-specific negative growth and mortalities) are presented in Table 1 below for the plots in Boone and Tucker Counties. AGBD and net annual growth are presented in the last two columns. By adjusting disturbance regime values for individual plots for about 60% of the stands, it was possible to generate estimates of AGBD in the wood pool that were within 10% of those observed in the field for 85% of the plots. These specific adjustments are presented in Tables 2 and 3.

Table 1. Boone and Tucker County Plots with Net Growth Estimates

FIA Plot	Climate Station	$/acre	%Removed	FolNCon	SLWmax	Latitude	AGBD (g/m2)	Net Annual Growth
Boone County, WV								
7518812010661	20	$1,864	0%	2.32	52	38	23,094	2.9%
7518642010661	20	$2,095	0%	2.26	47	38	21,243	3.5%
7516424010661	20	$1,774	0%	2.31	48	38	20,915	3.9%
7516896010661	20	$1,367	0%	2.21	69	38	20,592	2.0%
7518456010661	20	$1,466	0%	2.29	65	38	18,985	2.3%
7518722010661	20	$960	0%	2.27	45	38	17,322	1.6%
7517275010661	20	$849	0%	2.20	52	38	16,320	2.4%
7517204010661	20	$279	0%	2.25	38	38	14,446	3.1%
7516349010661	20	$686	0%	2.21	70	38	14,175	4.0%
7519217010661	20	$746	0%	2.24	40	38	13,562	0.8%
7519627010661	20	$336	0%	2.25	41	38	13,079	-3.4%
7518032010661	20	$490	0%	2.30	46	38	12,280	2.9%
7517450010661	20	$452	0%	2.22	52	38	10,786	1.0%
7516984010661	20	$540	0%	2.21	48	38	9,791	7.7%
7517385010661	20	$620	0%	2.24	47	38	8,449	1.0%
7516501010661	20	$310	73%	2.27	47	38	7,762	1.1%
7519031010661	20	$72	91%	2.21	61	38	6,158	5.3%
7516728010661	20	$47	93%	2.19	85	38	6,659	7.3%
7517766010661	20	$240	0%	2.15	72	38	5,644	5.6%
Tucker County, WV								
7640442010661	40	$2,935	0%	2.28	39	39	30,131	3.4%
7641325010661	40	$1,965	0%	2.58	35	39	23,064	4.3%
7640129010661	40	$4,601	54%	2.33	72	39	22,459	3.2%
7641474010661	40	$1,076	0%	2.17	61	39	19,355	1.2%
7641238010661	40	$1,381	0%	2.49	45	39	16,421	3.2%
7640555010661	40	$2,797	63%	2.35	60	39	16,116	1.5%
7640851010661	40	$655	27%	2.20	51	39	15,209	0.2%
7641652010661	40	$753	0%	2.36	46	39	14,820	5.9%
7641572010661	40	$1,260	70%	2.29	42	39	10,027	-1.2%

Table 2. Comparison of Field and PnET-CN modeled AGBD for Boone and Tucker Counties

	Field Measured Plots						First Tier Performance				Second Tier Performance		
FIA Plot	%Removed	FolNCon	SLWmax	Latitude	YR2000 AGBD g/m2	Net Annual Growth	Ratio (FIA/ PnET)	YR 2000 AGBD g/m2	YR2100 AGBD g/m2	Ag	Ratio (FIA/ PnET)	YR2000 Adjusted AGBD g/m2	YR2100 Adjusted AGBD g/m2
Boone County, WV													
7518812010661	0%	2.32	52	38	23,094	2.9%	19%	19465	22235	0.0	-2%	23611	25069
7518642010661	0%	2.26	47	38	21,243	3.5%	22%	17457	19905	0.0	-2%	21732	23395
7516424010661	0%	2.31	48	38	20,915	3.9%	17%	17916	20451	0.0	-6%	22158	23820
7516896010661	0%	2.21	69	38	20,592	2.0%	-1%	20722	22251	0.0	Fit During First Tier		
7518456010661	0%	2.29	65	38	18,985	2.3%	-9%	20909	22803	0.0	Fit During First Tier		
7518722010661	0%	2.27	45	38	17,322	1.6%	5%	16525	18793	0.0	Fit During First Tier		
7517275010661	0%	2.20	52	38	16,320	2.4%	-16%	19433	22192	0.0	-1%	16560	22117
7517204010661	0%	2.25	38	38	14,446	3.1%	7%	13475	15249	0.0	Fit During First Tier		
7516349010661	0%	2.21	70	38	14,175	4.0%	-14%	16465	19502	0.1	0%	14175	22240
7519217010661	0%	2.24	40	38	13,562	0.8%	-4%	14191	16088	0.0	Fit During First Tier		
7519627010661	0%	2.25	41	38	13,079	-3.4%	-10%	14564	16528	0.0	Fit During First Tier		
7518032010661	0%	2.30	46	38	12,280	2.9%	-28%	17054	19410	0.0	7%	11486	18461
7517450010661	0%	2.22	52	38	10,786	1.0%	5%	10228	11716	0.1	Fit During First Tier		
7516984010661	0%	2.21	48	38	9,791	7.7%	3%	9481	10898	0.1	Fit During First Tier		
7517385010661	0%	2.24	47	38	8,449	1.0%	-9%	9277	10673	0.1	Fit During First Tier		
7516501010661	73%	2.27	47	38	7,762	1.1%	135%	3309	11150	0.1	1%	7683	17101
7519031010661	91%	2.21	61	38	6,158	5.3%	211%	1978	12657	0.1	6%	5800	18253
7516728010661	93%	2.19	85	38	6,659	7.3%	272%	1791	12238	0.1	0%	6630	26570
7517766010661	0%	2.15	72	38	5,644	5.6%	-54%	12178	13708	0.1	-4%	5864	13573
Tucker County, WV													
7640442010661	0%	2.28	39	39	30,131	3.4%	130%	1309	13570	0.0	68%	17934	17212
7641325010661	0%	2.58	35	39	23,064	4.3%	93%	1194	12364	0.0	42%	16271	16271
7640129010661	54%	2.33	72	39	22,459	3.2%	120%	1020	20873	0.0	25%	17918	27844
7641474010661	0%	2.17	61	39	19,355	1.2%	7%	1802	19699	0.0	Fit During First Tier		
7641238010661	0%	2.49	45	39	16,421	3.2%	12%	1464	15289	0.0	-2%	16790	17194
7640555010661	63%	2.35	60	39	16,116	1.5%	112%	7589	17578	0.0	15%	13972	22851
7640851010661	27%	2.20	51	39	15,209	0.2%	25%	1216	16926	0.0	0%	15280	19002
7641652010661	0%	2.36	46	39	14,820	5.9%	-1%	1490	15590	0.0	Fit During First Tier		
7641572010661	70%	2.29	42	39	10,027	-1.2%	104%	4914	12690	0.0	6%	9497	15826

Table 3. Comparison of Field and PnET-CN modeled AGBD for Boone and Tucker Counties

FIA Plot	AGBD g/m2	Second Tier Adjustments: Ag	1915 Mortality	1915 Removal	1935 Mortality	1935 Removal	1950 Mortality	1950 Removal	Other Adj Comments
Boone County, WV									
7518812010661	23,094	0.0	0.50	0.50	0.25	0.25	0.00	0.00	
7518642010661	21,243	0.0	0.50	0.50	0.25	0.25	0.00	0.00	
7516424010661	20,915	0.0	0.50	0.50	0.25	0.25	0.25	0.20	
7516896010661	20,592	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7518456010661	18,985	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7518722010661	17,322	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7517275010661	16,320	0.0	0.95	0.70	0.25	0.25	0.25	0.20	Removal moved from 1950 to 1987
7517204010661	14,446	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7516349010661	14,175	0.0	0.95	0.70	0.25	0.25	0.50	0.40	Removal moved from 1950 to 1987
7519217010661	13,562	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7519627010661	13,079	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7518032010661	12,280	0.0	0.95	0.70	0.25	0.25	0.50	0.40	Removal moved from 1950 to 1987
7517450010661	10,786	0.1	0.95	0.70	0.25	0.25	0.25	0.20	
7516984010661	9,791	0.1	0.95	0.70	0.25	0.25	0.25	0.20	
7517385010661	8,449	0.1	0.95	0.70	0.25	0.25	0.25	0.20	
7516501010661	7,762	0.0	0.95	0.70	0.25	0.25	0.00	0.00	Removal moved from 1997 to 1992
7519031010661	6,158	0.0	0.95	0.70	0.25	0.25	0.00	0.00	Removal moved from 1997 to 1992
7516728010661	6,659	0.0	0.95	0.70	0.25	0.25	0.00	0.00	Removal moved from 1997 to 1990
7517766010661	5,644	0.1	0.95	0.70	0.25	0.25	0.80	0.60	Removal moved from 1950 to 1987
Tucker County, WV									
7640442010661	30,131	0.0	0.00	0.00	0.00	0.00	0.00	0.00	SLWmax too low
7641325010661	23,064	0.0	0.00	0.00	0.00	0.00	0.00	0.00	SLWmax too low
7640129010661	22,459	0.0	0.00	0.00	0.00	0.00	0.00	0.00	Removal moved from 1997 to 1988
7641474010661	19,355	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7641238010661	16,421	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7640555010661	16,116	0.0	0.00	0.00	0.00	0.00	0.00	0.00	Removal moved from 1997 to 1988
7640851010661	15,209	0.0	0.95	0.70	0.25	0.25	0.25	0.20	
7641652010661	14,820	0.0 1	0.95	0.70	0.25	0.25	0.25	0.20	
7641572010661	10,027	0.0	0.00	0.00	0.00	0.00	0.00	0.00	Removal moved from 1997 to 1988

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Curriculum Vitae

Sean B. Donahoe graduated *summa cum laude* from Fairmont State University in 1985 with a Bachelor of Science degree (double major) in Mathematics and Biology. He then received a Master of Science degree in Biology with an emphasis in quantitative ecology from West Virginia University in 1987. From that point he was employed as an environmental consultant in the Northern Virginia region for over 20 years. While continuing to work as a consultant, he completed his Doctor of Philosophy in Environmental Science and Policy at George Mason University in 2011.