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SUSTAINABILITY AND ECONOMICS OF WHITE OAK (*Quercus alba*) TIMBER SUPPLY IN KENTUCKY

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in Forest and Natural Resource Sciences in the
College of Agriculture, Food and Environment
at the University of Kentucky

By

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Lexington, Kentucky

Director: Dr. Thomas O. Ochuodho, Assistant Professor of Forest Economics and Policy

Lexington, Kentucky

2021

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ABSTRACT OF THESIS

SUSTAINABILITY AND ECONOMICS OF WHITE OAK (*Quercus alba*) TIMBER SUPPLY IN KENTUCKY

Sustained timber supply relies upon balanced forest age distribution, where the level of harvesting and mortality is compensated by regeneration and growth among younger age classes. However, current forest inventory trends from the white oak growing region reveal sustainability threat from declining white oak regeneration and recruitment leading to disproportionate inventory structure. Consequently, there exists growing concern among stakeholders on long-term sustainability of white oak timber and its economic implications, particularly in Kentucky, because of the significance of the species to the state's economy. This research aims to examine past and current inventory levels of white oak in Kentucky using Forest Inventory and Analysis (FIA) data; project inventory levels of white oak sawlogs in Kentucky, based on timber quality, by employing Forest Vegetation Simulator (FVS) together with FIA data; and assess potential economy-wide impacts of projected white oak timber supply to dependent industries in Kentucky using Computable General Equilibrium (CGE) model. Results indicate that white oak dominated forest structure is rapidly transforming to forest largely dominated by large-diameter trees with remarkable decline in small-diameter trees. While the overall projected inventory levels of white oak sawlogs remain adequate to support current harvest levels until 2058, inventory levels of high-quality white oak sawlogs would be continuously declining throughout the projection period (2018 to 2068). Economically, the overall potential impact of projected white oak timber supply during the 40-year planning horizon (2018 to 2058) would be negative as reflected by reductions in GDP and welfare, which is driven mostly by the reduced supply of high-quality white oak sawlogs to distilleries sector. These results can be used to advocate for more proactive forest management practices to stabilize a sustainable supply of high-quality white oak timber in Kentucky against the economic consequences of the status quo under business as usual scenario.

KEYWORDS: white oak, Forest Inventory and Analysis data, Forest Vegetation Simulator, Computable General Equilibrium model, timber supply, high-quality

Gaurav Dhungel

6/29/2021

Date

SUSTAINABILITY AND ECONOMICS OF WHITE OAK (*Quercus alba*)
TIMBER SUPPLY IN KENTUCKY

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DEDICATION

To my parents (Madhavi Dhungel and Kamal Prasad Dhungel) and my brother (Saurav Dhungel) for all that I am and that I hope to be.

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First and foremost, I would like to extend my heartfelt gratitude to my advisor, Dr. Thomas O. Ochuodho, for his unwavering support, constant guidance, and tutelage during the course of my MS degree. I am very grateful to my committee members, Dr. Jeffrey W. Stringer and Dr. John M. Lhotka, for their constructive comments, mentorship and warm encouragement. I would like to pay my special regards to Dr. Tom Brandeis and Dr. John D. Shaw of the US Forest Service for helping me navigate through my first chapter: data acquisition, addressing technical questions related to FIA data, and instructing me to perform growth modeling using FVS. My appreciation goes to Allison Davis for helping me with data management in RStudio and Zachary Hackworth for always being extraordinarily tolerant to resolve issues related to growth modeling during the initial phase of my research. I owe my deepest gratitude to my friends - Anna, Ashutosh, Bini, Domena, Jena, Jordan, Kamana, Kate, Nate, and Sarah, for their emotional support for the past two years; this journey wouldn't have been easier and memorable if they had not been there. Last but not the least, I will forever be indebted to my family for their support all through my studies.

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CHAPTER 1. GENERAL INTRODUCTION

1.1 INTRODUCTION

Sustainable supply of white oak (*Quercus alba* L.) timber, especially of high-quality, is indispensable to white oak dependent industries, particularly wood products sector for manufacturing wide-range of primary and secondary wood products, and distilleries since they require barrels made from high-quality white oak for aging the bourbon. Given the importance of wood products manufacturing and distilleries sectors to the economy of Kentucky (Kornstein and Coomes, 2019; Stringer et al., 2019), sustainable management of white oak dominated forests is a desirable goal. However, sustainable oak management is one of the biggest challenges in eastern US as the ongoing ecological shift in the historically oak dominated forests (Nowacki and Abrams, 2008) is thwarting the ability of oak species to both regenerate and recruit into the overstory (Dey, 2014). In addition, soaring demand of high-quality white oak stave logs, climate change, pathogens, and emerging threats such as rapid white oak mortality (Conrad et al., 2020; Reed et al., 2017; Stringer et al., 2019) can further complicate oak management. All of these aggravating factors suggest constraints in sustained supply of white oak sawlogs in posterity. Realizing the economic significance of the pertinent issues, key stakeholders are supportive toward preemptive actions such as incentivizing sustainable forest management, and addressing poor harvesting practices to ensure long-term supply of white oak (Thomas et al., 2021). Within this context, the intent of this thesis is to shed light on sustainability of white oak in Kentucky and the potential economic impacts of simulated projected supply of white oak sawlogs in both wood product manufacturing and distilleries sectors in the Commonwealth using Computable General Equilibrium (CGE) model.

The organization of this chapter is as follows: Section 1.2 provides background information about issues concerning white oak sustainability, Section 1.3 sketches the critical research gaps that this study attempts to fill in, Section 1.4 describes the research objectives, and Section 1.5 outlines the research framework of this thesis that comprises the overall organization, general research methods, and models that are applied in each chapter.

1.2 BACKGROUND

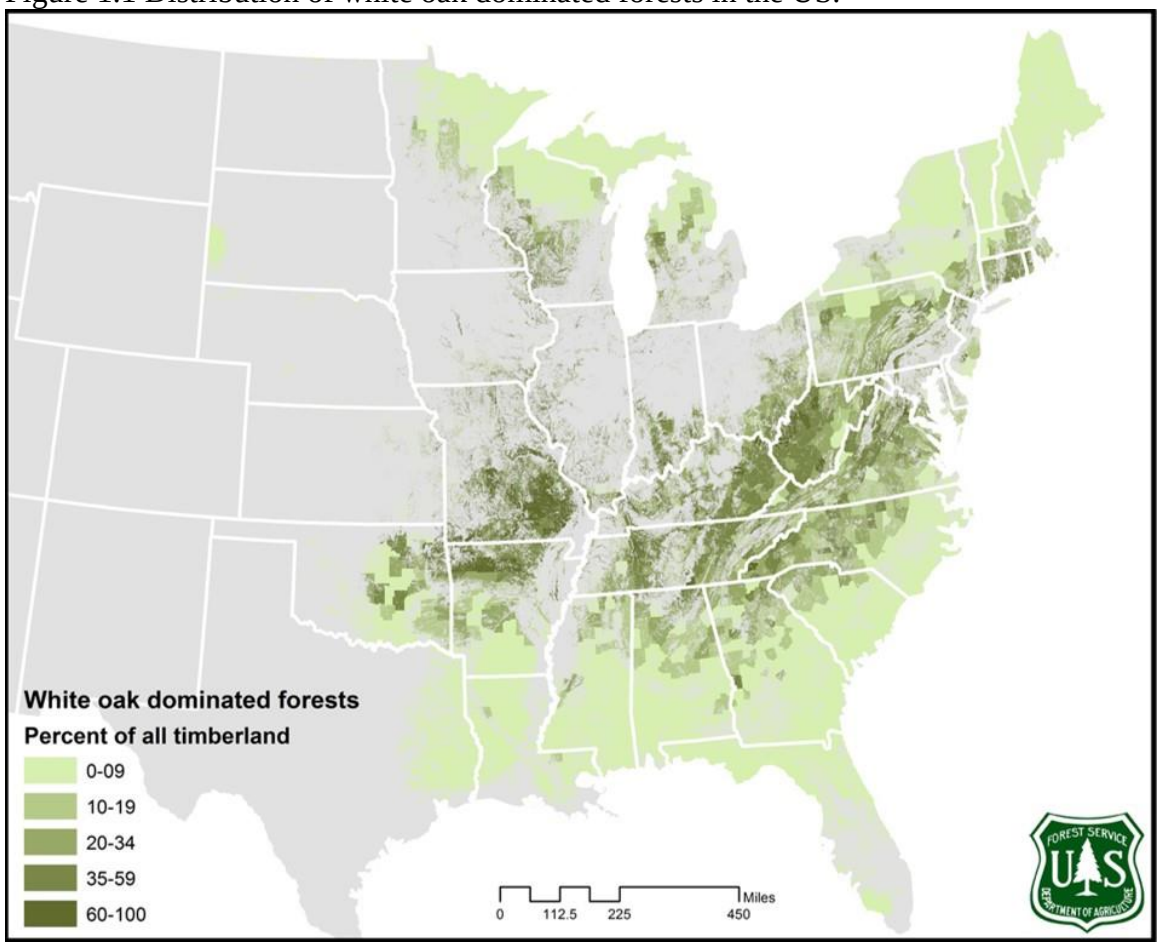
White oak is a major commercial tree species and an important resource in Kentucky. The Commonwealth accounts for approximately 7% of white oak growing stock in the US (USDA Forest Service, 2020a), and about 14% of the entire white oak resource in the southeast US (Oswalt, 2015). The timber is highly valued for a wider range of primary and secondary forest products including lumber, veneer, flooring, cabinetry, and cooperage. However, white oak is the primary species used in barrel production for aging bourbon. While the federal law mandates American bourbon be made in charred new oak barrels (Office of the Federal Register, 2018), the structural features of white oak (presence of medullary rays and tyloses) makes its woods impervious (Conner et al., 2003), thus making them ideal for tight cooperage. Bourbon barrels made from white oak is the state's top wood-related exports (Stringer et al., 2020), and distilleries that require these barrels for aging the bourbon is a major contributor to the state's economy (Kornstein and Coomes, 2019). As such, sustainable supply of white oak timber is critical to white oak dependent industries and the economy at large.

Hardwood inventory levels from the white oak growing region (Figure 1.1), including Central Hardwood Forest Region[1] show that the growing stock volume of larger-sized white oak has been increasing, but that of smaller-sized has been declining (Luppold and Bumgardner, 2018). This suggests that current white oak growing stocks are sufficient to meet current demand; however, it also foreshadows a shortage of large white oak trees in the future. The decline in white oak is a culmination of gradual alteration in forested lands resulting from agricultual activities, development of road networks, excessive grazing, selective harvesting and fire-suppression policies after the 1930s (Abrams, 2003; Dey, 2014; Nowacki and Abrams, 2008). Besides, accelerated harvesting suggested by growing demand for white oak logs and lumber in both domestic and overseas markets (Kornstein and Coomes, 2019; Stringer et al., 2019; Wang et al., 2010) is augmenting the ecological changes taking place. Hence, a sustainability problem is looming for white oak dependent industries.

The Forest Inventory and Analysis (FIA) program of the US Forest Service collects, organizes, archives, analyzes, and reports nation-wide inventory information (Smith, 2002; Woudenberg et al., 2010). The program yields one of the largest repository of ecological datasets in the world by spatial and temporal extent (Tinkham et al., 2018), making FIA database an expansive and powerful resource for monitoring the status and trends in forest attributes at both individual tree level and subcontinental scale (Tomppo et al., 2010).

[1] The Central Hardwood Forest Region is the forested region in the US overwhelmingly dominated by deciduous hardwood species, mostly oaks and hickories. The physiographic provinces comprise the unglaciated Blue Ridge Mountains, Appalachian Plateaus, Interior Low Plateaus and Ozark Plateaus, and the glaciated Central Lowlands (Fralish, 2003).

Figure 1.1 Distribution of white oak dominated forests in the US.



Source: USDA Forest Service, Southern Research Station FIA Program. 2018. Unpublished data. Knoxville, TN.

Understanding changes of timberland base together with the trends in timber inventory is the fundamental resource concern in determining future growth and yield (Deal and White, 2005). Forest Vegetation Simulator (FVS) – the distance-independent individual tree class of growth and yield model, is a standard model used by the USDA Forest Service and is extensively used by the forest managers to summarize current stand conditions, update inventory levels, and forecast stand conditions under various management alternatives (Dixon, 2002a). The model has been widely used throughout the US, and its applicability well-documented (DeRose et al., 2008; Greenberg et al., 2014; Guertin and Ramm, 1996; Moss and Heitzman, 2013; Radtke et al., 2012; Smith-Mateja and Ramm, 2002).

Computable General Equilibrium (CGE) modeling framework has been applied to studies of wide and growing range of economic problems/policies. What makes CGE modeling framework a powerful tool is its ability to describe an economy as a whole, flexibilities in its specifications, and the interactions among its parts (Burfisher, 2016). Traditionally, CGE models have been used to study international trade, taxation, developmental policies, and other economic policies (Centeno Stenberg and Siriwardana, 2005; Shoven and Whalley, 1984). More recently, CGE models have been applied to study forest sector policies as well (Gan, 2005; Wiebelt, 1994). Most recently, CGE models have been applied to assess economic impacts associated with reduced timber supply (Corbett et al., 2016; Das et al., 2005; Withey et al., 2018; Zhang et al., 2005). However, there are few studies (Karttunen et al., 2018) that combine components of individual tree growth simulation with CGE models to address economic impacts of long-term timber supply.

1.3 CRITICAL RESEARCH GAPS

White oak is a long-lived species, sometimes surviving for 400 years or more (Shumway et al., 2001). The slow-growing nature of white oak underscores the significance and urgency of holistic approach that must be geared towards conserving and sustainably managing white oak dominated forests. As the contemporary age structure of Kentucky's forest skews towards the older age classes (Oswalt et al., 2014), a tipping point will be reached where oak drain exceeds regeneration and growth, which will have negative implication on economic sectors that depend on white oak resource. Therefore, this research attempts to champion for proactive forest management practices by capturing the economic implications of threatened long-term sustained supply of high-quality white oak timber in Kentucky.

While a few research efforts suggest a lurking sustainability problem of white oak (Abrams, 2003; Dey, 2014; Luppold and Bumgardner, 2018), studies quantifying future white oak timber supply and its associated economic impacts on industries are almost non-existent in literature. Furthermore, less is known about the future trends of high-quality white oak trees in the state. However, studies concerning sustainability of white oak is slowly gaining momemtum with the establishment of White Oak Initiative[2]. To this end, this research is an effort to fill this gap.

[2] White Oak Initiative is a partnership comprised of diverse group of people and organizations (industry, agency, university, and non- profits) to bring together white oak dependent stakeholders; the Initiative is designed to actively develop, coordinate, and facilitate the implementation of practices directed to conserve and sustainably manage white oak dominated forests (Stringer, 2018).

1.4 RESEARCH OBJECTIVES

The overall objective of this research is to estimate the potential economic impacts of projected white oak timber supply simulation in Kentucky. Specific objectives are:

1. To examine historical inventory levels of white oak on Kentucky's timberland, and estimate future trends in inventory levels of white oak sawlogs – including tree grade.
2. To assess potential economy-wide impacts of projected white oak sawlogs supply for wood products manufacturing sector and projected supply of high-quality white oak sawlogs for distilleries sector in Kentucky.

1.5 RESEARCH FRAMEWORK

The organization of this thesis is outlined in the next few paragraphs, which is essentially presented in an "article" format. This chapter (Chapter 1), sets the stage by providing a backdrop of the research problem and its significance that prompted this research. It also outlines the two specific objectives, and the general methodological approaches used to achieve the objectives.

Chapter 2 uses FIA data to examine the historical inventory levels of white oak in Kentucky in terms of volumetric changes across diameter size class, and acreage changes of white oak dominated stands in 1988, 2004, and 2016. Second, it entails the use of FVS to perform inventory level analysis of projected supply of white oak sawlogs over a 50-year horizon (2018-2068). Third, it also assimilates available plot-level FIA data on tree grade to further estimate future inventory levels of white oak by tree grade.

Chapter 3 develops a recursive, dynamic CGE model to assess potential economy-wide impacts of projected white oak timber supply in Kentucky over a 40-year horizon (2018-2058). Specifically, it models timber supply as implied from stumpage payments and barrel expenditures assuming that change in inventory levels of white oak sawlogs is consistent with a change in stumpage in the wood products sector and a change in inventory levels of high-quality white oak sawlog is consistent with a change in barrel expenditures in the distilleries sector. The analysis captures the potential impact of projected supply of white oak sawlogs as well as projected supply of high-quality white oak sawlogs simultaneously on household welfare and other macroeconomic variables.

Finally, Chapter 4 provides a summary of the research findings and sheds light on general limitations of the study that may serve as grounds for future research.

CHAPTER 2. HISTORICAL AND PROJECTED INVENTORY LEVELS OF WHITE OAK IN KENTUCKY

ABSTRACT

White oak is a major commercial tree species and an important timber resource in Kentucky. However, current forest inventory trends from white oak growing region in the US reveal sustainability threat from declining white oak regeneration and recruitment leading to disproportionate inventory structure. In this study, first, we examined past and current inventory levels of white oak in Kentucky. Second, we projected growth and yield of white oak growing stock for the next 50 years (2018-2068) at state level and performed base run analysis of projected inventory levels of white oak sawlogs to better understand whether inventory levels remain adequate to support current harvest levels of white oak in the future. Third, the projections were further analyzed by tree grade to have a general understanding on quality of white oak timber growing in Kentucky's forests in posterity. Using Forest Inventory and Analysis (FIA) data, we found that white oak dominated forest structure is rapidly transforming to forest largely dominated by large-diameter trees with remarkable decline in small-diameter trees, and this trend would continue for the next 50 years based on growth and mortality submodels of Forest Vegetation Simulator (FVS) model. The base run analysis indicated that projected inventory levels of white oak sawlogs remain inadequate to support current harvest levels from 2058 onwards. In addition, the long-term trends in inventory levels of high-quality white oak sawlogs would be continuously declining while that of low-quality sawlogs would be steadily increasing. On the brink of these seismic shifts augmented by ecological and economic forces, our study calls for proactive forest management approaches to stabilize the white oak timber resource supply in Kentucky and beyond.

2.1 INTRODUCTION

White oak is the most important commercial oak species in the US (Core, 1971). Its native range extends throughout most of the eastern US from west to southeastern Minnesota; south to eastern Texas; east to northern Florida, and north to southwestern Maine (Rogers, n.d.; Stein et al., 2003). White oak is a valuable hardwood species primarily used for interior decorative applications such as furniture, cabinets, millwork, and hardwood flooring as well as industrial applications such as caskets, railroad ties, mine timbers, pallets, and truck flooring (Cassens, 2007). Veneer quality logs and lumber are commonly exported to Europe as a substitute for European white oak. The exclusive use for tight cooperage (whiskey barrels and wine casks) is what makes white oak unique from other oak species. In fact, one of the federal standards of identity for the distilled spirits requires American bourbon be made in charred new oak containers (Office of the Federal Register, 2018).

White oak is a cornerstone species of Kentucky forests. The Commonwealth accounts for approximately 7% of white oak growing stock in the US (fifth highest), around 18% of white oak growing stock in the Central Hardwood Forest Region, nearly 11% of growing stock volume in Kentucky (USDA Forest Service, 2020a), and about 14% of the entire white oak resource located within all southeastern states (Oswalt, 2015). Similarly, about 42% of Kentucky's timberland area is covered by white oak dominated forests (USDA Forest Service, 2020a). Moreover, select white oak[3] group consists of greatest standing growing stock volume of all species group (white oak being the second most

[3] Select white oak is a group of species in the genus *Quercus* that primarily includes white oak (*Quercus alba*), swamp white oak (*Quercus bicolor*), bur oak (*Quercus macrocarpa*), swamp chestnut oak (*Quercus michauxii*), and chinkapin oak (*Quercus muehlenbergii*) (Smith et al., 2004).

voluminous species after yellow-poplar (*Liriodendron fastigiatum*)) and accounts for greatest sawlog volume on timberland across all species groups in the state (Oswalt, 2015). The significance of white oak is further enhanced by the economic contribution of white oak timber industry to Kentucky's economy. White oak is the top species for lumber production in the state (Kentucky Energy and Environment Cabinet, 2014). Distilling industry, a major contributor to the state's economy, largely depends on high-quality stave logs from white oaks to make wooden casks/barrels for aging the bourbon and other spirits. In 2020, white oak barrels ($112 MM) and oak lumber ($53 MM) were the top wood-related exports from Kentucky (Stringer et al., 2020). Therefore, white oak timber resource plays a pivotal role in Kentucky's economy and the lives of Kentuckians by supplying livelihoods, wood, wood products, and myriad goods and services.

Sound natural resource management demands an assimilation of the interplay between natural and social processes (Holechek et al., 2003). Whilst natural processes are largely ecological, social processes are chiefly economical. As such, sustainable supply of timber hinges on understanding of underlying ecological and economic forces. "Oak regeneration problem" is one of the most important and widely discussed issue in the eastern US forests (Abrams, 2003, 1998, 1992; Dey, 2014; Loftis and Mcgee, 1993; Nowacki and Abrams, 2008). The understory of historically oak dominated forests in the eastern US are now disproportionately represented by shade-tolerant species like red maple, and the present oak seedlings and saplings are failing to recruit to larger diameter size class (mid-story and overstory) due to the mesophytic microclimate - unsuitable to oak development - created by flourishing shade-tolerant species. This ongoing ecological shift has had the greatest negative impact on the highly valued white oak as its recruitment has

been limited to few sites (Abrams, 2003). Besides, accelerated harvesting suggested by growing demand for white oak logs and lumber in the national and overseas market (Kornstein and Coomes, 2019; Stringer et al., 2019; Wang et al., 2010) is augmenting the ecological changes taking place. In addition, lack of active forest management and the practice of high grading in the Central Hardwood Forest Region including Kentucky (Brandeis, 2017; Butler and Butler, 2016) poses serious challenges to long-term availablity of high-quality white oak. Given the importance of white oak to the industries that are reliant on it and the ecosystem values it provides, a holistic approach to examine its sustainability is imperative to forestall a future white oak crisis.

While future trend of growing stock volume provides a crucial outlook on timber sustainability, it is also important to have a better understanding of the quality of timber growing in the forests, especially in case of hardwood species. Timber quality is an important factor in hardwood markets because it largely influences market price and main use of timber. For instance, Kentucky delivered log prices of white oak in first-half of 2019 ranged from $1127 per MBF (high-quality) to $327 per MBF (low quality) (Stringer et al., 2019). Logs of higher quality generates clear lumber of greater volumes, which is used in the production of higher value-added secondary hardwood products, including kitchen cabinets, flooring, furniture, and millwork (Luppold and Bumgardner, 2016). Both high-quality logs and lumber also constitute an important hardwood exports (Wang et al., 2010). Tree quality is often measured by assigning US Forest Service tree grades (1 to 5), although it may vary by species (USDA Forest Service, 2019). In case of hardwood species, butt logs of tree grades 1 and 2 are usually processed into lumber, veneer or exported; grade 3 may be sawn into appearance or industrial lumber products; and grades 4 and 5 are highly

likely to be used for industrial, pulp, or composite products, given the local market conditions (Luppold and Bumgardner, 2019). Tree grades incorporate tree size and defects (surface and interior), which directly affect the quality and quantity of lumber contained in the tree (Hanks et al., 1980). Therefore, information on availability of hardwood timber quality in posterity is critical to timber industries that depend on sustained supply of high-quality timber.

Understanding the changes in timberland base is the fundamental resource concern in determining future growth and yield, and trends in timber inventory provides outlook on the ratio of growth to harvest- a key measure of the sustainability of the forests by most definitions (Deal and White, 2005). Growth and yield models can be used to forecast changes in timber supplies for large ownerships, as well as the timber supply outlook at local, regional, state, and national levels (Dale and Hilt, 1989). However, very few studies have explored timber sustainability at large scale using a contemporary individual tree growth and yield model. As research concerning white oak sustainability is slowly gaining momentum with the establishment of White Oak Initiative, this would be one of the first study to examine white oak resource sustainability at state level using a regional growth modeling tool.

The overall goal of this study is to examine the sustainability of white oak timber supply for the next 50 years in Kentucky. First, using Forest Inventory and Analysis (FIA) data, past and current inventory levels of white oaks are temporally analyzed in terms of commonly used FIA metrics: volumetric change across diameter-size class and change in timberland area across stand-size class. Second, Forest Vegetation Simulator (FVS), a distance-independent individual tree growth model developed by the USDA Forest

Service, is used to project growth and yield of white oak growing stock; the volumetric estimates are analyzed in terms of diameter-size class and tree grade. Third, the base run analysis of projected inventory levels of white oak sawlogs (a function of earlier inventory, projected growth, and current harvest level) - including based on tree grade, is performed to better understand whether we can expect a sustainable supply of white oak timber, especially of high-quality in the future.

This study provides an overall baseline assessment of future timber supply of white oak in Kentucky; however, it must be regarded as a first step that incrementally improves through collection of new data, model validation, and refined analyses. Hence, the purpose of this modeling effort is to use the best available information about Kentucky's forests to explore the long-term trends in white oak timber supply.

2.2 LITERATURE REVIEW

2.2.1 Oak regeneration problem in the eastern US

White oak was the predominant oak species in the eastern US before European settlement (Abrams, 1992; Whitney, 1994). The domination of white oak was accounted to low to moderate biotic and abiotic intervention such as increased use of fire and warmer climate in the Holocene epoch (Whitney, 1994; Abrams, 2003). During pre-settlement, periodic fire disturbance arrested the development of fire sensitive species and favored the regeneration of oaks (Abrams, 2003). With European settlement, a number of factors contributed to the modern expansion of oaks in eastern North America from about the 1850s to the 1930s: consistently frequent and ubiquitous fire, selective or commercial clearcut timber harvest practices, drastic reduction of wildlife populations browsing oak

reproduction, and prolific coppicing of hardwood species such as oaks in areas of charcoal production to fuel the manufacture of iron (Dey, 2014). These suite of forest disturbances allowed oak seedlings to grow toward the canopy whenever gap in the overstory was formed (Abrams, 1996; Orwig and Abrams, 1994). Hence, the origin of many of present day mature oak forests throughout the eastern US is from the forest disturbances in the latter 19th and early 20th centuries (Dey, 2014).

Selective logging (high grading) or single-tree selection were predominant methods of harvesting in eastern hardwoods, since the early 20th century (Clark, 1993; McGee, 1972). After decades of fire suppression beginning around the 1920s (Nowacki and Abrams, 2008), it became apparent that these harvest methods favored shade-tolerant species to replace oak and encroach forest understories in the absence of fire (Dey, 2014). Concurrently, disturbances such as clearcutting practice of the early 19th century and chestnut blight of the early 20th century catalyzed the expansion of relatively fast-growing red oaks into vast areas of eastern forest dominated by white oak and chestnut oak (Abrams, 2003). Hence, changes in fire regimes (exclusion of native burning and fire-suppression policies around the 1920s), agricultural activities, development of road networks, excessive grazing, management and/or harvesting methods influenced forest dynamics over time, including changes in composition to more mesophytic and shade-tolerant species (Brose et al., 2001; Miller and Kochenderfer, 1998; Nowacki and Abrams, 2008), thereby setting the stage for oak regeneration problem in the eastern US.

Regeneration (initiation of seedling) and recruitment (ascension of sapling in the overstory) are the two pillars of sustainable oak management; however, the regeneration potential of oak in many stands in eastern US is declining over the period of time as

overstory oaks mature and forest understories become increasingly dominated by shade-tolerant species that are recruiting into the overstory (Dey, 2014). Because of the maturing of the region's forests, and the limited ability of white and red oak to regenerate under shade, regeneration of these species is of concern. Even though oak seedlings can survive in shade for several years, they must have adequate sunlight to successfully develop (Schmidt and Mcwilliams, 2003). The substantial presence of shade tolerant species like red maple in a closed understory is imposing physiological light limitation on oak, thus hindering the recruitment of oak seedlings into large size classes (Abrams, 1992). Red maple (depending on locale, sugar maple and American beech too) reigns supreme in the understory and mid-canopy of many oak and northern hardwood forests, and augmenting its supremacy is its two key ecological traits: the ability to act as both an early and late successional species, and to grow well in disparate edaphic conditions (Abrams, 1998). Nowacki and Abrams (2008) coined the term "mesophication" to describe the domination of shade-tolerant mesophytic species in lieu of fire-adapted heliophytic species, given the acceleration of mesic microenvironmental conditions. Consequently, a positive feedback loop ensues further ameliorating conditions for shade-tolerant species and worsening for shade-intolerant species, mainly oaks. Hence, shade-tolerant species such as red maple, sugar maple and beech will most certainly persist in the overstory of historically dominant oak forests of the eastern US during the next century (Nowacki and Abrams, 2008).

Although climate projections indicate habitat expansion for oak dominated forests in the northeastern US (Rustad et al., 2012), the case for rejuvenation of white oak to its former dominance due to rise in temperatures in the eastern US seems unlikely because in the last two centuries anthropogenic activities have almost certainly altered the ecological

dynamics of eastern forest irreversibly (Abrams, 2003). While climate change and pathogens pose serious threats to oak forests in the eastern US in the future (Conrad et al., 2020), new threats such as rapid white oak mortality are emerging (Reed et al., 2017). Nowacki and Abrams (2008) have warned that time for restoring oak-dominant ecosystem in the eastern landscapes may be ticking away, as systems may be approaching critical ecological thresholds and near-irreversible state shifts.

2.2.2 Changing forest structure in the Central Hardwood Forest Region

The Central Hardwood Forest Region (CHFR) is well known for its domination of oak-hickory forest resources for the past 5000 years where they function as keystone species (Spetich, 2004), and provide significant ecological as well as economic benefits to local, regional, and national communities (Ma et al., 2016; Schmidt and Mcwilliams, 2003). The region boasts over half of the total volume of oak growing stock in the East (Fei et al., 2011), and about 42% of white oak growing stock in the US (USDA Forest Service, 2020a).

Luppold and Bumgardner (2018) used FIA data to examine the structural changes of hardwood growing stock in the CHFR (they used state boundaries of 8 states to represent the region: Kentucky, West Virginia, Tennessee, Missouri, Iowa, Illinois, Indiana, and Ohio). They found that between 1989 and 2012, the cubic volume of select white oak growing stock on timberland in large diameter size class ((≥ 17” dbh) had more than doubled; however, pole timber volume (5 to 10.9” dbh) had been decreasing since 2002. Such transitioning from a poletimber dominated to a large size sawtimber dominated structure was pronounced for oak species across all states of CHFR, but less evident for other species groups such as hard maple, soft maple, and hickory. Fei et al. (2011) also

used FIA data to provide comprehensive quantification of the change in oak abundance in the eastern US between 1980-2008, and found that decline in oak abundance was notable in the CHFR. Of note, white oak - the most prevalent species - had a significant decrease in relative density (3.4 to 2.8%), relative volume (8.2 to 8.1%), and overall abundance (5.8 to 5.4%). By quantifying decline in relative density and volume of oaks, these studies corroborates the overall impression of scores of literature citing loss of oak forests in the eastern US. The results of these studies substantiate that the current poletimber volume of white oak in its growing region is alarmingly low and if the trend continues, it puts the white oak timber resource at risk because forest without good proportion of young trees cannot sustain itself in long term horizon.

The loss of dominant keystone oak species through succession will result in loss of biota ecologically and evolutionarily associated with oak-hickory forest (Spetich, 2004). Ma et al. (2016) used Climate Sensitive Matrix model as a function of climate, fire disturbance, and shifting forest population structures to quantify suit of economic and ecological changes in Central Hardwood Forests. They found that future forest dynamics of CHFR would be characterised by the domination of opportunistic red maple in oak-hickory forests, decline in species diversity, substantial declines in stand basal area, reduction in stand volume, and diminishing total stumpage value from nearly $1317 billion to $529–599 billion.

2.2.3 Kentucky's forest resources: Importance and concerns

Forest is an important and abundant resource in Kentucky. Nearly half of state's land area is covered by forests, of which about 99% is considered suitable for timber

production (Oswalt, 2015). It is from these timberland that more than 3500 forest industries in the state derive raw materials for forest based production and services (Kentucky Energy and Environment Cabinet, 2014). Kentucky is among the top three producers of hardwood in the nation and is the leading producer of sawlog and veneer in the southeastern region (Kentucky Energy and Environment Cabinet, 2014). In 2018, forest sector directly contributed an estimated $8.52 billion to Kentucky's economy employing more than 26,500 people directly in the sector (Stringer et al., 2018). As such, forests play a pivotal role in Kentucky's economy and the lives of Kentuckians by supplying wood, wood products, food, fuel, cover, habitat, recreation, and many other goods and services.

Although the acreage of forestland in Kentucky has been increasing since 2004 (Oswalt et al., 2014), changes in state's forests by species and size-class deserve closer examination. In a study by Fei et al. (2011), a widespread decrease in oak density was found in the Cumberland Plateau in Kentucky and a majority of the central Appalachia, both of the region falls in eastern Kentucky. Acreage of large-diameter stands[4] (≥ 11" dbh) in Kentucky is increasing while that of medium (5" ≤ dbh <11") and small-diameter stands (< 5" dbh) has been decreasing (Oswalt et al., 2014). In 1988, an estimated 58 percent of all forest land in Kentucky was in large diameter stands; however, the proportion increased to 65 percent and 68 percent in 2004 and 2009, respectively. Meanwhile, stands classified as medium diameter declined from 26 percent in 1988 to 24 and 21 percent in 2004 and 2009, respectively. Concurrently, between 1988 and 2009, the area of small diameter stands declined from 16 percent to 10 percent (Oswalt et al., 2014). Since 2004, forest land area in large diameter stands increased by 20 percent as opposed to a 17 percent decrease

[4] The diameter specification of large, medium, and small diameter stands is for hardwood species.

in medium diameter stands and an 8 percent decrease in small-diameter stands over the same time frame (Brandeis et al., 2016). The smaller diameter classes provide a good indication of dominant timberland species 50 to 70 years in the future if there is no major disturbance (Schmidt and Mcwilliams, 2003). The fact that Kentucky's contemporary forests are skewed towards the older age class with very few acres of young forest land is concerning, given the ecological and economic importance of forests in the state. Besides, the present condition of regeneration (seedling and sapling) can have substantial long-term effects on future stand dynamics, management options, and whether or not management goals are achieved (Wagner et al., 2018).

Apart from natural constraints, there are social constraints to oak management in Kentucky that mainly relates to challenges in hardwood forest management. Of the 70% of Kentucky's forest that are owned by the family forest owners, < 20% are actively managed (Butler and Butler, 2016). Similarly, partial harvest is the predominant harvesting practice in Kentucky with white oak being the top species removed under this harvesting regime (Brandeis, 2017); this practice of selective harvesting results in insufficient forest floor light levels optimal for oak regeneration and establishment. In addition, there is a practice of high grading in Kentucky. As a result, trees are increasingly likely to be left in partially harvested stands as their tree grade decreased in quality, regardless of the tree species. In fact, the study by Brandeis (2017) found that: relative to a grade 1 tree, a grade 2 tree was 2 times, a grade 3 tree was 5-6 times, a grade 4 was 5 times, and a grade 5 was 6-7 times as likely to be left relative to a grade 1 tree. The selective removal of commercially valuable trees provides immediate high returns at the expense of reduced revenue potential and further downgrades the inventory of high-quality hardwood timber base in posterity.

2.2.4 Forest growth and yield model

Forests are long-lived dynamic biological systems. Thus, understanding and projecting the trajectory of change is essential for informed forest management decision making (Peng, 2000). Growth and yield models are the production functions that underpin timber management. Forest growth models aim to quantify growth of a forest and are generally used for two purposes: predicting the future status of forests and applying alternative management practices based on the nature of the harvest (Vanclay, 2006). Growth and yield models explain the dynamics (growth, mortality and associated changes in the stand) and thus, have been extensively used in managing the forest, owing to their ability to update inventories and predict future growth and yield (Burkhart and Brooks, 1990; Vanclay, 1994). Reliable prediction of yield is also integral for managing the forest sustainably. Planning harvest efficiently requires forecast of when, where, and how much timber can be harvested. Thus, inference about sustainability can only be put forward if we can anticipate the next harvest schedule (Vanclay, 2003).

Conventionally, growth and yield models are classified into whole stand model and individual tree model (Burkhart and Brooks, 1990). Whole stand model provides little or no information about individual trees in the stand and are useful for plantation (Vanclay, 1994). However, individual tree models simulate each individual tree as a basic unit with respect to establishment, growth and mortality, and sum the resulting individual tree estimates to estimate stand level values (Peng, 2000). Forest growth and yield forecasts have been in use in the US since about 1900 (Burkhart and Brooks, 1990), but were limited to specific species in narrowly defined geographic areas such as even-aged conifer stands (Crookston and Dixon, 2005). The need for a standard growth model to provide national

direction for managing national forests was identified in about 1980. Hilt (1985) developed a distance-independent individual tree growth model OAKSIM for even-aged upland oak stands in southern Ohio and southeastern Kentucky based on a thinning study in white, black, and scarlet oak stands, but the model is hardly used because of its limited functions and inconsistency (Brooks and Miller, 2011). After gauging the structures of prevalent models, the Prognosis Model was chosen as a common modeling platform in the United States Department of Agriculture (USDA), Forest Service, which was later renamed Forest Vegetation Simulator (Crookston and Dixon, 2005). Forest Vegetation Simulator (FVS) belongs to the distance-independent, individual tree class of models. FVS is a standard model used by the USDA Forest Service and is extensively used by the forest managers to summarize current stand conditions, update inventory levels, and forecast stand conditions under various management alternatives (Dixon, 2002b). Since then, FVS has been widely used throughout the US, and its applicability well-documented (DeRose et al., 2008; Greenberg et al., 2014; Guertin and Ramm, 1996; Moss and Heitzman, 2013; Radtke et al., 2012; Smith-Mateja and Ramm, 2002). Different variants of FVS have been developed for North America by imbedding tree growth, mortality and volume equations for a particular geographic area using data from FIA (Keyser, 2008).

The development of the southern variant of the FVS (FVS-Sn) model began in 1998, and it included 27,487 observations of white oak trees for the model fit (Keyser, 2008). The Sn variant uses subregions within the ecoregion classification system as means to identify major geographic regions within the southern US (Cleland et al., 2007; Mcnab and Keyser, 2011). These subregions, aggregated into ecological units, affect species site index transformation and large tree diameter growth; thus, helps to refine tree growth

models (Keyser, 2008). The ecological units used in the southern variant for Kentucky are: Continental Eastern Broadleaf Forest (subregions: Eastern Knobs Transition, Kinniconick and Licking Knobs, Outer Bluegrass, Inner Bluegrass, Western Bluegrass, Northern Bluegrass); Oceanic Eastern Broadleaf Forest (subregion: Rugged Eastern Hills); and Central Appalachian Broadleaf Forest (subregions: Western Coal Fields, Eastern Coal Fields, Black Mountains, Southern Cumberland Mountains, and Pine and Cumberland Mountains). While the variant of the FVS model performs reasonably well in projecting yields for forested stands in the geographic area for which the model was fit, the FVS model also employs additional features for calibration as the model may perform poorly due to considerable variation in site conditions (Dixon, 2002b). The additional calibration is achieved through increment models and random effect features contained in FVS. Under increment model, if diameter growth is measured on five or more sample trees of a species of at least 3" at the beginning of the growth period, available periodic diameter increment data is used to calibrate the model for that species. Under randomization, when there are many tree records, the effects of any one random deviation on the growth rate of one tree would be blended with many other trees, and the stand totals should be quite stable estimates; and when there are few tree records, a process called tripling is employed. Under tripling, two additional records of each tree record are added. These new records duplicate all characteristics of the tree except the predicted change in diameter and the original TPA represented by the source tree record. The trees per acre (TPA) value of the original tree record are diminished to 60 percent of its current value, and the two new records are given 15 and 25 percent of the original value; hence, the three records together still represent the same number of TPA.

It is important that growth and yield models give realistic and reasonable estimates of future stand dynamic as forest management decisions of the landowners are incumbent on those future estimates. While there are scores of published work on validating various submodels of FVS, only handlful of them have looked at their validations with FIA data at state or regional level. Guertin and Ramm (1996) attempted validation of the Lake States TWIGS variant of the Forest Vegetation Simulator (FVS-LS) for upland hardwoods in the northern Lower Penninsula in Michigan. They found that 5-year diameter growth was predicted within ± 0.3" for the five species studied, and mean error for TPA was within ± 20 TPA for almost all species studied. Smith-Mateja and Ramm (2002) examined validation results for red pine in Michigan using FVS-LS variant. In simulations that included calibration i.e., when the model used past diameter growth to calibrate future diameter growth, FVS-LS almost always predicted dbh within ±1" for projections up to 27 years long. DeRose et al. (2008) reported unrealistic size-density predictions at large diameters for longleaf pine (*Pinus palustris*) using FVS-Sn. Gould et al. (2011) revised the FVS variant developed for the Pacific NorthWest to study the growth and survival of Oregon white oak (*Quercus garryana*) because Oregon white oak was not a major species and only 12 observations of the species were used in th original model. In the first ever extensive accuracy assessment of FVS-Sn documented in published literature, Radtke et al. (2012) assessed the prediction accuracy for projected basal area and TPA in the southern Appalachian upland hardwoods that included portions of seven states: Alabama, Georgia, Kentucky, The Carolinas, Tennessee, and Virginia. They found that baseline FVS-Sn predictions for standardized 5-year growth intervals for either BA (basal area) or TPA (trees per acre) were within ±15% of observed values (PA-15) for 88% of the FIA field

plots in mixed hardwood forest types for 4-9-year projections and the projections were biased, on average, by 3.5% for BA and 4.1% for TPA. While modification of mortality equations improved PA-15 for both BA and TPA to over 90% for most of the forest types (notably white oak/red oak/hickory, white oak, yellow poplar/white oak/red oak, and chestnut/black/scarlet oak), their applicability is limited to projections below 10 years. This means the span of the available remeasured FIA plots is not long enough to validate long-term projections as in this study, where the projection runs for 50-year.

2.3 METHODS

2.3.1 Overview of Forest Inventory and Analysis (FIA) database and method

To examine temporal changes in inventory levels of white oak as well as white oak dominated stands within Kentucky, I used Forest Inventory and Analysis (FIA) data collected by Southern FIA unit of the USDA Forest Service for the years 1988, 2004, and 2016. The FIA program of the US Forest Service collects, organizes, archives, analyzes, and reports nation-wide inventory information (extent, condition, volume, growth and drain of forest resource) on all ownerships for forestland in the US, and has continued to exist since 1928 (Smith, 2002; Woudenberg et al., 2010). For this part of study, data were accessed using EVALIDator Version 1.8.0.01 (USDA Forest Service, 2020b). EVALIDator is a web-based tool that provides interactive access to the Forest Inventory and Analysis Database (FIADB) (Woudenberg et al., 2010). Drawing from the FIA data, the tool generates a large variety of population estimates and their sampling errors for user selected forest attributes such as forest area, volume, carbon, growth, removals and mortality, inter alia (USDA Forest Service, n.d.). Data used for the year 1988, which is the

earliest FIA data available for Kentucky, are based on periodic survey while that of the year 2004 and the year 2016 are based on multi-year panel process, using the plot design as described in Bechtold and Patterson (2005). Until mid-1990s, forest inventories were conducted in a periodic cycle; however, it was the year 1998 when inventories were annualized by collecting a proportionate share (15% in the east and 10% in the west) of the State's plots each year (Smith, 2002). As a result, a seven to ten-year cycle would represent full complement of inventory data for a state. Of note, the annual inventory cycle for Kentucky began in 2000; the first data available were for panels ending in 2004 (2000 to 2004) whereas the most recent were for panels ending in 2016 (2011 to 2016) as of March 2020.

The metrics used for analyzing changes in white oak inventory are individual tree volume of white oak trees, and stand-size class of white oak in white oak dominated forests. Based on individual tree dbh, growing stock volume of white oak trees are grouped into 3 categories: poletimber (5" to 10.9"), mid-size trees (11" to 16.9"), and large-size trees (≥ 17"). This classification aligns with the one employed by Luppold and Bumgardner (2018) in their study of structural changes in the growing stock of important tree species in the central hardwood region. Likewise, stand-size class, a commonly used FIA metrics, is a classification based on stocking and the diameter of the majority of the live trees in a stand (Oswalt et al., 2014). This enables reckoning of the successional status and potential future development of the forest. The classification used by FIA are small, medium, and large diameter equivalent to seedling-sapling, poletimber, and sawtimber respectively. For hardwood species, small-diameter stands are forested areas where the majority of the trees are <5" dbh, medium-diameter stands are ≥5" dbh but less than 11", and large-diameter

stands are ≥11 dbh". This attribute was filtered to include white oak trees growing in white oak dominated forest[5]. All references to a specific inventory year for this part of study will be the panel ending year except as otherwise specified. While the data used for analyzing changes in inventory were collected using two different survey methods, the results are deemed comparable based on similar studies by Fei et al. (2011), Luppold and Bumgardner (2018), and Oswalt et al. (2014).

2.3.2 Overview of Forest Vegetation Simulator (FVS) database and method

The projection of white oak growth was performed in the most recent version of FVS software called FVS graphical user interface (GUI). Specifically, I used southern variant of the FVS model. When tree growth, mortality and volume equations imbedded in the FVS framework are fitted for a particular geographic region, the resultant model is called a geographic variant of FVS (Dixon, 2002a). The southern variant of the model is suggested for use in all of the southeastern states i.e. Kentucky, Florida, Tennessee, Arkansas, Virginia, Georgia, Alabama, Louisiana, the Carolinas, Mississippi, eastern Texas and Oklahoma (Keyser, 2008). I used a local configuration of the GUI for which installation of the suite of FVS tools (a GUI, FVS, and Post-processors) is required. The configuration employs web browser to run the interface (Dixon, 2002b). FVS is an individual tree, distance independent forest growth model widely used by forest managers in the United States including government agencies (USDA Forest Service, USDI Bureau of Indian Affairs and USDI Bureau of Land Management) for simulating future stand dynamics and aiding decision-making (Crookston and Dixon, 2005; Dixon, 2002a). FVS

[5] In this study, white oak dominated forest includes 3 forest types: white oak/red oak/hickory (FIA code 503), white oak (FIA code 504), and yellow poplar/white oak/northern red oak (FIA code 506) (see Appendix 1 for detailed forest types).

is well-adapted to FIADB codes (species, forest types) as a result FIA data forms the primary source of input for projections (Dixon, 2002a). FIA data, however, is not FVS-readable per se; the input information must be processed into an FVS-readable format via translation process. Previously, FIA2FVS 1.0 was used for translation of FIA data into FVS, nevertheless, the translator was discontinued, and a new application FIA2FVS 2.0 has been developed. Among several improvements over its predecessor, one important feature of FIA2FVS 2.0 is to remove the translation burden from the end-user rendering FVS applicable and friendly across broad user base (Shaw and Gagnon, 2019). Since FVS-friendly FIA data was still not under public domain at the time this research began, I obtained beta version of the data for Kentucky in MS Access database format upon request to the US Forest Service. Dr. John D. Shaw, the Biological Scientist at Rocky Mountain Research Station, made the data available, who is directly involved with the Forest Service in setting up FIA2FVS 2.0.

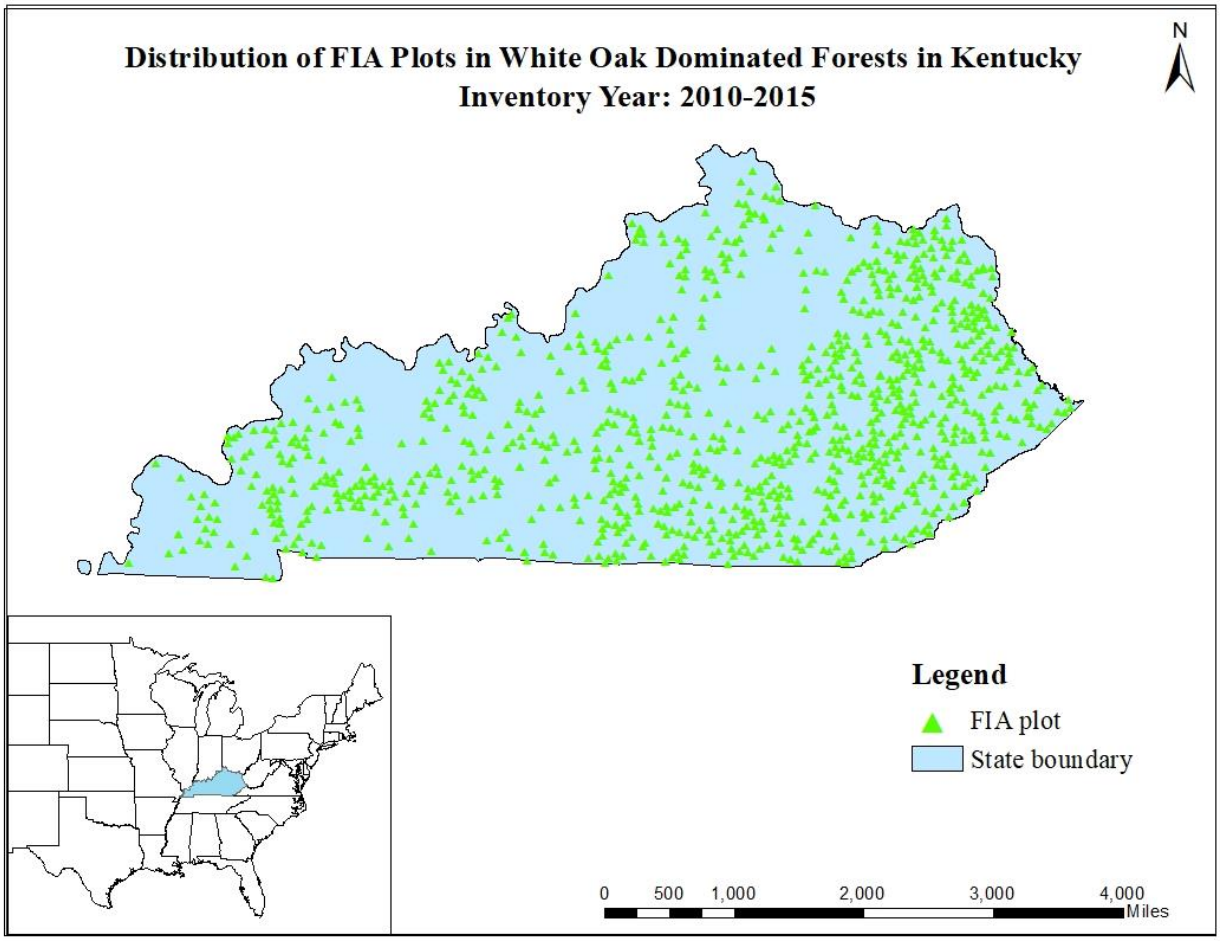
In FVS input database, each plot sampled within a stand is linked to the stand via unique identifier (Stand ID), as a result associated tree data of each plot in a stand are also linked to the stand by the ID. This allows projection of individual tree growth whenever stand or plot is selected as a projection unit. Depending on plot design, an FIA plot is typically represented as a stand in FVS and FIA subplots as FVS plots (Shaw and Gagnon, 2019). For this study, stand (equivalent to FIA plots) is selected as a projection unit. The important variables recorded for each stand are as follows: stand sequence number, stand ID, variant, inventory year, coordinates, ecoregion, age, aspect, slope, elevation, basal area factor, sampling weight, site species, and site index, among others. Interestingly, the FVS Groups variable assemble categories such as inventory year, plot measurement year,

ownership, forest type et cetera permitting greater flexibility in selection of desired categories in setting up simulations over large areas (Shaw and Gagnon, 2019). Similarly, some of the important tree variables recorded are stand sequence number, stand ID, tree sequence number, tree count, species, diameter, height, crown ratio, and crown class.

For this study, inventory data from the year 2010 to 2015 were used as a full complement of data to evaluate future growth of white oak trees in Kentucky (Figure 2.1). Since my interest is on timberland, the database was filtered based on FIADB where the reserved status code of 0 signifies “not reserved” and 1 signifies “reserved” for restricting land management for the production of wood products. Timberland are forestland that is producing or is capable of producing at least 20 cubic feet per acre per year of industrial wood in natural stands and not withdrawn from timber utilization by statute or administrative regulation (Woudenberg et al., 2010). Data were further filtered for white oak dominated forest based on FIA code i.e., 503, 504, and 506. A total of 1,099 stands were simulated in the FVS GUI. The stands include live trees of all size: seedling (dbh < 1”), sapling (1” ≤ dbh < 5”), pole (5” ≤ dbh < 11”) and sawtimber (dbh ≥ 11”). The spatial scope of the simulation was specified by selecting a group of stands based on forest inventory year and forest type. Then, the temporal scope of the simulation was specified by setting a projection cycle of 50 years, starting 2018 with a 5-year interval of growth reporting period. Tree list was selected as an output of simulation. The tree list output is a complete list of all tree records generated in the projection cycle. Relevant data fields contained in the tree list were stand ID, year, species, trees per acre, mortality per acre, dbh, and height. Once the simulation starts, the model dumps the output in SQLite database file. The simulation was run based on an “out-of-the-box” condition using all default

settings. Only the diameter growth, height growth, and mortality submodels of FVS-Sn at default settings were used (Appendix 3). However, a NOCALIB keyword was inserted in each run; the keyword suppresses the calculation of scale factors for large tree diameter increment model and small tree height increment model based on past growth. On long-term projections, the base model is assumed to be a more stable estimate of growth potential than is the scale factor (Dixon, 2002b).

Figure 2.1 Distribution of FIA plots (FVS stands) simulated in FVS growth model.



Note: Locations are approximate based on plots' coordinates as recorded in FIA database; applies to white oak dominated forests: white oak/red oak/hickory, white oak, and yellow poplar/white oak/northern red oak forest types. (prepared using ArcMap 10.5.1)

The tree list output file was filtered for white oak (FIA species code 802), and the resulting file was exported in R Version 3.6.3 (R Core Team, 2020) for further analysis involving volume calculation. Tree volume calculation are based on Southern FIA Volume Equation User's Guide (Oswalt and Conner, 2011). Similarly, growth and mortality equations employed by FVS model are described in Dixon (2002b) and Keyser (2008); some of the important equations are summarized in Appendices 2 and 3.

Once volume of trees on each plot was calculated and scaled to per acre basis using corresponding trees per acre (TPA) value, volume per acre was scaled to population-level estimates using appropriate expansion factor for each plot. Expansion factors can be understood as the number of acres that a plot represents. Thus, plot's contribution to the attribute total for target population was achieved by multiplying plot value per acre with appropriate expansion factor for each plot (Bechtold and Patterson, 2005). Although computation of population estimates may seem straightforward, expansion factor per se is a tricky component. Expansion factors depend on 3 variables: total area, stratum weight, and number of plots in the stratum. Under the current annual inventory design, new plots are added or inventoried each year, and it is rarely the case that equal number of plots are sampled each year owing to inaccessibility, fire hazards or other reasons (Bechtold and Patterson, 2005; Woudenberg et al., 2010). As a result, expansion factors are dynamic, and it may differ from year to year. Besides, expansion factor for an individual plot varies by attributes of population estimate i.e., area, volume, growth, removal, and mortality. Hence, it is possible for a given plot to have number of expansion factors. In my case, I used expansion factors that were recorded as sampling weight variable in FVS readable database. The field is populated with most recent basic evaluation (volume, area, growth)

and is adequate for a good approximation of most of the attributes (J.D. Shaw, personal communication, May 14, 2020). Once the expansion factor for each plot is established, we can use the same throughout because the number of plots in the simulation remains constant.

In case of hardwoods, tree grade is an important consideration affecting commercial use as well as market price of timber. Therefore, volume of white oak trees based on tree grades (1 to 5) was also projected. Tree grades indicate the quality of timber and apply to the sawlog portion of sawtimber trees. The most important features that define tree grades are the presence of a 16' butt (length of the grading zone), dbh criteria, and the clarity on the 3rd best log face (Luppold and Pugh, 2016). A face is one-fourth of the surface of the grading section as divided lengthwise. Tree grade 1 for most hardwood species must be ≥ 16" dbh and have an 83% yield on the 3rd best face. Tree grade 2 must be ≥ 13" dbh and have a 67% yield in the 3rd best face. Tree grade 3 trees must be ≥ 11" dbh and a 50% yield on the 3rd best face. A grade 4 tree has a gradable 16' butt log grading below 3. A tree grade 5 does not contain a 16' butt log but has at least two noncontiguous 8' logs or one 12' log. Additional information on tree grade procedures adopted by Southern FIA unit are described in FIA National Core Field Guide (USDA Forest Service, 2019). Tree grade data for those plots used as input database in FVS were obtained from FIADB. FVS's stand level input database and FIA plot level database were joined by a common column header called unique plot sequence number (abbreviated as PLT_CN); this was performed in RStudio using "inner_join" - a function within "dplyr package". Once the proportion of white oak trees of particular grade growing on each plot was determined, projected volume for each tree grade category on each plot was estimated by factoring plot level volume

estimates obtained from FVS with the individual tree grade proportion in each plot assuming that proportion remains the same. However, it is important to mention the caveat of this assumption. Diameter and surface defects are important factors in classifying tree grade (USDA Forest Service, 2019). As forests grow, trees belonging to grade 3 (≥ 11” dbh) may graduate to grade 2 (≥ 13” dbh) and even grade 1 (≥ 16” dbh) in the future (Miller et al., 2008). Similarly, trees belonging to grade 2 may also graduate to grade 1 solely based on dbh. Additionally, the present surface defects may exacerbate over time or new surface defects may develop in the future, thereby downgrading tree quality (Miller et al., 2008). Consequently, both factors could distort tree grade proportion on individual plots, which in this study was assumed constant.

2.4 RESULTS AND DISCUSSION

2.4.1 Past and current inventory levels of white oak

Between 1988 and 2016, the cubic volume of white oak poletimber (5"-10.9") decreased while that of mid-sized (11"-16.9") and large-sized white oak growing stock (≥ 17”) increased with the latter increasing twofold (Table 2.1). Table 2.1 is based on individual white oak tree’s dbh size in Kentucky. The proportional volume of white oak in small diameter class reduced by almost half (26.5% to 13.3%) and the medium diameter decreased slightly (45% to 42.8%) whereas the large diameter class had the largest increase (28.5% to 44%). Between 1988 and 2016, the area of timberland covered by small diameter white oak stands decreased precipitously whereas large-sized stands had more than doubled (Table 2.2). Table 2.2 is based on average dbh size of white oak stands in white oak dominated forest. The proportional area of white oak in small diameter stands sharply

reduced to 1.7% from 13.6% and medium diameter stands reduced to 13.7% from 23.9% whereas the large diameter stands had the largest increase from 62.5% to 84.5%.

Table 2.1 Cubic and proportional volume of growing stock (trees ≥ 5” dbh) on timberland across three size classes for white oak in Kentucky in 1988, 2004 and 2016.

	1988		2004		2016		1988-2016	
Tree size class (dbh)	Million cuft	Percent	Million cuft	Percent	Million cuft	Percent	Million cuft (% change)	Percent (point change)
5"-10.9"	480	26.5	406	17.5	323	13.3	-32.7	-13.2
11"-16.9"	816	45	1,077	46.6	1,039	42.8	27.3	-2.2
≥ 17"	517	28.5	830	35.9	1,068	44	106.6	15.5

Note: Developed using EVALIDator application of USDA Forest Service; figures are the volumetric sum across all plots of white oak trees within each tree size class irrespective of forest types.

Table 2.2 Acres and proportional area of white oak on timberland across three stand-size classes in white oak dominated stands in Kentucky in 1988, 2004 and 2016.

	1988		2004		2016		1988-2016	
Stand-size class	Thousand acres	Percent	Thousand acres	Percent	Thousand acres	Percent	Thousand acres (% change)	Percent (point change)
Small diameter	269	13.6	62	1.9	55	1.7	-79.4	-11.9
Medium diameter	474	23.9	646	19.7	441	13.7	-6.9	-10.2
Large diameter	1,239	62.5	2,572	78.4	2,718	84.5	119.4	22

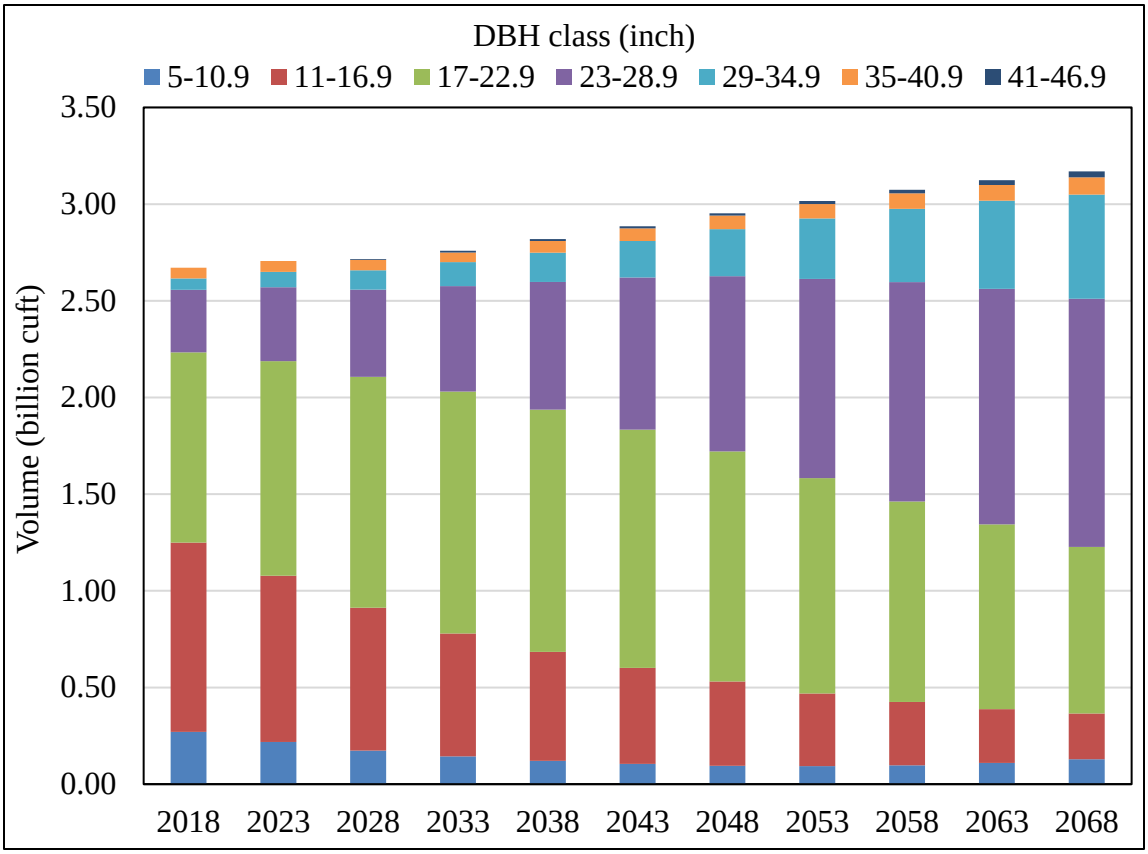
Note: Developed using EVALIDator application of USDA, Forest Service; Small diameter (dbh < 5”), Medium diameter (5 ≤ dbh < 11”) and Large diameter (dbh ≥ 11”).

While changes in white oak forests in Kentucky are consistent with the changes in oak forest types in the eastern US including the Central Hardwood Forest Region (Fei et al., 2011; Luppold and Bumgardner, 2018), the speed with which white oak forests have skewed towards large-sized diameter trees is accentuating. The remarkable decline in timberland area of small diameter stands (dbh < 5”) and the subsequent reduction in timberland area of medium diameter white oak stands (5-10.9”) coupled with reduction in cubic as well as proportional volume of white oak poletimber (5"-10.9") suggest the problem of regeneration and recruitment of white oaks in Kentucky. This results align with the long-observed and widely discussed oak regeneration issues in the eastern forests (Abrams, 2003, 1998, 1992; Dey, 2014; Loftis and Mcgee, 1993; Nowacki and Abrams, 2008; Spetich, 2004). Similarly, slower ingrowth from the poletimber white oaks could have potentially reduced the cubic and proportional volume of mid-sized sawtimber (11"-16.9") between 2004 and 2016. In contrast, the consistent and rapid advancement of large-sized sawtimber (≥ 17”) from 28.5% in 1988 to 44% in 2016 reflects increasing mid-size trees transitioning to large-sized trees. The presence of large-sized trees would be beneficial to hardwood processing industries in the short-run because of reduced sawing costs (Rast, 1974). In addition, larger logs are more valuable than smaller logs because they contain more lumber, and typically contain more defect-free wood (Hanks et al., 1980). However, as trees ≥ 17” are harvested or die without healthy timber base to replenish the larger size class, it casts shadow on the sustainable supply of white oak timber in the state.

2.4.2 Projected growing stock volume of white oak by diameter-size class

Figure 2.2 shows the output of projected growing stock volume of white oak by dbh class as obtained from FVS model. The stacked bar chart shows a steady decline in growing stock volume of 5-10.9” and 11-16.9” dbh class. Since the model does not account for ingrowths resulting from regeneration, part of this steady decline over time might be an outcome of it. However, we also cannot ignore the current forest structure of white oak dominated forests in Kentucky illustrated in Table 2.3. The presence of shade-tolerant species like sugar maple, red maple, and green ash exceeds that of white oak in seedling category; white oak is not even among the frequently found species in sapling category dominated by red maple, sugar maple, and another shade-tolerant species American beech; and sugar maple and red maple dominate white oak in the poletimber category. Only the sawtimber category or overstory is dominated by white oak. In terms of shade tolerance, the southern variant of the FVS model classifies sugar maple and American beech as “very tolerant”, green ash and red maple as “tolerant”, and white oak as “intermediate” (Keyser, 2008). The density-related mortality rates for individual trees in the model generally depends on shade tolerance (the more intolerant species have higher mortality rates than the tolerant species), its social position (understory trees receive heavier mortality than overstory trees), and crown vigor (Dixon, 2002b). It implies that the growth of seedling and sapling stages of intermediate species such as white oak are more likely to be suppressed than that of shade tolerant species. Hence, the substantial presence of shade tolerant species in a closed understory could have hindered the recruitment of oak seedlings and saplings into two immediate large size classes i.e., 5-10.9” and 11-16.9”.

Figure 2.2 Projected volume of white oak growing stock across dbh class in Kentucky (without harvest).



Notes: Trees ≥ 5" dbh comprise growing stock volume; volume denotes total cubic-foot volume of wood inside bark without deductions for rotten, missing, or broken-top cull; the projection is based on FVS model. (Data attached in appendix 4)

Table 2.3 Overview of species composition in white oak dominated forests by diameter size-class on timberland of Kentucky.

Seedling		Sapling	
Species	**Relative Frequency (%)**	**Species**	**Relative Frequency (%)**
hickory spp.	9.11	red maple	13.08
green ash	6.48	sugar maple	11.32
red maple	6.44	American beech	8.45
sugar maple	6.28	yellow-poplar	6.10
white oak	5.41	hickory spp.	5.28
Unknown dead hardwood	4.69	blackgum	4.68
American beech	4.60	eastern redbud	4.34
blackgum	4.53	flowering dogwood	3.98
flowering dogwood	4.13	sourwood	3.71
sassafras	3.51	winged elm	3.36
Pole		**Sawtimber**	
Species	**Relative Frequency (%)**	**Species**	**Relative Frequency (%)**
hickory spp.	14.53	white oak	18.86
sugar maple	11.11	hickory spp.	16.90
red maple	9.67	yellow-poplar	10.57
white oak	7.37	northern red oak	5.21
yellow-poplar	7.27	black oak	5.19
redcedar/juniper spp.	4.81	sugar maple	4.79
American beech	3.88	red maple	4.39
blackgum	3.44	chestnut oak	4.06
sourwood	3.29	American beech	3.42
white ash	2.42	scarlet oak	2.50

Note: The figure corresponds to 2015 FIA data (6-year cycle: 2010 to 2015) for Kentucky; only relative frequency of ten frequently found species by diameter size-class is depicted.

It is also important to note the sensitivity of the mortality submodel in FVS for aging stands. FVS base model mortality predictions are intended to reflect background or normal mortality rates; the base model accounts mainly for mortality in stands that are dense enough for competition to be the causal agent as discussed in the above paragraph. Mortality associated with the breakup of over mature stands is mainly age related and this type of mortality is not simulated in the base FVS system unless specifically invoked by the user (Dixon, 2002b). Using tree size as a surrogate indicator of tree age, we can infer from Table 2.3 that contemporary white oak forests in Kentucky are skewed towards older age class with few young-aged white oak trees. Given that the projection spans 50 years, many white oak stands might be too old until 2068 to accrue continued growth in the larger diameter size classes, especially those ≥ 29" (Figure 2.2). Since the base FVS system used in this analysis does not account for age-related mortality occurring in aging stands, projected volumetric trends across larger-diameter size class or older stands may not follow the pattern as depicted in the figure above insofar as there might not even be white oak trees in 41-46.9" dbh class.

The stacked bar chart also shows that the growing stock volume ≥ 23" dbh class has been steadily increasing. The rise in volume of large-sized sawtimber can be expected for a certain period as sawtimber or overstory is apparently dominated by white oak (Table 2.3), but the continuous rise is because the simulation neither reflect commercial harvest of large sawtimbers nor invokes age-related mortality associated with over mature stands, both of which would result in volumetric loss in the future.

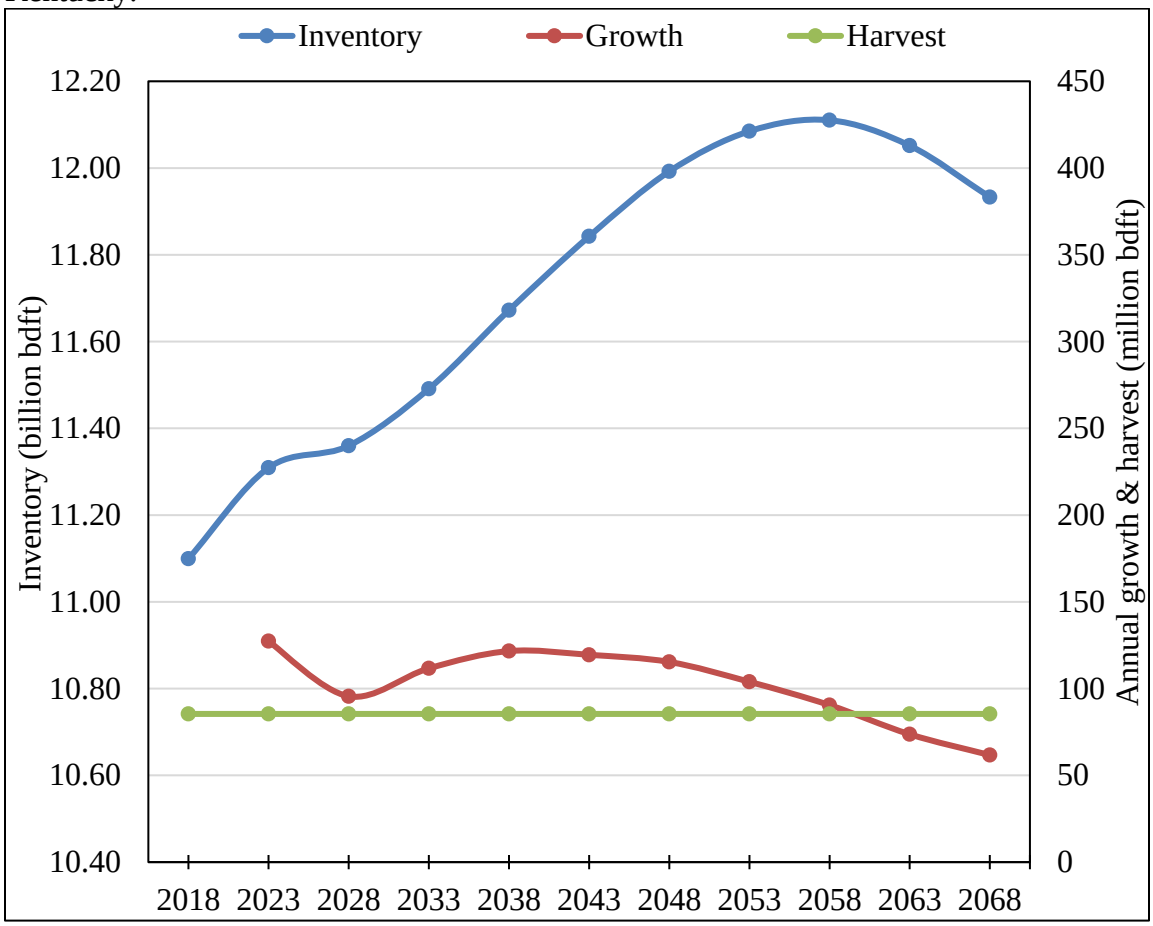
2.4.3 Projected inventory levels of white oak sawlogs

The line chart (Figure 2.3) depicts the projected inventory levels of white oak sawlogs after accounting for growth and a specified level of harvest. The inventory level at time 't' was estimated using a typical inventory accounting approach (Abt et al., 2009) and adjusting the inventory accounting to fit 5-year growth reporting feature of FVS:

$$Inventory_t = Inventory_{t-5} + growth - harvest$$

For instance, the inventory level at year 2023 was estimated by adding inventory level at year 2018 to periodic growth between 2018 and 2023, and then subtracting a specified level of harvest between those periods. The periodic growth was obtained from the FVS growth model whereas the projected harvest level was assumed to be constant based on 10-year average annual harvest between 2006 and 2015 i.e., 85,418,291 bdft (obtained from the EVALIDator application). The rationale behind using constant harvest level was to conduct a base run analysis simulating the long-term impacts of current harvest levels on timber supply. Hence, the line chart represents the base run analysis for projected inventory levels of white oak sawlogs in Kentucky.

Figure 2.3 Projected inventory levels of sawlog volume of white oak sawtimber in Kentucky.



Notes: Sawlog is portion of the main stem of sawtimber-sized trees from a 1' stump to a minimum top d.o.b. 9.0"; unless otherwise specified, board-foot volume in this chapter is the international 1/4" gross board feet volume without deductions for total board-foot cull; growth was obtained from FVS and harvest fixed at specified level based on 10-year average annual harvest between 2006 and 2015 as obtained from EVALIDator application. (Data attached in appendix 5)

The base run analysis of inventory levels of white oak sawlogs was performed to better understand the long-term impacts of current harvest levels on sustained supply of white oak timber in Kentucky. The forest inventory represents the potential supply available for harvest and utilization; economic and biological constraints may prevent portions of the inventory from being available as supply, but "supply" and "inventory" are treated equal in this study and the term used interchangeably. For this purpose, sustainability is defined as a long-term (50-year) balance between growth and harvest of white oak sawlogs which results in a stable white oak inventory in the state. As long as growth exceeds current harvest levels, timber supply can be considered sustainable – resulting in increased inventory levels. The base run analysis indicates that while inventory levels can sustain current harvest levels for four decades, the continued imbalance between growth and harvest from 2058 onwards cannot be considered sustainable as indicated by declining inventory levels (Figure 2.3). The precipitous drop in available inventory beginning 2058 suggests that the current mix of forest management techniques in white oak dominated forests are inadequate to maintain the balance between growth and harvest of white oak sawlogs for the next 50 years. Hence, the result suggests that sustainability crisis of white oak timber supply in Kentucky is on the horizon.

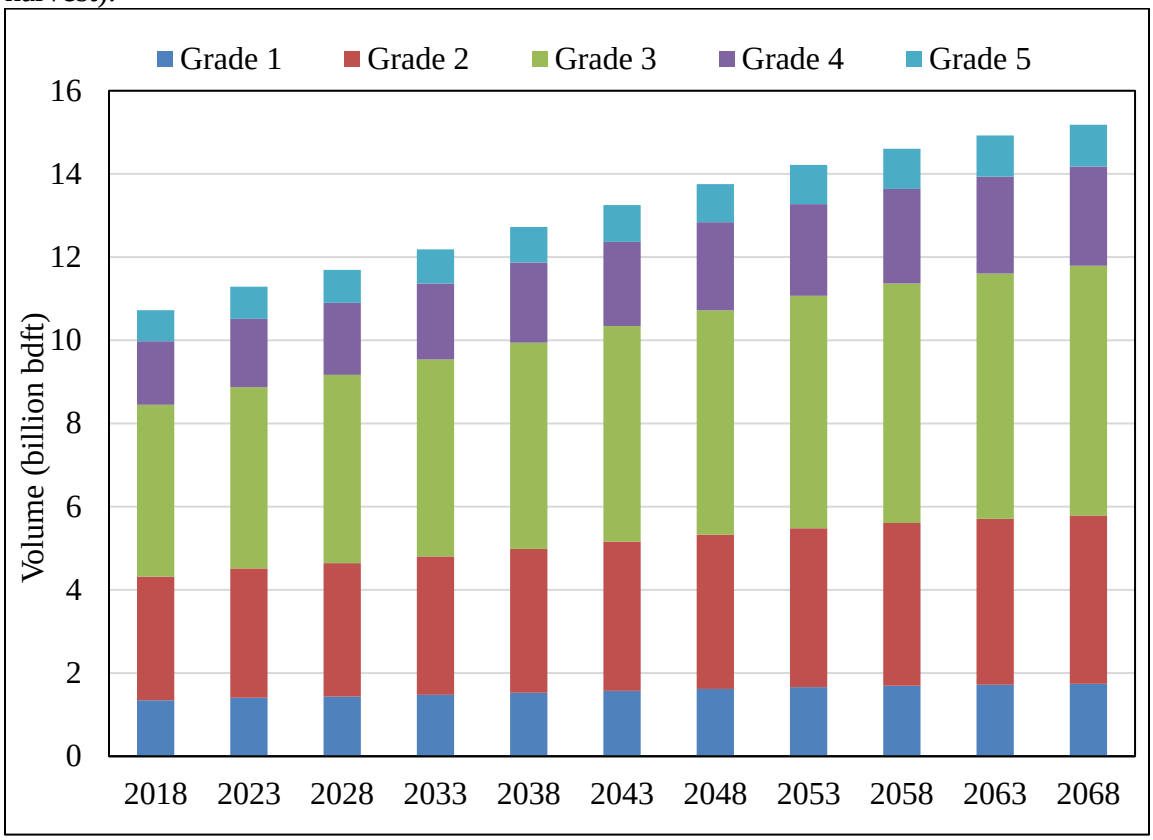
The validity and broad applicability of the results should be interpreted with caution due to caveats and underlying assumptions of the involved analyses. First, any changes in harvest levels can change the trajectory of projected inventory levels – higher harvest levels in the future would shift the tipping point (when inventory starts declining) further left than predicted and vice versa. Second, these results do not consider biophysical and social constraints that may hinder timber availability i.e., we are assuming feasibility of the entire

inventory for harvests. Third, we have not considered removal due to land use such as forestland that might be lost to development in the future. Fourth, the growth model does not incorporate age-related mortality occurring in overmature stands as well as other event-driven mortality that might occur in the future (mortality resulting from insects, pathogens, fire, logging damage, animal damage, and wind events), so the resulting drain in white oak dominated forests has not been accounted for. Lastly, there occurs no ingrowth of seedlings in the regeneration category during the projection entirety, so the growth model reflects the projected volumetric change of existing white oak dominated forests in the absence of new regeneration. However, we do not expect ingrowth to alter our projection trends because volumetric projection in this study focuses on sawtimber sized trees with no within-stand disturbance, thus minimizes the potential impact of newly regenerated trees on volume estimates. All things considered, this base-run analysis might be the most optimistic scenario or the best-case scenario.

2.4.4 Projected sawlog volume and inventory level of white oak by tree grade

The steady increase in the projected volume of white oak sawlogs across all grades (Figure 2.4) reflect that there is no drain in terms of harvest removal in the model, and the proportion of number of white oak trees in each grade remains constant throughout the projection period. In the input database i.e., 2015 inventory data for white oak dominated forests in Kentucky, the proportion of white oak trees of grades 3 and 2 were higher than grade 1, 4, and 5, so the share of volume of tree grade 3 and 2 are higher than the other grades throughout the projection period.

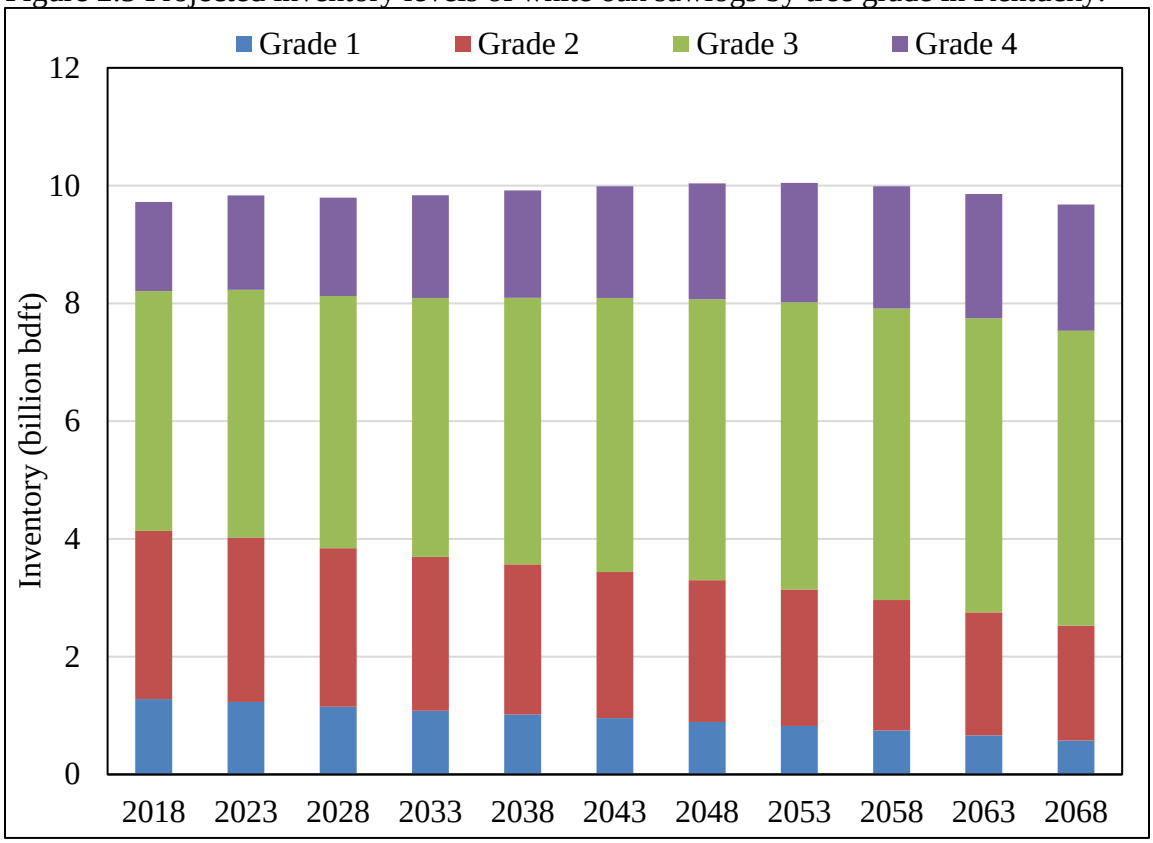
Figure 2.4 Projected volume of white oak sawlogs by tree grade in Kentucky (without harvest).



Notes: Tree grade applies to the sawlog portion of sawtimber trees; the projection is based on FVS model and FIA tree grade data. (Data attached in appendix 6)

The stacked bar chart (Figure 2.5) represents the base run analysis for projected inventory levels of white oak sawlogs across four grade categories in Kentucky. The inventory levels by tree grade were projected using the same approach as mentioned earlier. The harvest level was assumed to be constant based on 10-year average annual harvest between 2006 and 2015 i.e., 22,054,784 bdft for grade 1, 39,509,576 bdft for grade 2, 18,770,081 bdft for grade 3, and 4,605,825 bdft for tree grade 4 (obtained from the EVALIDator application). Since 10-year average annual harvest for tree grade 5 was not available, it was discarded from the inventory level analysis. The stacked bar chart reveals two important trends: decreasing inventory levels of grade 1 and 2 (high-quality) white oak sawlogs and increasing inventory levels of grade 3 and 4 (low quality). It is because current harvest levels of high-quality white oak sawlogs exceed their projected growth contributing to decreasing inventory levels of grade 1 and 2 (illustrated in detail in latter section - Figures 2.9 and 2.10), whereas the projected growth of low-quality white oak sawlogs is well above the current harvest levels contributing to increasing inventory levels of grade 3 and 4 (illustrated in detail in latter section - Figure 2.11 and 2.12). Hence, the base run analysis foreshadows a long-term high-quality white oak supply issue looming for white oak-dependent industries in Kentucky.

Figure 2.5 Projected inventory levels of white oak sawlogs by tree grade in Kentucky.



Notes: The projection is based on FVS and FIA tree grade data; growth was obtained from FVS and harvests for individual tree grade were fixed at specified level based on 10-year average annual harvest between 2006 and 2015 as obtained from EVALIDator application and was maintained throughout the projection horizon; the projection is based on the FVS model and FIA database. (Data attached in appendix 7)

2.4.5 Sensitivity analyses of projected white oak sawlogs inventory

Similar approach as described in section 2.4.3 was employed to conduct sensitivity analyses of projected white oak sawlogs inventory at different harvest levels. Since harvest is exogenous in the model, harvest levels were changed based on external information, specifically Timber Product Output (TPO) data for Kentucky (USDA Forest Service, 2020c). Growth was obtained from FVS model. For sensitivity analyses, harvest was fixed at two levels: historic high harvest level of 2015 and the historic low level of 2009. Results of this analyses are illustrated in Figure 2.6 and Figure 2.7.

Table 2.4 Timber Product Output data for roundwood volume harvested in Kentucky between 1997 and 2019.

Year	Roundwood volume harvested for sawlogs (International 1/4" bdft)
1997	98,493,890
1999	115,965,620
2001	116,350,920
2003	107,116,230
2005	105,777,150
2007	112,253,920
2009	**78,536,530**
2011	122,554,720
2013	121,929,080
2015	**128,969,100**
2017	123,511,340
2018	104,457,160
2019	110,808,090

Note: Roundwood volume harvested for sawlogs applies to select white oak species group: white oak (*Q. alba*), swamp white oak (*Q. bicolor*), bur oak (*Q. macrocarpa*), swamp chestnut oak (*Q. michauxii*), chinkapin oak (*Q. muhlenbergii*), and durand oak (*Q. durandii*); these are harvest as coming from the growing stock portion of sawtimber trees; historic high and historic low harvest levels are in bold; under TPO, sawlogs constitute rough lumber, ties, staves, pallets etc.

Figure 2.6 Projected annual growth and annual harvest for historic high and historic low harvest levels runs.

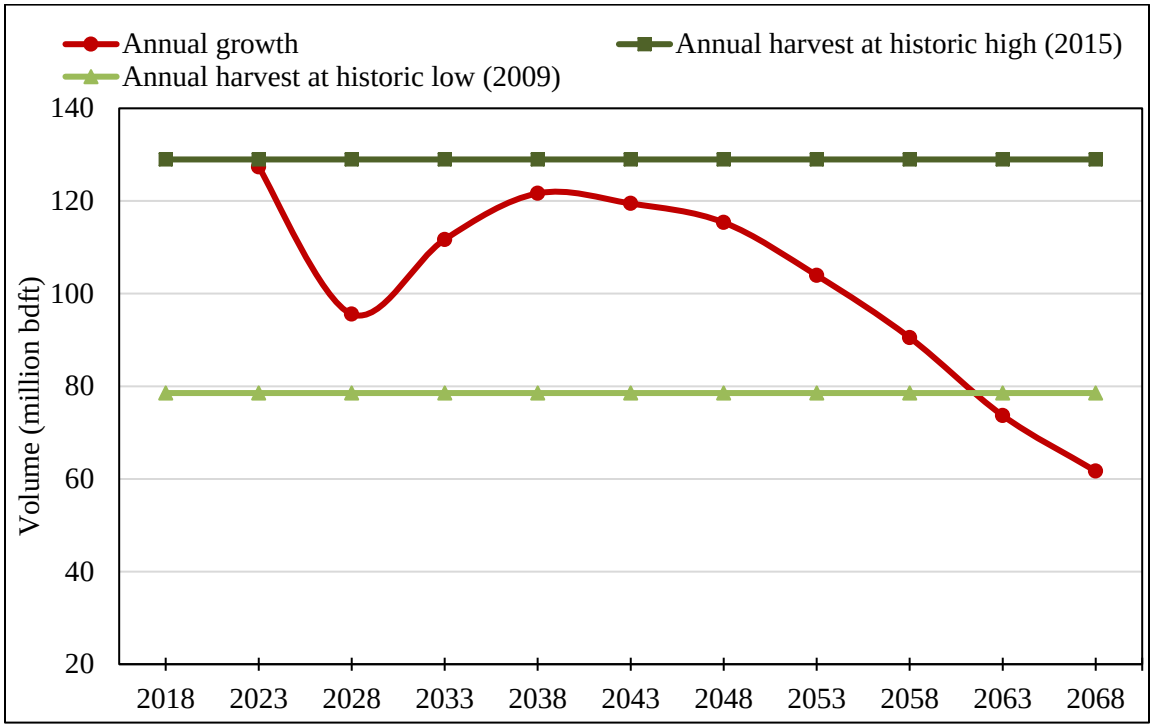
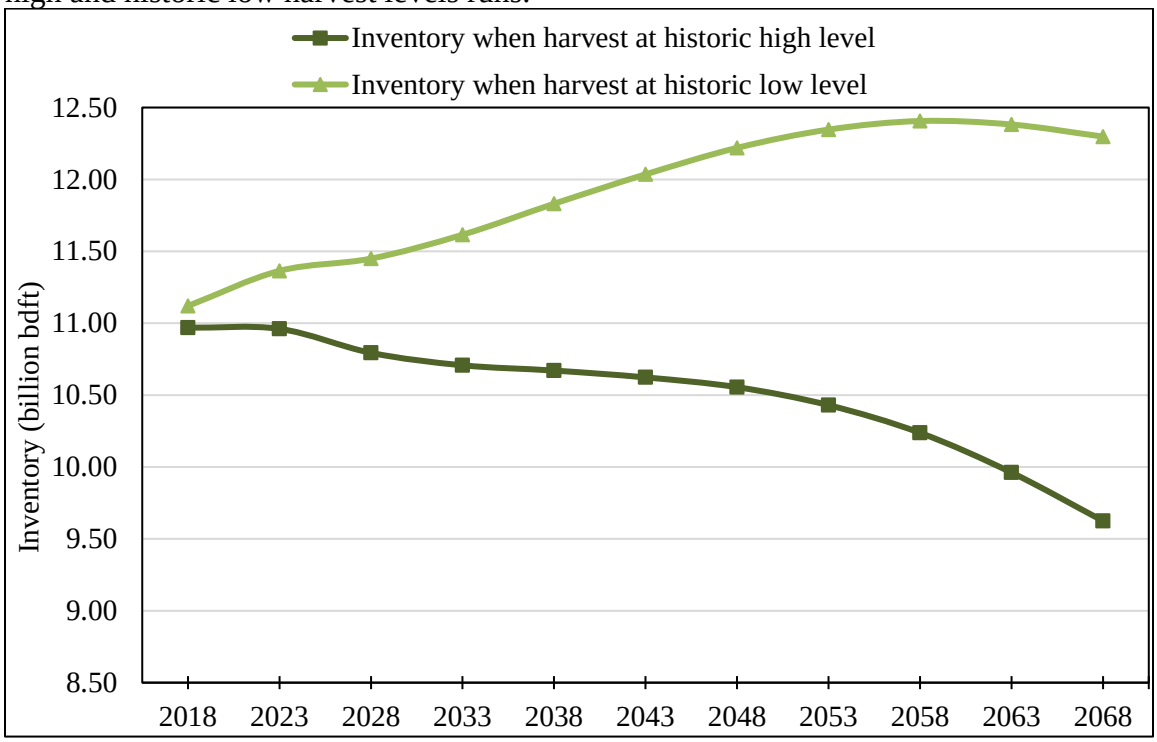


Figure 2.7 Projection of statewide inventory of sawlog volume of white oak for historic high and historic low harvest levels runs.



When harvest at historic low, inventory levels of white oak can be considered sustainable until 2058 as growth exceeds the harvest resulting in upward inventory trends; however, downward inventory trends from 2058 onwards suggest lurking sustainability problem in the future as harvest surpasses growth. This result is akin to the one described in section 2.4.3 (Figure 2.2), when harvest was fixed at a level based on 10-year average annual harvest. Hence, the case of sustainable supply of white oak sawlogs in Kentucky until 2058 appears to be the most optimistic scenario. On the other hand, when harvest at historic high, current and future inventory levels of white oak in the state cannot be considered sustainable as harvest exceeds growth resulting in downhill inventory trends over the projection entirety. Hence, this appears to be a pessimistic scenario suggesting that sustainability issue of white oak timber supply in the state is already underway. However, there are caveats to using this harvest level: (1) these harvest levels include not only white oak (*Q. alba*) but also other species in the select white oak species group, and (2) these harvest levels are not limited to harvest occurring in white-oak dominated forests but includes harvest of select white oak species group coming from all forest types. It is important to note these caveats because our earlier inventory analysis apply to white oak-dominated forest. Nevertheless, the bottom line remains the same: sustainability crisis of white oak in Kentucky is looming.

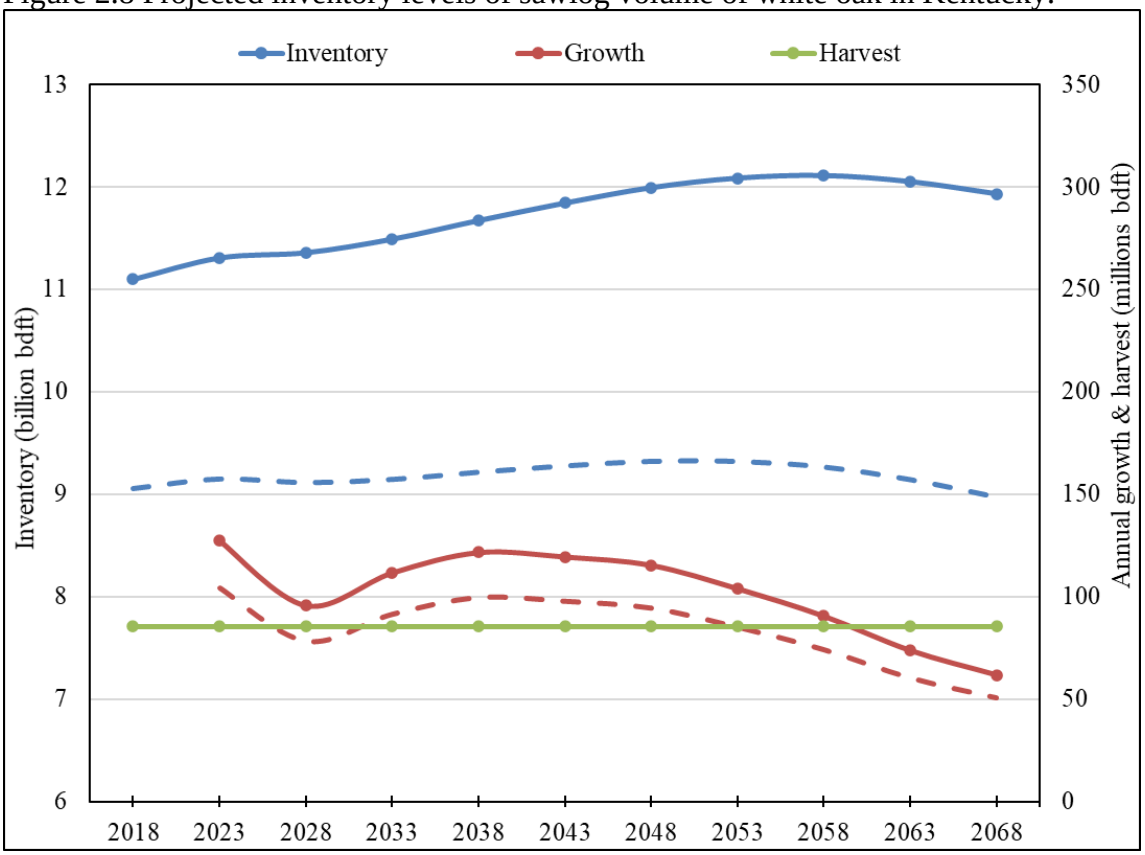
2.4.6 Social availability of projected baseline inventory of white oak sawlogs

Not all projected inventory of sawlog volume of white oak depicted in Figure 2.3 and Figure 2.5 would be available for harvest; the availability of wood for harvest is constrained by social (size of forest holdings or parcel size, distance from residence, ownership type, landowners attitudes) and biophysical factors (terrain, tree size, site productivity) (Butler et al., 2010; Silver et al., 2015). In order to understand what can realistically be extracted, precise estimation of inventories must take into account these factors and adjust total inventory by removing volume that is unlikely to be available for harvest. Butler et al. (2010) found social constraints to be the primary factor influencing availability of wood for harvest on family forestlands in the northern US insofar as reducing availability by 60%. To establish the inventory that is socially available for harvest, total inventory was adjusted by removing public lands and private non-industrial private forestland (family forest land) < 10 acres in size. The former was removed due to the uncertainty of harvest availability of public lands in Kentucky and the reserved inventory, encompassed totally in public ownership. The latter was removed as the <10-acre ownership size represents a threshold that significantly impacts the ability to harvest. However, the relatively short tenure of forest ownership indicates that a large portion of family forest inventories may be ultimately available for harvest and all the family forest land > 10 acres in size was left in the socially available inventory, even though a significant portion of the inventory may not be accessible at any point in time. Using the assumption that acreage percentage can be applied to volume, forests under public ownership were removed from the available inventory, which equates to approximately 12% reduction (Butler and Butler, 2016). Private ownership in Kentucky (88% of the total forestland) is

comprised of both private industrial ownership (15% of total forestland) and the remainder (73% to total forestland) classified as family forest owned (Butler and Butler, 2016). The latter is composed of ownerships containing parcels as small as one acre in size. The National Woodland Owner Survey (NWOS) data for Kentucky was accessed to determine the inventory growing on family forest ownerships < 10 acres, an acreage threshold that significantly impacts the ability to harvest. Removing the latter acreage indicates an estimate reduction of 6% to the total inventory. In summary the reduction in total inventory through the removal of public-owned and small family forest acreage resulted in a socially available inventory 18% below total inventory volumes.

The projected baseline inventories of white oak sawlogs including based on tree grades with social availability component are illustrated through Figure 2.8 to Figure 2.12. Figures are standalone and are essentially described earlier: Figure 2.8 is an extension of Figure 2.3 with social availability component on growth and inventory; Figures 2.9 to 2.12 are behind the scenes of Figure 2.5 with social availability component on growth and inventory and three harvest levels i.e., historic high, historic low, and 10-year average annual harvest.

Figure 2.8 Projected inventory levels of sawlog volume of white oak in Kentucky.



Note: Dashed line represents social availability.

Figure 2.9 Projected inventory levels of grade 1 white oak trees in Kentucky.

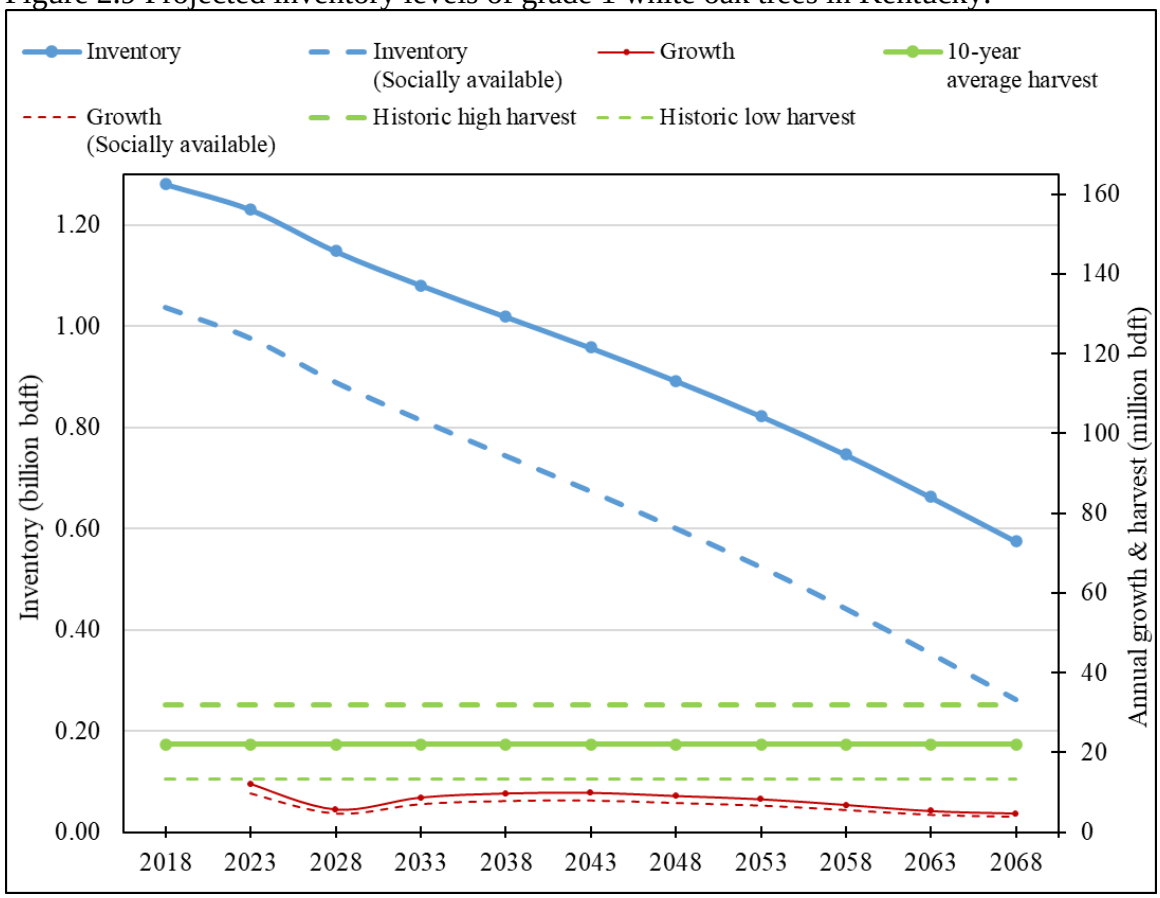


Figure 2.10 Projected inventory levels of grade 2 white oak trees in Kentucky.

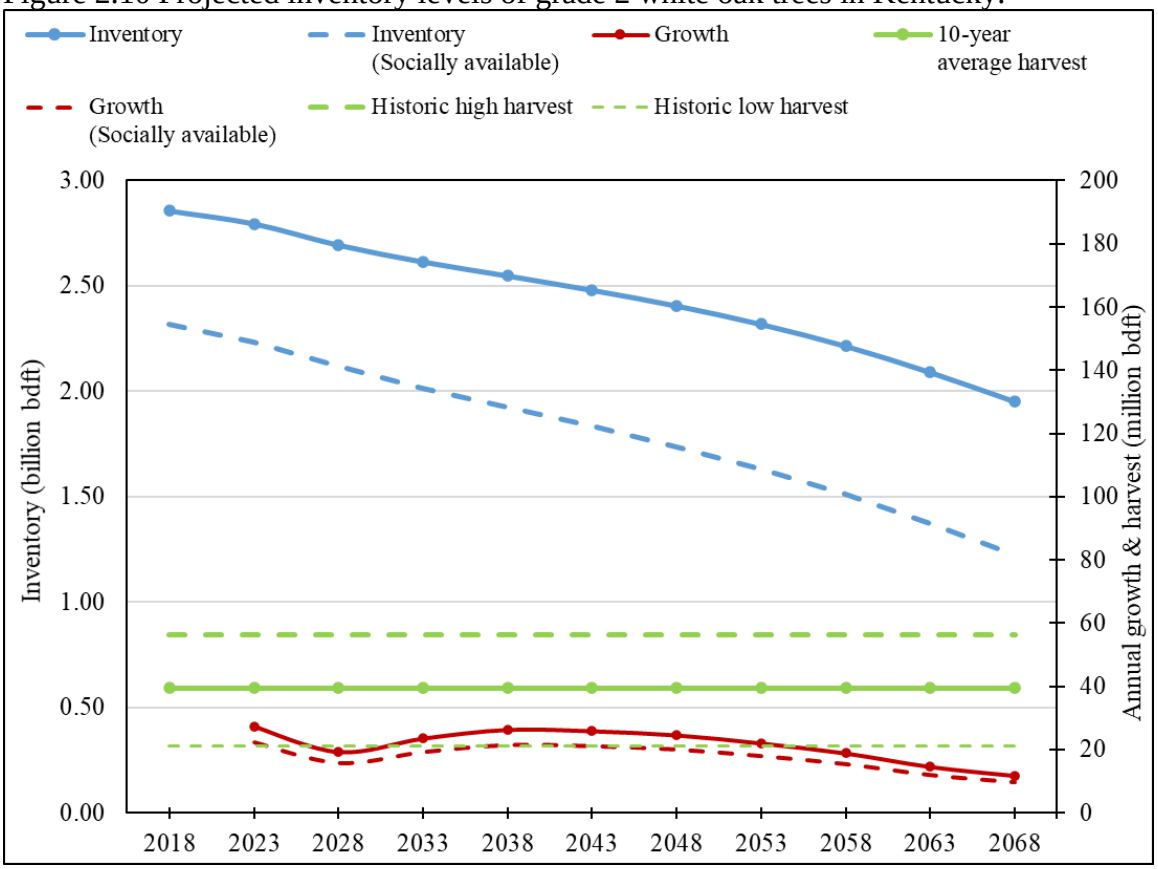
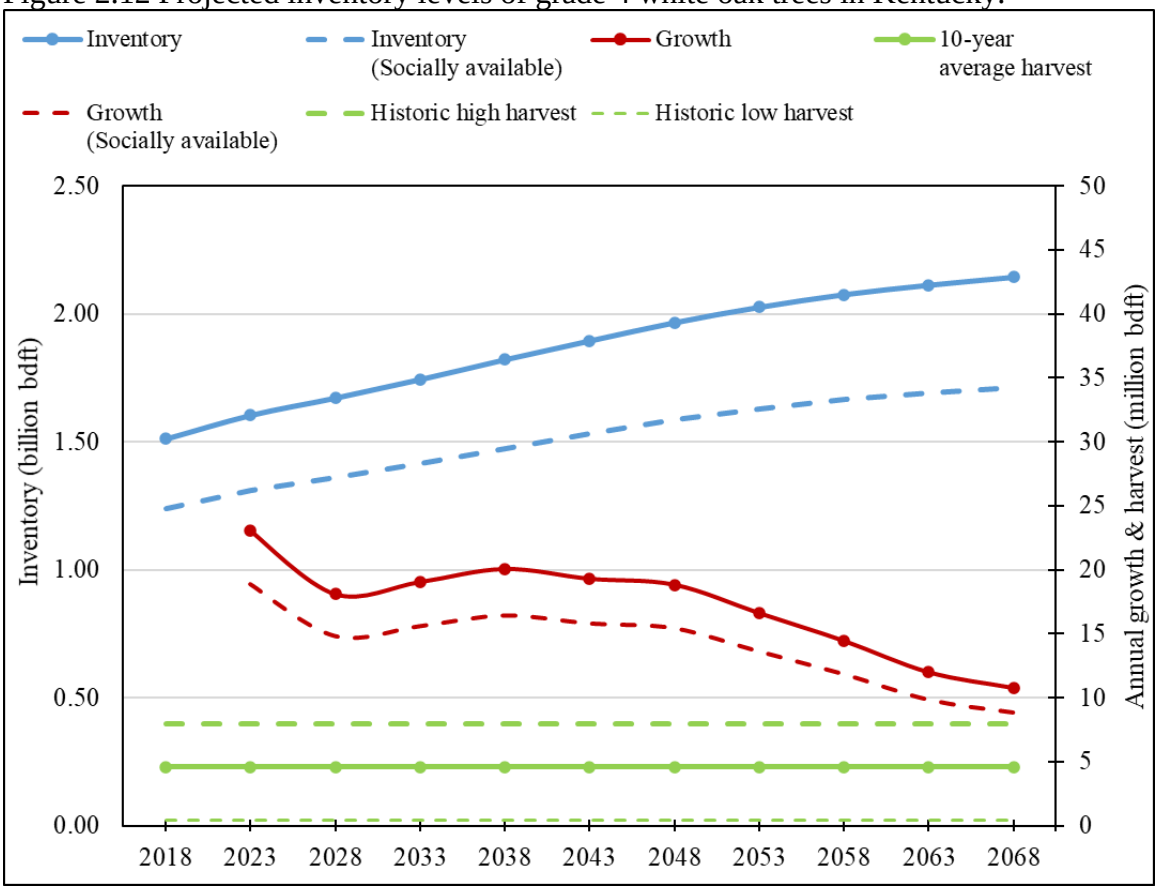


Figure 2.11 Projected inventory levels of grade 3 white oak trees in Kentucky.

Figure 2.12 Projected inventory levels of grade 4 white oak trees in Kentucky.



2.5 SUMMARY AND CONCLUSION

In summary, this study examined past and current inventory levels of white oak in Kentucky in terms of volumetric change across diameter-size class and change in timberland area by stand-size class. Second, the study projected growth and yield of white oak growing stock in white oak dominated stands for the next 50 years (2018-2068) at state level. Third, base run analysis of projected inventory levels of white oak sawlogs (a function of past inventory, projected growth, and current harvest level) was performed to better understand whether inventory levels can be considered sustainable to support current harvest levels of white oak in the future. The projections were further analyzed by tree grade to have a general understanding on quality of white oak timber growing in Kentucky's forests in posterity. Using Forest Inventory and Analysis (FIA) data, we found that white oak dominated forest structure is rapidly transforming to forest dominated by large-diameter trees with remarkable decline in small-diameter trees, and this trend would continue for the next 50 years based on growth and mortality submodels of Forest Vegetation Simulator (FVS) model. The base run analysis indicated that projected inventory levels of white oak sawlogs cannot be considered sustainable to support current harvest levels from 2058 onwards. In addition, the long-term trends in inventory levels of high-quality white oak sawlogs would be continuously declining while that of low-quality sawlogs would be steadily increasing. The current rate of white oak growth in Kentucky's forests cannot sustain indefinitely the current level of white oak timber harvest. Since it takes 70-100 years for a white oak tree to reach harvestable size preemptive actions such as investments in intensive silviculture and improved management of state's white oak stands should be immediately considered to stymie imminent white oak crisis. Although

the study used the best available inventory database and an advanced individual tree growth model capable for analysis at state and regional level, the FIA data and the FVS model each have an element of error and uncertainty as the precision of the projection attenuate over time. Besides, the validity and applicability of the discussed results should be interpreted with caution, considering caveats and underlying assumptions of the analyses they entail. Modeling natural systems is inherently fraught with uncertainties and sometimes speculative, and simulation results also become less precise over longer projection periods (Gadzik et al., 1998). These data and analytical tools are employed to make the best assessment possible; however, it must be regarded as a first step that incrementally improves through collection of new data, model validation. and refined analyses.

CHAPTER 3. ECONOMY-WIDE IMPACTS OF PROJECTED WHITE OAK TIMBER SUPPLY IN KENTUCKY

ABSTRACT

Demand for high-quality white oak sawlogs in Kentucky has been increasing for decades, which implies that sustainable forest management is a desirable goal. Kentucky is also witnessing ecological shifts in the historically white oak dominated forests mirroring the structural changes in oak forests in the rest of eastern US. These scenarios present growing concern among stakeholders on long-term sustainability of white oak timber supply and its economic implications. Thus, novel studies capturing the economy-wide impacts of potential white oak timber supply in the state, where sustained supply of high-quality white oak sawlogs is critical to dependent industries, are critical. The objective of this study was to assess potential economic impacts of projected white oak timber supply following increased supply of white oak sawlogs for wood product manufacturing and reduced supply of high-quality white oak sawlogs for distilleries. A dynamic Computable General Equilibrium (CGE) modelling framework was applied to assess economy-wide impacts of simulated projected levels of white oak sawlogs supply in Kentucky. Results indicate a cumulative present value GDP reduction of $3.66 billion (-0.085%), $0.71 billion (-0.47%) decline in consumer welfare, and other sectoral contractions over the 40-year horizon (2018-2058). These results can be used to advocate for more proactive and targeted forest management practices to stabilize and streamline a sustainable long-term supply of high-quality white oak timber.

3.1 INTRODUCTION

White oak is a prominent timber resource in Kentucky's forests, which plays critical economic role in the state's economy. Nearly 11% of growing stock volume in the Commonwealth comprises of white oak, and about 42% of Kentucky's timberland area is under white oak dominated forests (USDA Forest Service, 2020a). In 2018, about 13% of all round woods harvested in the state was select white oak (USDA Forest Service, 2020c). Bourbon barrels made from white oak ($112 MM) and oak lumber ($53 MM) were two of the state's top wood-related exports in 2020 (Stringer et al., 2020). Therefore, sustainable management of highly valued white oak forests is a desirable goal in Kentucky.

Sustainable supply of white oak timber is critical to white oak dependent industries, especially wood products manufacturing and distilleries sectors - two of the largest sectors that use white oak logs in their production process. The primary and secondary wood manufacturing industries that constitute wood manufacturing sectors use white oak logs for lumber, railway ties, pallets, wood containers, and other wood products, whereas the distilling industries use barrels exclusively made from high-quality white oak stave logs for aging the bourbons. While the federal law mandates American bourbon be made in charred new oak containers (Office of the Federal Register, 2018), it is the peculiar structural features of white oak i.e., the presence of medullary rays and tyloses, that renders its woods impervious, thus making them ideal for tight cooperage (Conner et al., 2003). In 2019, wood manufacturing sectors contributed around $3.24 billion directly to the state's economy, directly generating more than 16,000 employments (Stringer et al., 2019). Likewise, Kornstein and Coomes (2019) estimated the total annual economic contribution

of the distilling industry in 2018 to be 20,100 jobs, with annual payroll of $1 billion, producing $8.6 billion of economic output.

Economic value of forests is vulnerable to disturbances, both natural and social, that reduce timber supply and may cause significant economic losses. The ongoing ecological shift in the eastern US forests, where non-oak species like red maple and American beech are replacing the historically oak dominated forest structure (Nowacki and Abrams, 2008), is thwarting the process of oak regeneration and recruitment critical to sustainable oak management, and this has had the greatest negative impact on highly valued white oak (Abrams, 2003). Our own analysis of historical inventory levels of white oaks in Kentucky from the previous chapter of this thesis indicates a declining volume of small-sized white oak trees as well as declining timberland area of small-sized white oak stands from 1988 to 2016. On the other hand, the establishment of new log yards to receive stave logs (Stringer et al., 2019) and a nearly 7.5 million bourbon barrels in Kentucky's warehouses as of 2018 (Kornstein and Coomes, 2019) are signaling a strong market for white oak logs. As the prevalent ecological and economic forces are casting shadow on the long-term availability of white oak timber supply, stakeholders seem to support forest policy and management decisions that encourage sustainable forests management, and address poor harvesting practices (Thomas et al., 2021).

Our study on projected white oak timber outlook in Kentucky (Chapter 2) showed an uplift in inventory levels of white oak sawlogs from 2018 to 2058 followed by reduction from 2058 to 2068 and decline in inventory levels of high-quality white oak sawlogs (grade 1 and grade 2) from 2018 to 2068. The sawlog inventory level represents the potential supply available for harvest and utilization. While economic and biological constraints may

preclude portions of the inventory from being available as supply, supply and inventory are treated as equal in this study similar to a statewide analysis of timber supply in Maine (Gadzik et al., 1998).

The objective of this study is to estimate the economy-wide impacts of projected white oak timber supply in Kentucky using a dynamic, state-level Computable General Equilibrium (CGE) model over the 2018-2058 period. This timeframe simultaneously captures the increasing inventory levels of white oak sawlogs and the decreasing inventory levels of high-quality white oak sawlogs. We modelled timber supply as implied from stumpage payments and barrel expenditures assuming that a rise in inventory levels of white oak sawlogs is consistent with a rise in stumpage in the wood products sector and a drop in inventory levels of high-quality white oak sawlogs is consistent with a drop in barrel expenditures in the distilleries sector. We then captured the impact of increasing supply of white oak sawlogs and decreasing supply of high-quality white oak sawlogs simultaneously. We then assessed economy-wide impacts on various economic variables, including, household welfare and macroeconomic variables such as consumption, income, domestic production, and GDP, among others.

Figure 1 illustrates an overview of the CGE modeling process (Shoven and Whalley, 1984). First, input-output (IO) dataset for the study region is collected and then adjusted so that total receipts equal total outlays for each account. The IO data represents the so-called benchmark general equilibrium. This data, along with specific assumptions regarding producer and consumer behavior, represents one equilibrium solution of the economic model. Since the benchmark is considered to represent a unique equilibrium solution, the benchmark data is used to calibrate the parameter values for the functional

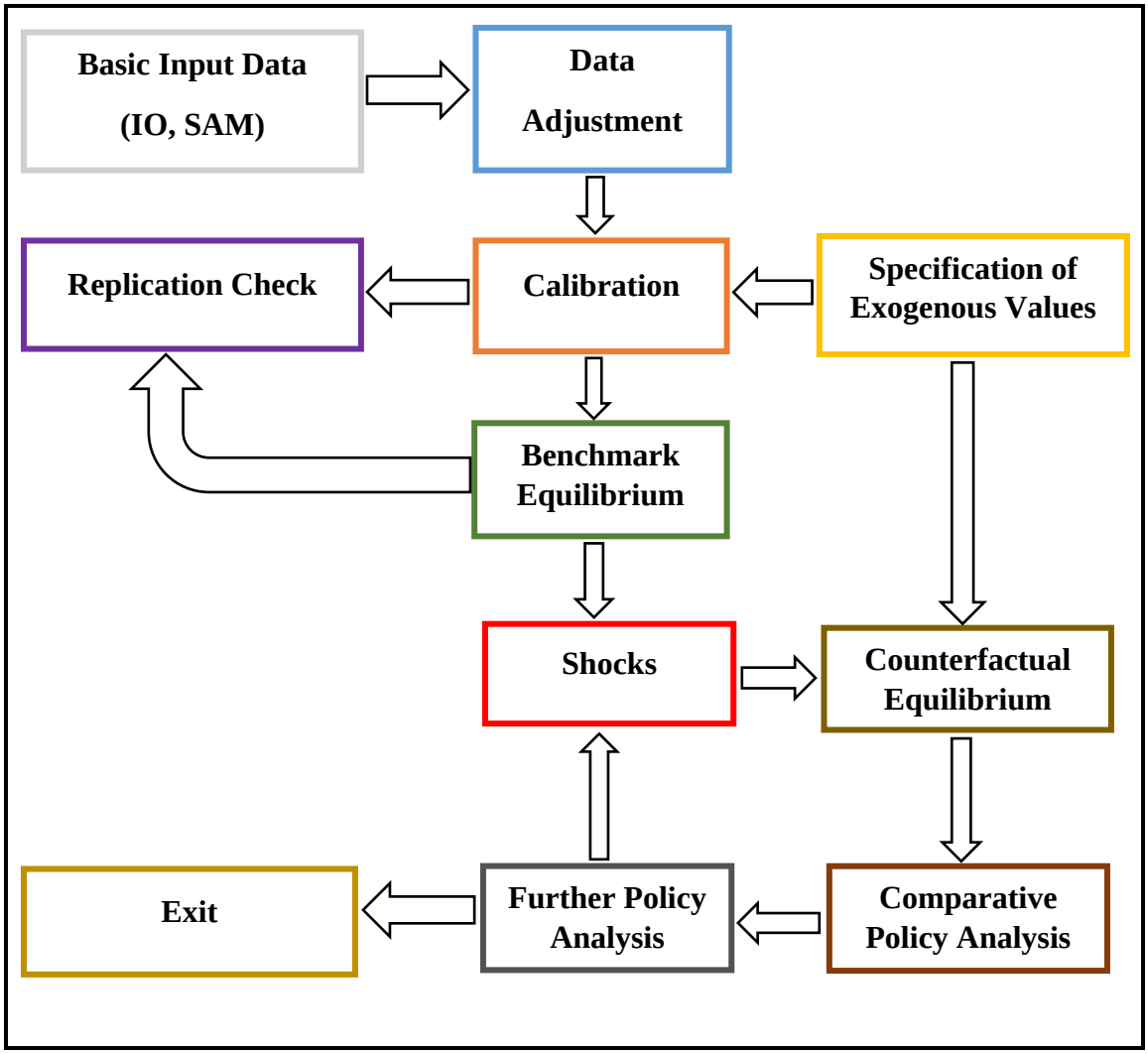
forms. While some parameters are calibrated endogenously, some parameter values such as elasticities are not be determined by the calibration process and are supplied exogenously. After calibration, the model undergoes standard technical tests[6] for well-specified CGE model. Once it is confirmed that the model passes all the five standard technical tests, it can then be used in simulating desired shocks experiments. After imposing experimental shocks, the model solves once again to find the "counterfactual" equilibrium set of prices and quantities for all sectors. These variable levels in the counterfactual equilibrium are then compared to the baseline solution levels. The difference between the two levels are the impacts of the shocks imposed.

The economy-wide impact of timber supply has been modelled using CGE framework in a number of studies (Das et al., 2005; Zhang et al., 2005; Chang et al., 2012; Ochuodho et al., 2012; Corbett et al., 2016; Ochuodho et al., 2017; Karttunen et al., 2018; Withey et al., 2018) some of which have been discussed in literature review section below. This study supplements and extends the CGE literature on timber supply impacts analysis in a number of ways. First, this would be the first study to model economy-wide impacts of white oak timber supply using a CGE model in Kentucky, one of the world's leading producer of this important species with trending high demand. Second, this would be the first study to incorporate timber quality aspect in economic impact assessment using CGE modeling framework. Results from this study will help stakeholders, especially woodland owners, forest industry, and distillery industry, understand the potential impacts of white oak timber supply on the state's economy and provide guidance for future forest

[6] 1) Is the model square; 2) Are all the equations satisfied with ITERLIM=0 (LHS=RHS); 3) Does it replicate the database; 4) Is the model homogenous of degree zero; and 5) Is the Walras law satisfied i.e., when there are n markets, of which (n-1) are cleared, then the nth market is automatically cleared.

management policies aimed at addressing sustainable white oak management practices in Kentucky and beyond.

Figure 3.1 Diagram of CGE Modeling Process (Adapted from (Shoven and Whalley, 1984)).



3.2 LITERATURE REVIEW

3.2.1 CGE model

Computable General Equilibrium (CGE) model is a system of equations that describes an economy *en masse* as well as the interactions among its parts (Burfisher, 2016). The meaning of each component of CGE sheds light on the basic features of a CGE model: *Computable* implying the capability of the model to quantify the impact of a shock or experiment on an economy, *General* meaning the model engulfs all the economic activity (production, consumption, investment/savings, taxes, and trade) and their linkages in an economy simultaneously, and *Equilibrium* meaning aggregate supply equals aggregate demand at some set of prices (Burfisher, 2016). Strictly, a CGE model is a system of linear and non-linear equations describing the efficiency-maximizing behavior of firms, the utility-maximizing behavior of consumers, influences of these microeconomic aspects to the macroeconomic behavior of an economy, and equilibrium conditions and constraints imposed by the economic environment (Karttunen et al., 2018). Thus, the basic framework of a CGE model underpins set of equations that aims to capture the structure of the economy and behavioral response of agents (households, firms, and governments), allowing simulation of policy changes and trace the impact on key economic variables.

While input-output (IO) analysis is an extensively used approach for assessing economic impact of a project or policy (Banerjee and Alavalapati, 2014), the underlying assumptions of IO model arrest its broader applicability. The assumption of fixed prices implies that the supply of inputs or outputs has no influence on factor or product prices; hence IO model fails to adequately capture the behavior of producers and consumers since the level of production and consumption largely depends on factor costs and commodity

prices, respectively. Similarly, IO models preclude the possibility of substitution between factors of production i.e., there is no trade-off between labor and capital (Alavalapati et al., 1998). Because there is no constraint on supply, IO models rule out the premise of economics i.e., allocation of scarce resources among competing ends, rendering their application to only those industries with excess capacities. Moreover, the treatment of final demand as exogenous limits the use of IO models for international trade analysis. In a nutshell, IO models are demand-driven, the usefulness of which is frustrated by supply and substitution constraints (Robinson and Roland-Holst, 1988).

Like an IO model, a CGE model assumes the interdependence of sectors/industries in the production process resulting in intermediate outputs. However, CGE models allow flexibility in input prices with respect to changes in output prices, relaxes substitution possibilities by incorporating the substitution of cheaper products for relatively expensive one, accommodates supply constraints, and also explains final demand as endogenous variables (Alavalapati et al., 1998). Moreover, factor constraints are appropriately accounted for: capital is assumed to take some time to build with investment responding to changes in rates of return on existing capital, labor markets are typically assumed to respond slowly to changes in demand with lags between impacts and wage responses (Clark, 2018). Consequently, the less restrictive (more flexible) nature of CGE models renders results from its application more realistic compared to those from IO models. Further, assumptions in CGE modeling framework can be modified in compliance with the nature of the economy in question. For instance, inputs can vary on substitution spectrum from no substitution to perfect substitution, where the former implies fixed proportion of inputs are employed in the production process (no effect of relative prices) while the latter

suggests producers will replace relatively more expensive input with relatively cheaper input, for any change in relative prices of inputs. Likewise, elasticity of supply can also vary from low to high. All in all, CGE models incorporate relative prices that better reflect the economic scarcity of outputs and inputs together with greater flexibility in the specification of economic behavior of agents.

CGE models can be static or dynamic; what differentiates a static CGE model from a dynamic one is a treatment of time (Clark, 2018). In a static model, time is not explicitly treated to reflect the economic changes through a sequence of points in time. Rather, they model the response of the economy at single point in time, usually one year. Once the model is shocked with the desired experiment, the results (variable levels) of this "counterfactual equilibrium" is compared against the initial equilibrium of "business-as-usual scenario", not representing the process of adjustment to the new equilibrium, especially the reallocation of labor and capital across sectors. To put it differently, in static model specific variables that reflect the manner the economy adjusts over a period of time are held fixed or the adjustment paths are not described. The time period over which the impacts are estimated is typically one year, and it is thus, assumed that input factors i.e., labor supply and capital stocks are fixed. On the other hand, the dynamic models are long-run models that allow for explicit treatment of time. Typically, a base case with business-as-usual growth path is developed, then an alternative case with policy in question is run, and the impacts are then estimated by the comparison of new policy-induced growth path with that of base case. The dynamic CGE models allow for more realistic market structure such as adjustment of capital stocks accumulated over time at certain rate of return, and gradual adjustment of labor supply by providing a logistic growth path for labor. Thus, the

dynamic model considers the adjustment of economic shocks over time with results provided for each year of the simulation.

Depending on the region(s) being considered, CGE models can be single-region or multi-region. Generally, a regional or single-region model describes one region in detail, with a simple treatment of its export and import markets, whereas a multi-region model involves two or more regions and describe their economies elaborately along with each country's production, consumption, trade, taxes, tariffs, and others. Trade and sometimes capital or labor flows form the nexus among the regions in a multi-regional model (Burfisher, 2016). Regional models are confined to the economy of a particular region, and imports and exports are specified at aggregate level only (Ochuodho and Lantz, 2014). It suggests that in a single region model the behaviors of economic agents beyond the region are not captured, thus assuming an "enclave economy". On the contrary, multi-regional models take into account the interactive nature of inter-regional or global economy, thus capturing the behavior of economic agents in a region and beyond as well as market activities to and from several regions. Any shocks or model experiments in one region will have a spillover effect in other regions, as captured through trade flows. While a single-region model generates intra-regional effects, a multi-regional model results in inter-regional effects.

3.2.2 Application of CGE model in timber supply analysis

Das et al. (2005) used a static, multi-regional CGE model to analyze economic impacts of a 20% reduction in the harvest of timber (reduction in logging output in the forest sector) in the Pacific Northwest (PNW) compared to other regions. They found that log production in other regions would increase whereas market price of logging output in

the PNW would increase owing to the decline of log output in the region. Moreover, the study also demonstrated that export sales from other regions to PNW would rise, exports in forest products from the PNW to other US regions and rest of the world would decline, and the welfare of PNW region would decrease by approximately $204 million.

Ochuodho et al. (2012) performed a multi-regional CGE modeling analysis to assess the potential economic impacts of climate change and adaptation in forests of six Canadian regions from 2010 to 2080. The study assessed economic impacts under difference scenarios of climate change and timber supply across the regions. Specifically, the study developed *ad hoc* methods in establishing likely quantitative impacts of climate-induced changes in forest fires, forest productivity, and pest attacks on timber supplies with and without adaptation. The timber supply changes were converted into forestry and logging sector output and were used as inputs in CGE model to assess economic impact estimates. The study found that without adaptation, Manitoba, Saskatchewan and the Territories' forestry and logging sector could lose over 30% of their output value whereas other provinces such as Quebec could gain up to 2% in the forestry and logging sector output; however, with adaptations positive impacts were increased in all regions.

Corbett et al. (2016) used a dynamic, provincial computable general equilibrium (CGE) model to estimate the economic impacts of the effects of reduction in timber supply (annual allowable cut/harvest levels) in British Columbia (BC) forests over the 2009-2054 period resulting from mountain pine beetle (MPB) infestation. Reduction of timber supply in economic terms was implied from drop in stumpage payments in the forestry sector and subsequently, the model captured the resulting impact on welfare and other economic variables such as consumption, income, and GDP. By comparing baseline scenario

(absence of infestation) with MPB infestation scenario, the study found that there would be negative economic impacts of 1.34% loss in GDP and a $90 billion decline in household welfare.

Ochuodho et al. (2017) used dynamic, global multi-regional CGE model to estimate the economic-wide impacts of internet adoption in Canadian provinces, the US, and rest of the world modeled through the reduced demand in the pulp and paper industries as implied by reduced stumpage in pulp and paper sector. The study found that the more rapid full internet adoption by 2050 scenario would have cumulative GDP reduction of 17% in Canada and 5.8% in the US and increase GDP by 3.3% in the rest of the world from 2006 to 2030.

Karttunen et al. (2018) used CGE approach to investigate impacts of intensive forest management due to increased demand for wood biomass in Finland between 2014 and 2030. In the business-as-usual scenario (BAU), there were no new regional wood-based investments assuming that prevailing silvicultural activities as well as current demand for round wood would remain the same. However, in the intensive forest management scenario, the study employed "what if" situation i.e., increased the demand of forest biomass by the establishment of hypothetical sawmill and bio refinery, and thus, adjusted the forest management (increased commercial cuttings in the growth and yield model) to meet the demand. The increased supply of forest biomass was incorporated in the CGE model by disaggregating stumpage from the capital stock for the forest sector and it was assumed that stumpage would increase at a certain annual value. Hence, the study demonstrated that, under intensive forest management scenario, GDP would increase by

2.8%, private consumption by 1.5%, and employment by 1.6%, by 2030 relative to the business-as-usual scenario.

Withey et al. (2018) employed a dynamic CGE model analysis to quantify economic impacts of proposed conservation area in Alberta resulting from a reduction in land used for logging and oil and gas extraction. Stumpage in forest sector and royalties in the oil and gas sector were isolated from capital to model the economic impacts. Results showed that the conservation scenarios could reduce the GDP of Alberta by about $4.44 billion from 2011 to 2056.

3.3 METHODS

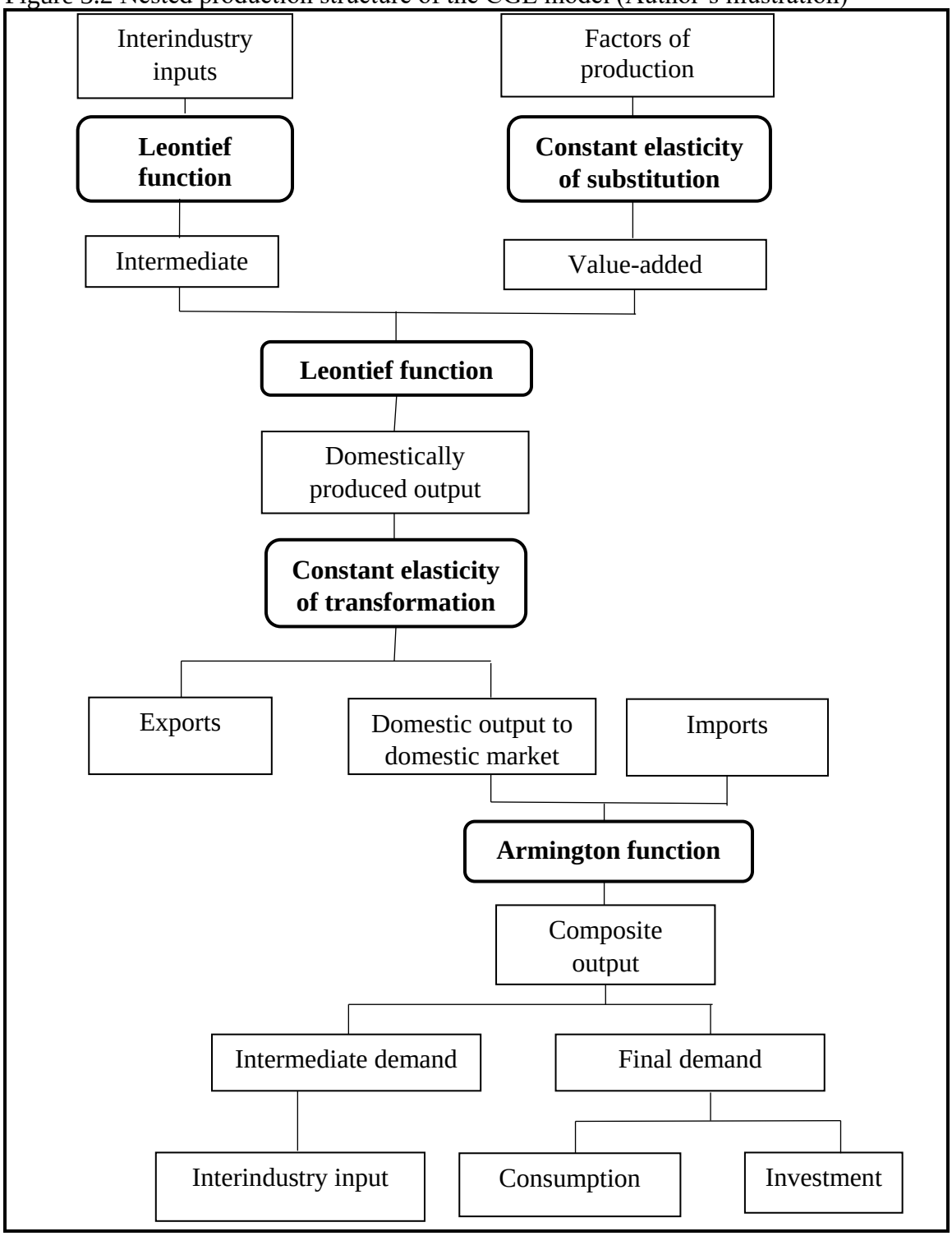
3.3.1 CGE model specification

We developed a single regional, recursive dynamic CGE model for the economy of Kentucky to examine economy-wide impacts of increased stumpage payments in wood products sector and decreased barrel expenditures in distilleries sector due to the increasing timber supply of white oak sawlogs and decreasing timber supply of high-quality white oak sawlogs (suitable for barrels production) in the Commonwealth, respectively.

We specify a CGE model (Figure 3.2) based on neoclassical economic theory similar to that of Ochuodho and Lantz (2014) in structure for single region. We calibrate the model using 2018 input-output (IO) database for Kentucky (Appendix 9). The model was formulated as a set of simultaneous linear and nonlinear equations defining: the behavior of economic agents (households, firms, banks, and rest of the world), market clearance, macroeconomic closures, intertemporal components, and steady-state economic growth path. Detailed description of model variables, parameters, and equations are

provided in Appendices 10, 11, and 12, and equation numbers from Appendix 12 are in parentheses in the ensuing paragraphs where appropriate.

Figure 3.2 Nested production structure of the CGE model (Author's illustration)



In line with a neoclassical model, our model assumes that the economy of Kentucky is so small such that it does not exert any influence on the world price of exports and imports. On the import (demand side), the domestic consumers discriminate between the domestically produced and imported goods through the constant elasticity of substitution (CES) Armington specification (eq. A18 and A19). The final ratio of imports to domestic goods is determined by the relative prices of each type of good as domestic demanders choose between domestic (within state) and imported (from other states and outside US) commodities based on their cost-minimizing decisions. Thus, an increase in the domestic-import price ratio causes an increase in the import-domestic demand ratio. The zero-profit condition of the domestic firm (eq. A20) suggests that total value of composite goods (domestic plus foreign) sold in the domestic market must be equal to the sum of total value of domestic goods sold in domestic markets and total value of aggregated imports factored by world import price and exchange rate and adjusted for tariffs (where applicable) (eq. A21).

On the export (supply side), the domestic firm or producer has the choice between selling its commodity in the domestic market or export to foreign market. Profit maximization drives producers to sell their output in markets where they can maximize profit. The decision of domestic firms is governed by a constant elasticity of transformation (CET) function, which differentiates between exported and domestic goods (eq. A22 and A23). As producers seek higher returns source, an increase in the export-domestic price ratio causes an increase in the export-domestic demand ratio. The zero-profit condition of the domestic firm (eq. A24) suggests that total value of domestically produced goods must be equal to the sum of total value of domestic goods sold in domestic markets and total

value of aggregated exports factored by world export price and exchange rate and adjusted for export tax (where applicable) (eq. A25). Balance of payments is established by equating aggregate imports to aggregate exports plus foreign savings at world prices (Zhang et al., 2005). Zero global trade balance ensures that the values of bilateral trade flows are cleared (eq. A26).

On the input side, our model assumes producers as profit maximizers combining four factors of production (labor, capital, stumpage, and barrel expenditures) with constant returns to scale technology. While most CGE models typically specify only labor and capital as input factors, including stumpage as input factor follows that of Ochuodho and Lantz (2014). Typically, stumpage payments are recorded in input-output tables and social accounting matrix as part of capital expenditures (Ochuodho and Lantz, 2014). While distillery industries purchase barrels on annual basis, these purchases are not recorded as intermediate inputs but as "capital" expenditures since it takes a number of years to mature bourbon in these barrels (Pers. Comm. with IMPLAN personnel). It therefore makes sense to specify barrel purchase expenditures as additional input factor. We disaggregated both stumpage and barrels expenditures from capital using external data, which is explained in model calibration section below. Producers face a nested production function specified through two levels: at the first level, there is a Leontief technology comprising a composite of value added and a composite of intermediate inputs; at the second level, factor of production is a constant return to scale CES technology (eq. A1). The zero-profit condition of the domestic firm (eq. A2) suggests that total value of domestic production must be equal to the sum of total value of factors of productions and total value of intermediate productions, which is obtained with factoring total value of domestic productions by

technical coefficients. While labor and capital are mobile among sectors, stumpage are specific to the wood products sector and barrel expenditures to distilleries sector. The supplies of factor inputs are exogenously determined in the model based on existing data (see model calibration section for details).

On the income side, households receive income (eq. A3) from supplying factors of production and from import tariff revenues from domestic government (eq. A10). Household savings (eq. A4) are a fixed proportion of their total income as determined by marginal propensity to save. Thus, it is the disposable income (eq. A5) that is spent on the consumption of a basket of commodities. The optimal allocation between consumption of commodities by household, after attaining minimum subsistence level, is achieved through maximization of a Stone-Geary utility function through a linear expenditure system (LES) subject to disposable income constraint (eq. A7). Under this system, the supernumerary income (eq. A6) – the income remaining after the consumer has purchased the minimum required quantities of commodities, is allocated over commodities based on fixed proportions (marginal budget shares). Total savings in the economy is the sum of household savings and foreign savings factored by exchange rate (eq. A8).

In the final demand, investment demand is determined by total savings factored by the Cobb-Douglas investment preference for each commodity (eq. A9). A Phillips curve is specified in the model to introduce involuntary unemployment (eq. A11). This explains the wage-unemployment relationship in the model using factor prices and supplies and the Laspeyres consumer price index (CPI) (eq. A12).

Equilibrium in the factor market requires that the demand for factors equal the supply. To achieve equilibrium, factor prices in the market must adjust to ensure that

demand equals supply. However, due to imperfect labor market, there is involuntary unemployment; therefore, market clearing in the labor market is relaxed to allow for unemployment in labor supply (eqs. A13 – A16). Equilibrium in the commodities market requires that demand for commodities equals supply. Aggregate demand for each commodity comprises household consumption spending (consumption, investment, and intermediate) on domestic and imported goods. Aggregate supply includes both domestic production and imported goods (eq. A17). All prices of commodities (except import price when there is tariff) and primary factors are normalized to unity in the initial equilibrium. Given prices are normalized to one, the "values" in the IO accounts can be interpreted as physical quantity indices per unit of currency in the commodity and factor markets. This practice of normalizing data considerably reduces the information required to build a CGE model database without compromising the capability of the model to generate results for prices, quantities, and values (Burfisher, 2016).

The CGE model is solved under the "square matrix condition" i.e., the number of single endogenous variables must equal the number of single equations. To achieve this condition, the model closure has to be specified in a way to ensure mathematical solvability while reflecting reality reasonably and meeting the modeler's needs depending on the context of the analysis (Lofgren et al., 2002). To achieve this, we exogenously fixed factor supplies and foreign savings while rendering the exchange rate adjustable. Foreign savings is set as the difference between the value of exports and the value of imports. The wage rate is exogenously fixed as the numeraire price (Zhang et al., 2005). An artificial objective function is included to help the model solve.

3.3.2 Model calibration

The model was calibrated using 2018 baseline symmetric input-output (IO) table database for Kentucky (Appendix 9) that was obtained from Input-Output - State and National Analysis Program (IO-SNAP), Regional Research Institute at West Virginia University. The original 70 industries in the IO table were aggregated into 11 sectors (Appendix 7). Because some industries/sectors of interest (forestry and logging, and distilleries) in our study were not stand-alone in the original database, we disaggregated these from their 'parent' sectors using total output data for these sectors using IMPLAN[7] 2018 database for Kentucky. Four primary factors of production were specified: labor, capital, stumpage (specific to wood products manufacturing), and barrel expenditures (specific to distilleries sector). Labor was measured employee's compensation in the IO table. Capital was aggregated as the sum of taxes of production and imports, other subsidies, and gross operating surplus in the value-added account of IO table. Stumpage in the wood products sector and barrel expenditures in the distilleries sector were not identified as input factors in the original IO table. Instead, these payments are embedded in each sector's 'other operating surplus' as a component of capital (Ochuodho and Lantz, 2014; Pers. Comm. with IMPLAN personnel, 2020). Since these payments were not readily available for Kentucky, we devised approaches to isolate them from the capital in the wood products and the distilleries sectors, respectively.

To isolate stumpage payments for wood products manufacturing sector, we relied on information from other sources. According to Kentucky Forest Sector Economic

[7] IMPLAN is a modelling system that uses input-output framework to estimate the economic impacts within a defined region with respect to dollar accrued to the economy and employment (IMPLAN Group LLC, 2004).

Contribution Report 2018 (Stringer et al., 2018), 731 million board feet of hardwood logs were harvested in Kentucky in 2018, with the woodland owners receiving, on the statewide average, $0.29 per board feet. This would give a statewide average stumpage payment of $211.99 million in 2018. Since Kentucky produces predominantly hardwoods – more than 80% of timber harvested in 2018 were hardwoods (USDA Forest Service, 2020c), we assumed that the estimated average stumpage payment was representative of the total statewide stumpage payments in 2018. As our species of interest was white oak only, we used the 2018 timber product output (TPO) data for Kentucky to tease out stumpage payment for white oak species assuming that stumpage payments are equal to the proportion of timber harvested by product type and species group. According to the TPO data (USDA Forest Service, 2020c), about 91% of hardwood logs harvested in 2018 were sawlogs, of which about 16% belongs to the select white oak species group. In this way, we estimated the statewide average stumpage payments of about $31 MM for white oak sawlogs in Kentucky and subtracted the stumpage value from capital in wood products sector.

Barrel expenditures by distilleries were also isolated using information from external sources. According to a report by Kornstein and Coomes (2019), about 1.7 million barrels of new bourbon were produced and added to warehouse inventory in Kentucky in 2018. Since a 53-gallon American white oak barrel is a standard size mostly used in all local Kentucky's distilleries with distillers paying, on average, $190[8] for a high-quality white oak barrel, we estimated the barrel expenditures for distilleries to be about $323

[8] Personal communication of proprietary information from cooperage and distilling industries.

million in 2018. This barrel expenditure was disaggregated from capital expenditures in the distilleries sector.

A suite of parameters was required to calibrate the model using IO data (Appendix 4). Endogenous parameters such as share, and shift parameters were calibrated using input data. Income elasticities of demand for commodities were obtained from Dimaranan (2006). Armington, CET, and CES elasticities were obtained from earlier CGE models (Corbett et al., 2016; Withey et al., 2018), which had been derived from Global Trade analysis Project (GTAP) database following sectoral aggregations. In addition, elasticities for some commodities were borrowed from Thurlow and van Seventer (2002). Annual state unemployment rate was obtained from Kentucky's labor force estimates (Kentucky Center for Statistics, 2019).

The model is first formulated as static model that meets five standard technical tests for a well-specified CGE model. With a well-specified static model, a recursive dynamic path was specified for 40-year (2018-2058). For every period, capital stock is updated via a capital accumulation equation based on an endogenous growth rate determined by return on capital rate and endogenous total savings (eqs. A31 and A32) (Alfsen et al., 1996; Chang et al., 2012). Labor is assumed to grow exogenously in the model. Assuming that labor supply growth projections are consistent with projected population trends (Ochuodho and Lantz, 2014), we estimated annual labor supply growth rates from Kentucky population projections between 2015 and 2040 for both sexes and all ages category (Kentucky State Data Center, 2016). Stumpage payment and barrel expenditures were exogenously fixed at 2018 levels over time under baseline conditions. Holding these variables constant is

consistent with other related studies that specified stumpage as input factor (Ochuodho and Lantz, 2014). The discount factor used for all present value calculations is 4%[9].

3.3.3 Model solution and simulations

The model equations were solved using the General Algebraic Modeling System (GAMS) software with a nonlinear programming (NLP) algorithm along with CONOPT3 solver (GAMS, 2012). After solving the model for the initial period equilibrium to replicate the 2018 benchmark IO data, a dynamic baseline growth path of the economy was simulated in the model following growth path described above. This baseline scenario is otherwise known as "business-as-usual" (BAU) path.

In the simulation scenario run, we considered economic impacts of projected white oak timber supply. Specifically, we targeted how the projected white oak timber supply would affect wood products manufacturing and distilleries sectors. The wood products sectors rely on white oak sawlogs for manufacturing myriad primary and secondary wood products while distilleries sector relies on high-quality white oak sawlogs for barrel manufacturing, a prerequisite for bourbon production. The supply (demand) of white oak sawlogs is captured in the model in the wood products sector by the stumpage paid by the sector, and the supply (demand) of high-quality white oak sawlogs is captured in the distilleries sector by the barrel expenses made by the sector as only high-quality white oak stave logs are used for barrel manufacturing. The 40-year trend of both variables are based on results from timber supply study (chapter 2 of this thesis). To capture these trends in the model, we assumed that stumpage will be increasing by the same average annual percent

[9] This rate approximates the average annual discount rate for the US over the 1983-2018 period (International Monetary Fund, 2018).

rate as the inventory levels of white oak saw logs from 2018 to 2058 (Figure 2.3) while capital expenditures on barrels by the distilleries will be reducing at the same average annual percent rate as the inventory levels of high-quality white oak sawlogs (grade 1 & grade 2) from 2018 to 2058 (Figure 2.5). Other studies in literature have used similar variables to capture timber supply impacts in CGE models (Ochuodho et al., 2012; Corbett et al., 2016; Withey et al., 2018). However, it is likely that as there is more white oak sawlog available but less of high-quality, the stumpage price for white oak sawlogs may fall and the capital expenditures on barrels may rise, and revenues may not fall/rise by the same amount as the fall/rise in inventory levels. Nevertheless, understanding the exact impact on prices is beyond the scope of this study. With the current methodology, we were able to capture the overall impact of the rise in stumpage payments due to the rise in inventory levels of white oak sawlogs, and the fall in capital expenditure on white oak barrels due to the fall in inventory levels of high-quality white oak sawlogs simultaneously, which is the thesis of this study.

The average annual stumpage expenditure increments amounted to 0.22% (2018-2058) for the timber supply simulation relative to the baseline. The average annual reduction in barrel expenditures amounted to 0.82% (2018-2058) for timber supply simulation relative to the baseline. Since stumpage and capital expenditures on barrels are exogenous in the model, prices are endogenously determined by the model under general equilibrium conditions. Both stumpage supply and barrels expenditures simulations were implemented simultaneously. Differences in economic variables' levels between simulation shock and BAU give economy-wide impacts of the simulated shocks.

3.4 RESULTS AND DISCUSSION

Table 3.1 provides a summary of the economy-wide impacts of the projected supply of white oak timber as simulated through increased supply of white oak sawlogs for wood product sector and reduced supply of high-quality white oak sawlogs for distilleries for bourbon barrels manufacture. The table presents both levels (discounted cumulative dollar values) and percent change impacts of the simulated shocks of timber supply as captured by overall increase in stumpage and decline in barrels expenditures over 40-year period (2018-2058).

Table 3.1 Discounted cumulative impacts ($ billion) of timber supply simulation relative to baseline scenario (2018-2058).

Variables	**Baseline Level**	**Timber Supply Simulation**	**Impact**	
			$	**%**
GDP	4296.235	4292.577	-3.658	-0.085
Household income	4294.475	4289.333	-5.141	-0.120
Compensating Variation	150.146	149.44	-0.706	-0.47
Consumption	3193.579	3193.216	-0.363	-0.011
Investments	768.324	768.837	0.512	0.067
Labor	2420.64	2421.775	1.135	0.047
Capital	1891.719	1891.929	0.210	0.011
Stumpage	0.611	0.632	0.021	3.490
Barrels expenditures	6.393	5.65	-0.743	-11.617
Total imports	1207.223	1205.611	-1.612	-0.134
Total exports	1564.599	1562.987	-1.612	-0.103
Total domestic output	7462.521	7460.191	-2.331	-0.031
Wood product output	18.998	19.149	0.151	0.792
Distilleries output	43.418	42.851	-0.568	-1.308

Note: A 4% discount rate was applied over a 40-year planning horizon (2018-2058).

Overall and as expected, the economic impacts for most of the key macroeconomic variables were negative. This is because the magnitude of the simulated negative shock we imposed was higher than the positive shock. The overall negative economic impacts of the simulated shocks are mostly driven by the negative shock imposed on the distilleries sector, which had three times (~ $6 billion) of total output to that of the wood product sector (~ $2 billion) in 2018 (Appendix 9), where we simulated positive shock. As a result, the negative economic impacts are mostly driven by declining annual barrel expenditures in distilleries sector consistent with the declining supply of high-quality white oaks sawlogs during projected timeframe.

The negative GDP impacts were driven by the negative impacts of its component elements, including consumption, net exports, and investment. Shocks to stumpage payments in wood product sector and barrels expenditures in distilleries sector impacted consumption in each sector, as well as in all other sectors through feedback effects (direct, indirect, and induced impacts), hence the economy-wide impacts. As production in distilleries sector declined due to declining supply of high-quality white oak sawlogs (a factor of production), it had a spillover effect on domestic output/production of some other sectors that indirectly depend on distilleries for intermediate supplies. Consequently, overall decline in domestic production led to overall rise in commodities' price; hence, the reduction in consumption. The percentage change in variables such as domestic production (output), consumption, and income followed a similar pattern to that of GDP.

In response to the simultaneous stumpage and barrels expenditures shocks, Kentucky's GDP reduced by a cumulative discounted value of around $3.66 billion (-0.085%), which averages approximately $91 million annually from 2018 to 2058. The GDP

reduction is driven by reductions in final demand components, including consumption (-0.011%) and exports (-0.103%), as well as reduction in household income (-0.12%) and domestic production (-0.031%), particularly production in distilleries sector (-1.308%) on the input side, which constituted 0.8% of state's GDP in 2018 (derived from Appendix 9). For the timber supply simulation, the cumulative present value of household income, consumption, exports, total domestic production, and distilleries production were simulated to decrease by $5.14 billion (~$128 million annually), $0.36 billion (~$9 million annually), $1.61 billion (~$40 million annually), $2.33 billion (~$58 million annually), and $0.57 billion (~$14 million annually), respectively. Tracing the causal paths further, some of the estimated impacts on key macroeconomic variables can be explained in relation to price changes, which is determined endogenously in the model. The reduction in domestic production of distilleries sector because of the shock we imposed in its factor of production drove the overall reduction in domestic production (-0.031%) under the timber supply shock simulation, and eventually income (-0.12%). As overall domestic production declined due to supply constraint, the supply price of domestically produced commodities rose (0.052%). Since the supply could not keep up with the domestic demand of commodities, the demand price of commodities rose (0.146%), which eventually led to decline in household consumption of commodities. Similarly, the price of the domestically produced commodities delivered to domestic markets grew by 0.288%, while the export prices fell by 0.076%. Consequently, exports fell by 0.103% under the shock simulation as foreign markets became less profitable for the producers than the domestic market.

Consumer welfare – measured by Compensating Variation[10] (CV) - reduced due to the timber supply shock, with cumulative present value of CV approximating $149 billion over the 40-year horizon. It means that under the timber supply simulation shock, consumer would be worse off by roughly $706 million relative to the baseline scenario. The welfare losses can be explained with the change in utility following simulation shock. Utility is essentially the function of commodities' prices and consumer income levels. As overall level in factors of production declined due to the shocks imposed, consumer income fell by 0.12%. In addition, as discussed earlier, the price of commodities rose by 0.146% following timber supply simulation. Consequently, utility fell by 0.036% under timber supply scenario, which means consumer would require additional $706 million to reach the original utility level at baseline before the timber supply shock.

In terms of inputs to production, labor expenditures increased by $1.14 billion (0.047%), which is the result of factor mobility specified in our model. Inevitably, reduction in labor expenditure in distilleries sector is compensated by the increment in labor expenditures in other sectors as skilled labors laid off from distilleries sector are hired to supply labor in other closely related sectors. Besides, as demand price of commodities rose (0.146%), demand for commodities in the domestic market fell (-0.016%); as a result, imports fell by 0.134%.

The results of this study are consistent with similar studies that used dynamic, single-region CGE model. Corbett et al. (2016) imposed stumpage shock in the forest

[10] Compensating Variation (CV) is a utility-based money metric measure of welfare that compares the cost of the new versus the old utility when both are valued in post-shock prices (Burfisher, 2016). Utility, which represents a consumer's level of satisfaction, is a function of prices and disposable income levels that is spent on the consumption of goods and services. CV is often expressed using an expenditure function (eq. A37).

sector reflecting fall in annual allowable cut due to mountain pine beetle infestation in British Columbia from 2009 to 2054; the study estimated that cumulative discounted value of GDP, household income, CV, consumption, imports, exports, total domestic production, and forestry sector production would reduce by around 57.37, 44.65, 89.77, 83.89, 73.47, 73.47, 189.90, and 15.23 billion Canadian dollars, respectively. Similarly, Withey et al. (2018) quantified economic impacts of conservation area scenarios in Alberta from 2011 to 2056 by imposing shocks in stumpage payments in the forestry and logging sector and royalties in the oil and gas sector. Results from the study indicated that the two scenarios may reduce the present value of GDP by as much as $4.44 billion, with consistent decline in GDP components such as consumption, investments, and net exports, and other economic metrics such as domestic production, income, and welfare losses.

3.5 SUMMARY AND CONCLUSIONS

In this study, we were able to capture both direct (sectors of interest) and induced (overall economy) dynamic impacts of the projected white oak timber supply using a CGE model for Kentucky based on the projected inventory levels. The results of this work provide estimates of the economy-wide impacts of increasing supply of white oak sawlogs and the simultaneous decline of supply of high-quality white oak sawlogs in Kentucky. Since the impacts are mostly negative, this study highlights the economic implications of sustained supply of “high-quality” white oak sawlogs, which has direct relevance to the ongoing White Oak Initiative spearheaded by University of Kentucky’s Department of Forestry and Natural Resources. By demonstrating the potential economy-wide impacts of decreasing supply of high-quality white oak sawlogs, forest managers including landowners and white oak-dependent industries in Kentucky will better understand the net

benefits of improved forest management practices geared towards growing high-quality white oak sawlogs.

Given the scale at which the study was conducted, and the level of exogenous data required to build a comprehensive CGE model, there are some obvious limitations as well as possibilities for future analysis. First, the IO database that we used for our model is highly aggregated in terms of industries; it lacks information on every primary and secondary industries that use white oak sawlogs in their production process. Furthermore, the problem of not having disaggregated sectors is aggravated by the lack of data on stumpage or timber product output of white oaks that would go into each of those primary and secondary wood manufacturing sectors. Having these numbers in the IO table would minimize the errors and inconsistencies that might occur when such data are derived externally. For instance, while the stumpage expenditures in wood product sector are increasing due to increasing supply of white oak timber, stumpage expenditures in some of the secondary wood manufacturing sectors aggregated within wood product sectors such as bourbon barrel manufacturing industries and veneer producing industries might be decreasing due to decreasing supply of high-quality white oak sawlogs. Hence, the estimated positive economic impacts on wood product sectors could be lower, and the estimated negative economic impacts on the overall economy could be higher than we simulated. Second, readers should keep in mind that CGE simulations are thought experiments of "what if" scenarios in an experimental world (Hertel et al., 2007); it is dubious that real world will be responding in an exact manner at an exact time as predicted by the model.

We acknowledge that there is a lack of region/sector-specific data for various parameters in the CGE model such as elasticities, Frisch, and Phillips curve. CGE model results tend to be sensitive to the parameters upon which the model is calibrated. Our elasticities are assumed to be the same as those in similar previous studies in Canada and the US. While region and sector-specific elasticities are preferred, generating such is a whole study by itself with panel data spanning many years required. Mostly CGE modeling studies typically use sourced elasticities rather than generate region-specific ones. Further, our single-region CGE model does not consider how white oak timber supply changes in other states may affect trade (import/exports) in Kentucky; a multi-regional CGE model that capture such impacts would be needed for this, which is an area for future research. Similarly, while the projected inventory levels of white oak sawlogs include the uplift from 2018– 2058 followed by the reduction in inventory levels from 2058-2068, we focus solely on the former in this study. In fact, the latter is another area that we would work on, if we could shock the annual timber supply change annually based on projected annual levels of white oak timber supply rather than using the annualized average. Overall, the main contribution of this study is to assess the economy-wide impact of the increasing supply of white oak sawlogs and the simultaneous decrease of supply of high-quality white oak sawlogs, using our own projected white oak inventory data combined with a dynamic CGE modeling framework. Despite these limitations, the results presented in this study are valuable first estimates that can be used to advocate for proactive forest management practices to stabilize and streamline a sustained supply of high-quality white oak timber in Kentucky and beyond against the economic consequences of the status quo if nothing is done.

CHAPTER 4. GENERAL SUMMARY AND CONCLUSIONS

4.1 INTRODUCTION

This thesis has presented an analysis of the potential economic impacts of projected white oak timber supply simulation in Kentucky.

Specific contributions included:

i. examining trends in historical and current inventory levels of white oak in Kentucky (Chapter 2);
ii. performing base-run analysis of future inventory levels of white oak sawlogs - considering timber quality (Chapter 2); and
iii. estimating the potential economy-wide impacts of projected white oak timber supply in wood products manufacturing sector and distilleries sector in Kentucky (Chapter 3).

These analyses are novel estimates that underscores the significance and urgency of bringing together both industrial and non-industrial interests to faciliate, coordinate, and work towards long-term sustainable white oak timber supply in Kentucky and beyond.

4.2 SUMMARY OF IMPORTANT FINDINGS

Key findings of the analyses in this thesis included the following:

i. white oak dominated forest structure in Kentucky is rapidly tranforming to forest largely dominated by large-diameter trees with remarkable decline in small-diameter trees;

ii. the projected inventory levels of white oak sawlogs can be considered sustainable to support current harvest levels only until 2058. The declining inventory levels of white oak sawlogs from 2058 onwards (till 2068) suggests that the current mix of forest management techniques is inadequate to maintain sustainable supply of white oak sawlogs in the long run;

iii. the long-term trends in inventory levels of high-quality white oak sawlogs would be continuously declining while that of low quality sawlogs would be steadily increasing for the entire forecast period (2018 to 2068) indicating looming long-term supply issue of high-quality white oak to the dependent industries in Kentucky;

iv. the increasing supply of white oak sawlogs to wood product manufacturing sector would increase its sectoral production whereas the decreasing supply of high-quality white oak sawlogs to distilleries would substantially decrease its sectoral production during the projection period considered (2018 to 2058); and

v. the overall impact of projected white oak timber supply during the 40-year planning horizon (2018 to 2058) would be negative as reflected by declining GDP and welfare, which is driven mostly by the reduced production in distilleries sector.

Results from this study demonstrate current and future trends of white oak resources in Kentucky coupled with the economic consequences of declining supply of high-quality white oak sawlogs in the state, and, therefore, should help key stakeholders – woodland owners, forest industry, distilleries industry, agency officials, and landowner organizations, toward promoting active forest management, shaping realistic expectations

about future white oak availability, and, in general, ensuring the sustained flow of white oak timber in Kentucky and beyond.

4.3 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Given the scale and novelty of this study, there are some general limitations that provide avenues for further research and improvements in future work.

4.3.1 Limitations

i. In Chapter 2, the FIA data have an element of error (high variability resulting from the use of expansion factors to generate population estimates) and the FVS model have an element of uncertainty (validity in the accuracy of growth projection) as the precision of the projection attenuate over time. As such, the estimates reported here are just that - estimates.

ii. Data availabilty was an issue in Chapter 3, where stumpage payments for white oak in wood products manufacturing sector and barrels expenditures in distilleries sector were generated from a number of sources using *ad hoc* methods. Hence, the resulting estimates obtained in Chapter 3 are ballpark figures.

iii. Welfare impact was limited to one aggregate household.

4.3.2 Future Research Directions

i. As the body of FIA data expands under annualized inventory system and remeasured plot data becomes increasingly available, future work could be directed towards using those plot remeasurements for validating the performance of FVS growth projections. Moreover, addition of “potential tree grade” feature in FIA

database would help refine projeciton of future tree grade inventory using the approach employed in this study.

ii. Future work needs to be directed toward refining the database employed in Chapter 3 so that more precise estimates of potential economic impacts can be obtained. Refined TPO data on tree volume harvested by detailed product type such as stave logs and veneer, would aid further disaggreagtion of white oak dependent industries.

iii. Future research should examine welfare impact on different households categorized by their level of income.

Overall, this thesis has employed best available data and analytical tools spanning the study area to make the best assessment possible, and we think of the approach presented here as a first approximation of a future estimate of statewide white oak availability. However, it must be regarded as a first step that incrementally improves through better data, model validation, and refined analyses. It is the author's intention to better the modeling effort to help concerned stakeholders improve their understanding of sustainability of white oak timber supply and its economic implications to Kentuckians and beyond.

APPENDICES

APPENDIX 1. FIA FOREST TYPE CODES AND NAMES (USDA FOREST SERVICE, 2008)

Code	Forest type/ type group
100	**White/red/jack pine group**
101	Jack pine
102	Red pine
103	Eastern white pine
104	Eastern white pine/ eastern hemlock
105	Eastern hemlock
120	**Spruce/fir group**
121	Balsam fir
122	White spruce
123	Red spruce
124	Red spruce/ balsam fir
125	Black spruce
126	Tamarack
127	Northern white-cedar
140	**Longleaf/ slash pine group**
141	Longleaf pine
142	Slash pine
160	**Loblolly/ shortleaf pine group**
161	Loblolly pine
162	Shortleaf pine
163	Virginia pine
164	Sand pine
165	Table Mountain pine
166	Pond pine
167	Pitch pine
168	Spruce pine
180	**Pinyon/ juniper group**
181	Eastern redcedar
182	Rocky Mountain juniper
183	Western juniper
184	Juniper woodland
185	Pinyon/ juniper woodland
200	**Douglas-fir group**
201	Douglas-fir
202	Port-Orford-cedar
220	**Ponderosa pine group**
221	Ponderosa pine
222	Incense-cedar
223	Jeffrey pine/ Coulter pine/ bigcone Douglas-fir
224	Sugar pine
240	**Western white pine group**
241	Western white pine
260	**Fir/ spruce/ mountain hemlock group**
261	White fir
262	Red fir
263	Noble fir
264	Pacific silver fir
265	Engelmann spruce
266	Engelman spruce/ subalpine fir
267	Grand fir
268	Subalpine fir
269	Blue spruce
270	Mountain hemlock
271	Alaska yellow-cedar
280	**Lodgepole pine group**
281	Lodgepole pine
300	**Hemlock/ Sitka spruce group**
301	Western hemlock
304	Western redcedar
305	Sitka spruce
320	**Western larch group**
321	Western larch
340	**Redwood group**
341	Redwood
342	Giant sequoia

Code	Forest type/ type group
360	**Other western softwoods group**
361	Knobcone pine
362	Southwest white pine
363	Bishop pine
364	Monterey pine
365	Foxtail pine/ bristlecone pine
366	Limber pine
367	Whitebark pine
368	Misc. western softwoods
370	**California mixed conifer group**
371	California mixed conifer
380	**Exotic softwoods group**
381	Scotch pine
382	Australian pine
383	Other exotic softwoods
384	Norway spruce
385	Introduced larch
400	**Oak/ pine group**
401	Eastern white pine/ northern red oak/ white ash
402	Eastern redcedar/ hardwood
403	Longleaf pine/ oak
404	Shortleaf pine/oak
405	Virginia pine/ southern red oak
406	Loblolly pine/ hardwood
407	Slash pine/ hardwood
409	Other pine/ hardwood
500	**Oak/ hickory group**
501	Post oak/ blackjack oak
502	Chestnut oak
503*	White oak/ red oak/ hickory
504*	White oak
505	Northern red oak
506*	Yellow-poplar/ white oak/ northern red oak
507	Sassafras/ persimmon
508	Sweetgum/ yellow-poplar
509	Bur oak
510	Scarlet oak
511	Yellow-poplar
512	Black walnut
513	Black locust
514	Southern scrub oak
515	Chestnut oak/ black oak/ scarlet oak
519	Red maple
520	Mixed upland hardwoods
600	**Oak/ gum/ cypress group**
601	Swamp chestnut oak/ cherrybark oak
602	Sweetgum/ Nuttall oak/ willow oak
605	Overcup oak/ water hickory
606	Atlantic white-cedar
607	Baldcypress/ water tupelo
608	Sweetbay/ swamp tupelo/ red maple
700	**Elm/ ash/ cottonwood group**
701	Black ash/ American elm/ red maple
702	River birch/ sycamore
703	Cottonwood
704	Willow
705	Sycamore/ pecan/ American elm
706	Sugarberry/ hackberry/ elm/ green ash
707	Silver maple/ American elm
708	Red maple/ lowland
709	Cottonwood/ willow
722	Oregon ash
800	**Maple/ beech/ birch group**
801	Sugar maple/ beech/ yellow birch
802	Black cherry
803	Cherry/ ash/ yellow-poplar
805	Hard maple/ basswood
807	Elm/ ash/ locust
809	Red maple/ upland
900	**Aspen/ birch group**
901	Aspen
902	Paper birch
904	Balsam poplar

Code	Forest type/ type group	Code	Forest type/ type group
910	**Alder/ maple group**	**950**	**Other western hardwoods group**
911	Red alder	951	Pacific madrone
912	Bigleaf maple	952	Mesquite woodland
		953	Cercocarpus woodland
920	**Western oak group**	954	Intermountain maple woodland
921	Gray pine	955	Misc. western hardwoods woodland
922	California black oak		
923	Oregon white oak	**980**	**Tropical hardwoods group**
924	Blue oak	981	Sable palm
925	Deciduous oak woodland	982	Mangrove
926	Evergreen oak woodland	989	Other tropical
931	Coast live oak		
932	Canyon live oak/ interior live oak	**990**	**Exotic hardwoods group**
		991	Paulownia
940	**Tanoak/ laurel group**	992	Melaleuca
941	Tanoak	993	Eucalyptus
942	California laurel	995	Other exotic hardwoods
943	Giant chinkapin	999	Nonstocked

*denotes white oak dominated forest types

APPENDIX 2. EQUATION FOR TREE VOLUME CALCULATION (OSWALT AND CONNER, 2011)

$$\mathrm{VOLCFGRS_{sapling}} = \mathrm{A_1} + \mathrm{A_2} * (\mathrm{DBH^2} * \mathrm{HT})$$

$$\mathrm{VOLCFGRS_{pole}} = \mathrm{C_1} + \mathrm{C_2} * (\mathrm{DBH^2} * \mathrm{HT})$$

$$\mathrm{VOLCFGRS_{sawtimber}} = \mathrm{D_1} + \mathrm{D_2} * (\mathrm{DBH^2} * \mathrm{HT})$$

$$\mathrm{R_{CUSAW}} = \mathrm{H_1} + \mathrm{H_2} * \left(\frac{1}{\mathrm{DBH} - 5}\right)^2$$

$$\mathrm{VOLCSGRS} = \mathrm{R_{CUSAW}} * \mathrm{VOLCFGRS_{sawtimber}}$$

$$\mathrm{R_{BD}} = \mathrm{I_1} + \mathrm{I_2} * \left(1 - \frac{1}{\mathrm{DBH}}\right)$$

$$\mathrm{VOLBFGRS} = \mathrm{R_{BD}} * \mathrm{VOLCFGRS_{sawtimber}}$$

VOLCFGRS = gross cubic-foot volume (from a 1' stump to a 4" top diameter outside bark (d.o.b.) for pole and sawtimber); VOLCSGRS = gross cubic-foot volume of the saw-log portion of the tree (from a 1' stump to 9" top d.o.b.); VOLBFGRS = gross board-foot volume in the saw-log portion; R_{CUSAW} = ratio of cubic-foot volume of the saw-log portion; R_{BD} = ratio board-foot volume; DBH = diameter at breast height; HT = total height; A_1, A_2, C_1, C_2, D_1, D_2, H_1, H_2, I_1 & I_2 are species-specific coefficients for each equations.

APPENDIX 3. EQUATION FOR INDIVIDUAL TREE GROWTH AND MORTALITY IN FVS-SN (DIXON, 2002A; KEYSER, 2008)

Tree height-diameter relationship

For large trees (DBH ≥ 3.0”),

$$HT = 4.5 + P_2 * \exp(-P_3 * DBH^{P_4})$$

For small tree (DBH < 3.0”),

$$HT = ((4.5 + P_2 * \exp(-P_3 * 3.0^{P_4}) - 4.51) * (DBH - Dbw)/(3 - Dbw)) + 4.51$$

HT = tree height; DBH = tree diameter at breast height; Dbw = bud width diameter at 4.51 feet; B1, B2, P2 - P4 are species-specific coefficients.

Small tree height growth

$$POTHT = C_1 * SI^{C_2} * [1.0 - \exp(C_3 * AGET)]^{(C_4 * SI^{C_5})}$$

POTHT = predicted tree height; SI = species site index; AGET = tree age; C_1 - C_5 are species-specific coefficients.

Large tree diameter growth

$$\ln(DDS) = B_1 + (B_2 * \ln(DBH)) + (B_3 * DBH^2) + (B_4 * \ln(CR)) + (B_5 * RELHT) + (B_6 * SI) + (B_7 * BA) + (B_8 * PBAL) + (B_9 * SLOPE) + (B_{10} * \cos(ASP) * SLOPE) + (B_{11} * \sin(ASP) * SLOPE) + FORTYPE + ECOUNIT + PLANT$$

DDS = predicted 5-year periodic change in squared inside-bark diameter; DBH = tree diameter at breast height; CR = crown ratio expressed as a percent; HREL = relative height of subject tree to the Top Height of the stand; SI = site index of the species; BA = stand basal area per acre; PBAL = plot basal area in larger trees; SLOPE = stand slope; ASPECT = stand aspect in radians; FORTYPE = current forest type group dependent coefficient; ECOUNIT = ecological unit group dependent coefficient; PLANT = managed pine stand coefficient; B_1- B_{11} = species-specific coefficients.

Large tree height growth

$$HTG = POTHTG * (0.25 * HGMDCR + 0.75 * HGMDRH)$$

HTG = periodic height growth; POTHTG = potential periodic height growth; HGMDCR = crown ratio modifier; HGMDRH = relative height modifier; CR = crown ratio expressed as a proportion.

Background mortality

$$\mathrm{RI} = [1/(1 + \exp(\mathrm{P_0} + \mathrm{P_1} * \mathrm{DBH}))] * 0.5$$

$$\mathrm{RIP} = 1 - (1 - \mathrm{RI})^{\mathrm{Y}}$$

RI = proportion of the tree record attributed to mortality; RIP = final mortality rate adjusted to the length of the cycle; DBH = tree diameter at breast height; Y = length of the current projection cycle in years; P_0 & P_1 = species-specific coefficients.

Density related mortality

$$\mathrm{StndMaxSDI} = \frac{\sum(\mathrm{MaxSDI_i} \,.\, \mathrm{BA_i})}{\mathrm{StndBA}}$$

StndMaxSDI = maximum stand density index (SDI) for the entire stand; $\mathrm{MaxSDI_i}$ = maximum SDI for species i; $\mathrm{BA_i}$ = total basal area of species i; StndBA = total basal area for the stand

$$\mathrm{SDI} = \sum\left(\mathrm{TPA_i} \,.\, \left(\frac{\mathrm{DBH_i}}{10}\right)^{1.605}\right)$$

$\mathrm{DBH_i}$ = diameter at breast height of tree record i; $\mathrm{TPA_i}$ = trees per acre of tree record i; Σ = summation over all trees for which the contribution to SDI is being calculated (for stand SDI the summation is over all trees in the stand).

APPENDIX 4. PROJECTED WHITE OAK GROWING STOCK VOLUME (CUFT) BY DBH CLASS IN WHITE OAK DOMINATED FORESTS IN KENTUCKY

	DBH class (inches)						
Year	**5-10.9**	**11-16.9**	**17-22.9**	**23-28.9**	**29-34.9**	**35-40.9**	**41-46.9**
2018	270,594,420.77	978,566,663.33	984,352,339.80	323,174,888.68	58,657,419.52	55,338,377.53	-
2023	218,320,489.54	860,009,841.03	1,109,175,848.68	382,946,177.36	79,172,251.61	56,393,381.01	-
2028	173,412,293.55	739,171,000.37	1,194,416,719.40	450,949,354.37	100,233,243.67	53,828,577.81	3,719,503.64
2033	144,150,991.37	635,057,783.00	1,251,124,190.88	545,194,487.16	124,234,971.75	49,777,679.59	9,167,301.19
2038	120,377,430.98	563,558,667.96	1,252,860,838.73	660,419,079.19	151,838,676.35	59,953,040.82	10,084,412.14
2043	104,838,961.26	496,317,761.57	1,232,733,525.92	787,114,947.74	188,258,036.48	64,999,926.95	10,928,841.84
2048	95,081,158.49	436,108,806.96	1,189,912,731.03	906,295,380.23	242,828,827.44	70,848,504.03	11,421,827.32
2053	93,081,152.98	376,052,164.44	1,113,698,410.02	1,030,617,985.69	312,317,209.84	74,321,601.12	15,663,971.94
2058	97,718,107.78	327,197,774.35	1,037,255,904.61	1,134,256,316.06	379,230,509.53	80,080,288.22	18,308,700.51
2063	110,112,274.27	277,879,290.98	956,069,068.87	1,217,970,833.85	456,136,683.61	80,434,582.52	25,287,279.34
2068	129,062,763.12	236,820,652.23	861,163,030.98	1,283,693,713.28	538,831,083.80	88,937,843.53	30,961,458.36

APPENDIX 5. PROJECTED INVENTORY LEVELS OF WHITE OAK SAWLOGS (BDFT) IN WHITE OAK DOMINATED FORESTS IN KENTUCKY

Year	**Inventory**	**Annual growth**	**Annual harvest**
2018	11,099,432,631.88	-	85,418,291.30
2023	11,309,041,959.89	127,340,156.90	85,418,291.30
2028	11,359,850,411.72	95,579,981.67	85,418,291.30
2033	11,491,203,051.47	111,688,819.25	85,418,291.30
2038	11,672,312,787.53	121,640,238.51	85,418,291.30
2043	11,842,540,791.23	119,463,892.04	85,418,291.30
2048	11,992,282,730.17	115,366,679.09	85,418,291.30
2053	12,084,870,755.19	103,935,896.30	85,418,291.30
2058	12,110,293,396.26	90,502,819.51	85,418,291.30
2063	12,051,601,245.22	73,679,861.09	85,418,291.30
2068	11,932,936,230.30	61,685,288.32	85,418,291.30

APPENDIX 6. PROJECTED WHITE OAK SAWLOG VOLUME (BDFT) BY TREE GRADE IN WHITE OAK DOMINATED FORESTS IN KENTUCKY

Year	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
2018	1,346,598,189.27	2,974,172,212.99	4,130,073,264.54	1,526,256,314.28	746,588,728.26
2023	1,406,600,721.49	3,110,984,701.83	4,355,349,983.77	1,641,527,925.30	775,248,472.12
2028	1,434,859,503.26	3,207,469,349.96	4,525,881,377.76	1,732,003,607.16	792,454,611.04
2033	1,477,970,077.16	3,325,355,512.83	4,735,183,873.39	1,827,200,128.45	820,172,383.61
2038	1,526,115,095.68	3,457,001,875.93	4,960,485,027.52	1,927,503,929.97	852,854,558.80
2043	1,575,015,269.14	3,586,386,427.53	5,180,794,289.69	2,023,986,803.55	884,041,331.60
2048	1,619,928,535.51	3,709,326,794.57	5,392,816,880.09	2,118,155,327.63	914,520,132.88
2053	1,660,794,941.84	3,819,420,302.92	5,591,747,886.19	2,201,220,338.00	941,665,692.10
2058	1,694,646,855.43	3,913,743,762.32	5,759,091,581.39	2,273,457,854.71	965,514,778.76
2063	1,720,837,465.86	3,986,786,864.91	5,895,553,442.61	2,333,439,877.86	986,223,333.40
2068	1,744,027,020.30	4,045,671,865.72	6,003,159,249.40	2,387,304,479.16	1,003,960,705.36

APPENDIX 7. PROJECTED INVENTORY LEVELS OF WHITE OAK SAWLOGS (BDFT) BY TREE GRADE IN WHITE OAK DOMINATED FORESTS IN KENTUCKY

Year	Grade 1	Grade 2	Grade 3	Grade 4
2018	1,280,433,837.27	2,855,643,484.99	4,073,763,023.04	1,512,438,838.38
2023	1,230,162,449.49	2,794,908,093.83	4,205,189,339.77	1,604,681,322.90
2028	1,148,147,311.26	2,693,844,861.96	4,281,870,331.26	1,672,127,878.26
2033	1,080,983,965.16	2,614,183,144.83	4,397,322,424.39	1,744,295,273.05
2038	1,018,855,063.68	2,548,281,627.93	4,528,773,176.02	1,821,569,948.07
2043	957,481,317.14	2,480,118,299.53	4,655,232,035.69	1,895,023,695.15
2048	892,120,663.51	2,405,510,786.57	4,773,404,223.59	1,966,163,092.73
2053	822,713,149.84	2,318,056,414.92	4,878,484,827.19	2,026,198,976.60
2058	746,291,143.43	2,214,831,994.32	4,951,978,119.89	2,075,407,366.81
2063	662,207,833.86	2,090,327,216.91	4,994,589,578.61	2,112,360,263.46
2068	575,123,468.30	1,951,664,337.72	5,008,344,982.90	2,143,195,738.26

APPENDIX 8. SECTORAL AGGREGATION SCHEME FOR THE CGE MODEL

Model aggregated sectors	**IO database industries§**
Agriculture (AGR)	Farms Wholesale and retail trade Fishing
Forestry and logging (FLG)	Commercial logging and forestry activities*
Oil, gas, and mining (ENER)	Oil and gas extraction Mining, except oil and gas Support activities for mining
Utilities (UTL)	Utilities
Construction (CON)	Construction
Wood products (WPD)	Wood products
Distilleries (DIST)	Distilleries*
All other manufacturing (OMAN)	Nonmetallic mineral products Primary metals Fabricated metal products Machinery Computer and electronic products Electrical equipment, appliances, and components Motor vehicles, bodies and trailers, and parts Other transportation equipment Furniture and related products Miscellaneous manufacturing Food and beverage and tobacco products Textile mills and textile product mills Apparel and leather and allied products Printing and related support activities Petroleum and coal products Chemical products Plastics and rubber products
Pulp and paper (PAP)	Paper products
Transportation and Warehousing (TRAN)	Air transportation Rail transportation Water transportation Truck transportation Transit and ground passenger transportation Pipeline transportation Other transportation and support activities

	Warehousing and storage
Services (SER)	Publishing industries, except internet (includes software)
	Motion picture and sound recording industries
	Broadcasting and telecommunications
	Data processing, internet publishing, and other information services
	Federal Reserve banks, credit intermediation, and related activities
	Securities, commodity contracts, and investments
	Insurance carriers and related activities
	Funds, trusts, and other financial vehicles
	Real estate
	Rental and leasing services and lessors of intangible assets
	Legal services
	Computer systems design and related services
	Miscellaneous professional, scientific, and technical services
	Management of companies and enterprises
	Administrative and support services
	Waste management and remediation services
	Educational services
	Ambulatory health care services
	Hospitals
	Nursing and residential care facilities
	Social assistance
	Performing arts, spectator sports, museums, and related activities
	Amusements, gambling, and recreation industries
	Accommodation
	Food services and drinking places
	Other services, except government
	Federal general government defense
	Total Government

*Disaggregated using IMPLAN database

[§]Input-Output- State and National Analysis Program (IO-SNAP), Regional Research Institute at West Virginia University

APPENDIX 9. IO DATABASE FOR KENTUCKY, 2018 ($ BILLION)

	AGR	FLG	ENER	UTL	CON	WPD	OMAN
AGR	2.879507	0.024584	0.132589	0.090257	1.546161	0.256683	11.08805
FLG	0.080529	0.006267	0.000373	0.00001	0.000001	0.045473	0.035128
ENER	0.037051	0.000061	0.158986	0.105476	0.180394	0.000677	0.952338
UTL	0.451302	0.000306	0.056478	0.194497	0.035455	0.015183	0.667743
CON	0.079018	0.000099	0.036447	0.062719	0.001951	0.001987	0.171579
WPD	0.061772	0.000129	0.003436	0.000118	0.405405	0.348806	0.317834
OMAN	1.958837	0.008366	0.367672	0.248375	2.63098	0.165412	31.44086
DIST	0.140182	0.000295	0.000542	0.00031	0.002474	0.000646	0.778712
PAP	0.132489	0.000024	0.005325	0.000702	0.027887	0.011782	1.107221
TRAN	1.89537	0.003863	0.107661	0.231004	0.305494	0.145097	3.168067
SER	9.811356	0.008395	0.363655	0.540172	1.105891	0.121533	5.677765
LAB	13.57751	0.114079	0.899979	0.839555	5.165479	0.496512	16.91912
CAP	16.22807	0.061842	1.105621	2.757645	3.651721	0.224252	16.51139
STU	0	0	0	0	0	0.030866	0
BAR	0	0	0	0	0	0	0
IMP	5.704442	0.023969	0.450525	0.700279	2.021826	0.369997	25.15235

	DIST	PAP	TRAN	SER	CNS	INV	EXP
AGR	1.536347	0.365454	0.702298	3.053893	22.56393	3.865642	4.932048
FLG	0.008812	0.027776	0.000047	0.019406	0.008236	0.000672	0.019549
ENER	0.006764	0.025512	0.006608	0.213802	0.044025	0.714142	1.243453
UTL	0.035038	0.075148	0.196375	1.236279	1.905054	0.027656	0.874605
CON	0.005366	0.012486	0.082725	2.017215	0.56903	13.69453	0.345965
WPD	0.003364	0.128514	0.039039	0.155394	0.01182	0.097753	0.661522
OMAN	1.08151	0.512115	1.575802	7.037063	16.59619	8.494299	41.87066
DIST	0.238647	0.008328	0.007321	0.377247	2.035864	0.023579	2.650108
PAP	0.168063	0.902359	0.097941	0.371597	0.0394	0.029639	2.210439
TRAN	0.289101	0.25476	2.464979	1.449753	3.649487	0.438387	6.812223
SER	0.32422	0.310375	3.794644	37.24919	106.2742	8.709485	14.18506
LAB	0.602478	0.664945	7.232546	69.88743			
CAP	0.782543	0.966155	2.787954	46.01817			
STU	0	0	0	0			
BAR	0.323	0	0	0			
IMP	0.859002	0.850941	2.226967	19.38947			

Note: LAB (Labor); CAP (Capital); STU (STUMPAGE); BAR (Barrel expenditures); IMP (Import); CNS (Consumption); INV (Investment); EXP (Export).
Source: Input-Output- State and National Analysis Program (IO-SNAP), Regional Research Institute at West Virginia University.

APPENDIX 10. CGE MODEL VARIABLES

Variables	Description
Production block	
FAD_{if}	Factor input demand
FAS_f	Factor supply
PF_f	Factor price
PD_i	Domestic output producer price (before production tax)
PDD_i	Consumer price of domestic output sold to domestic markets
X_i	Domestic sales of composite commodities
XD_i	Domestic production (output)
XDD_i	Domestic output delivered to home markets
Household block	
INC	Household total gross income
SAH	Household savings
CBUD	Household disposable income (budget) after tax and savings
SBUD	Household discretionary (supernumerary) budget
CON_i	Household consumption demand of commodities
SAT	Household total savings
INV_i	Investment demand for commodities
TRMT	Total import tariff revenues
UNEMP	Unemployment level (Phillips curve)
CPI	Consumer price index
Other prices block	
P_i	Composite commodities demand price
Foreign trade block	
IMP_i	Composite imports
EXP_i	Composite exports
PM_i	Domestic composite imports price
PE_i	Domestic composite exports price
PWE_i	World export price FOB inclusive of export tax or subsidy
PWM_i	World import price CIF inclusive of transportation costs
SAF	Regional savings
EXR	Exchange rate
OBJ	Dummy objective variable

Dynamic growth path variables	
RRR	Real rate of return on capital input
GRW	Initial steady-state labor growth rate
$TIME_t$	Time period into the future from base year 2018
GRW_t	Growth path for each time period

Note: FOB (free on board); CIF (cost, insurance, and freight). Subscripts *i* denote sectors (*i* = 1, 2, …., 11); subscript *f* denotes input factors (*f* = 1, 2, 3, 4); subscript *t* denotes the time period in years from the base year 2018.

APPENDIX 11. CGE MODEL PARAMETERS

Parameters	Description
Elasticities of substitution	
σV_i	Substitution in the composite value-added function
σA_i	Armington substitution between imports and domestic commodities
σT_i	CET substitution between domestic and export markets
σY_i	Income elasticities of demand for commodities
Share parameters	
γV_{if}	Share parameter in composite value-added input function
γA_i	CES share parameter in level one of the Armington aggregation function
γT_i	CET share parameter in transformation function
Efficiency (shift) parameters	
ΦV_i	Shift parameter in the composite value-added input function
ΦA_i	Shift parameter in the first level of Armington aggregation function
ΦT_i	Shift parameter in transformation function
Other parameters	
IO_{ij}	Technical coefficients of intermediate inputs
η	Phillips curve parameter
αI_i	Cobb-Douglas share parameter (preference) for investment goods
Ψ_i	Budget shares in nested-LES household utility function
μH_i	Household subsistence consumption level
λ_i	Marginal propensity to save
tm_i	Import tariff rate
te_i	Export tax / subsidy rate

Note: CES, constant elasticity of substitution; CET, constant elasticity of transformation; LES, linear expenditure system.

APPENDIX 12. CGE MODEL EQUATIONS

Equation		Description
Production block		
(A1)	$\mathrm{FAD}_{if} = \left(\frac{XD_i}{\Phi \mathrm{V}_i}\right)\left(\frac{\gamma \mathrm{V}_{if}}{PF_f}\right)^{\sigma \mathrm{V}_i}\left(\sum_{f=1}^{4}(\gamma \mathrm{V}_{if}{}^{\sigma \mathrm{V}_i} PF_f{}^{1-\sigma \mathrm{V}_i})\right)^{\frac{\sigma \mathrm{V}_i}{1-\sigma \mathrm{V}_i}}$, where $\sum_{f=1}^{4} \gamma \mathrm{V}_{if} = 1$,	Factor demand by firm
	f denotes labor and capital for all sectors, stumpage for the wood products sector only, and barrel expenditures for distilleries sector only	
(A2)	$PD_i XD_i = PF_f FAD_{if} + \sum_{j=1}^{11}(IO_{ji}\, XD_i P_j)$	Zero profit condition for the firm
Household block		
(A3)	$INC = \sum_{f=1}^{4}(PF_f\, FAS_f) + TRMT$	Household total gross income
(A4)	$SAH = \lambda_i \mathrm{INC}$	Household savings
(A5)	$CBUD = INC - SAH$	Household disposable income (budget)
(A6)	$SBUD = CBUD - \sum_{i=1}^{11} PC_i\, \mu H_i$	Household discretionary (supernumerary) budget
(A7)	$P_i CON_i = P_i \mu H_i + \Psi_i CBUD - \sum_{j=1}^{11} P_j\, \mu H_j$	Household consumption demand of commodities
(A8)	$SAT = SAH + SAF(EXR)$	Household total savings
(A9)	$P_i INV_i = \alpha I_i SAT$	Investment demand for commodities

(A10)	$TRMT = \sum_{i=1}^{11} tm_i \, IMP_i (PMW_i^{\,0}) EXR$	Total import tariff revenues
(A11)	$\left(\frac{PF_f/CPI}{PF_f^{\,0}/CPI^0} - 1\right) = \eta\left(\frac{UNEMP/FAS_f}{UNEMP^0/FAS_f^{\,0}} - 1\right)$, where f denotes labor	Unemployment level (Phillips curve)
(A12)	$\mathrm{CPI} = \frac{\sum_{i=1}^{7} P_i CON_i^{\,0}}{\sum_{i=1}^{7} P_i^{\,0} CON_i^{\,0}}$	Consumer price index

Market clearing block

(A13)	$\sum_{i=1}^{11} FAD_{if} = FAS_f - UNEMP$, *where* f denotes labor	Market clearing for labor
(A14)	$\sum_{i=1}^{11} FAD_{if} = FAS_f$, *where* f denotes capital	Market clearing for capital
(A15)	$FAD_{if} = FAS_f$, *where* f *denotes stumpage and* i denotes wood products sector	Market clearing for stumpage
(A16)	$FAD_{if} = FAS_f$, *where* f *denotes barrel expenditures and* i denotes distilleries sector	Market clearing for barrel expenditures
(A17)	$X_i = CON_i + INV_i + \sum_{j=1}^{11} IO_{ij} \, XD_j$	Market clearing for commodities

Foreign trade block

(a) Import side

(A18)	$\mathrm{XDD}_i = \left(\frac{1}{\Phi \mathrm{A}_i}\right)^{(1-\sigma A_i)} \left(\gamma \mathrm{A}_i \frac{P_i}{PDD_i}\right)^{\sigma \mathrm{A}_i} X_i$	Domestic demand for domestically produced goods

(A19)	$IMP_i = \left(\frac{1}{\Phi A_i}\right)^{(1-\sigma A_i)} \left((1 - \gamma A_i)\frac{P_i}{PM_i}\right)^{\sigma A_i} X_i$	Domestic demand for composite imported goods
(A20)	$P_i X_i = PDD_i XDD_i + PM_i IMP_i$	CES zero profit condition
(A21)	$PM_i = (1 + tm_i) PWM_i{}^0 EXR$	Domestic composite import price

(b) Export side

(A22)	$XDD_i = \left(\frac{1}{\Phi T_i}\right)^{(1-\sigma T_i)} \left(\gamma T_i \frac{P_i}{PDD_i}\right)^{\sigma T_i} XD_i$	Domestic supply of domestic output
(A23)	$EXP_i = \left(\frac{1}{\Phi T_i}\right)^{(1-\sigma T_i)} \left((1 - \gamma T_i)\frac{P_i}{PE_i}\right)^{\sigma T_i} XD_i$	Export demand for domestic output
(A24)	$PD_i XD_i = PE_i EXP_i + PDD_i XDD_i$	CET zero profit condition
(A25)	$PE_i = (1 + te_i) PWE_i{}^0 EXR$	Domestic composite exports price
(A26)	$\sum_{i=1}^{11} (PWM_i IMP_i) = \sum_{i=1}^{11} (PWE_i EXP_i) + SAF$	Regional balance of payments (foreign savings)

Artificial objective function

(A27)	OBJ = 1	Dummy objective variable

Macroeconomic closures

(A28)	$\overline{FAS_f} = FAS_f{}^0$	Exogenously fixed factor endowments
(A29)	$\overline{SAF_f} = SAF_f{}^0$	Exogenously fixed foreign savings
(A30)	$\overline{PF_f} = PF_f{}^0$, where *f* denotes labor	Fixed numeraire for all regions

Dynamic growth path		
(A31)	$RRR = PF_f{}^0 FAS_f{}^0 \left(\frac{GRW^0}{SAT^0}\right)$, where *f* denotes capital	Real rate of return on capital
(A32)	$GRW_t = \frac{SAT(RRR)}{PF_f FAS_f}$, where *f* denotes capital	Growth rate factor for each time period
(A33)	$\overline{FAS}_f = (1 + GRW_t)FAS_f$, where *f* denotes capital	Exogenously determined capital growth path
(A34)	$\overline{FAS}_f = (1 + GRW^0)FAS_f$, where *f* denotes labor	Exogenously determined labor growth path
(A35)	$\overline{FAS}_f = FAS_f{}^0$, where *f* denotes stumpage in wood products sector	Exogenously determined stumpage growth path
(A36)	$\overline{FAS}_f = FAS_f{}^0$, where *f* denotes barrel expenditures in distilleries sector	Exogenously determined barrel expenditures growth path
Consumer welfare		
(A37)	$CV = SBUD^1 - SBUD^0 CPI$	Measure of consumer welfare following policy shock

Note: Superscript 0 denotes an initial equilibrium level, and 1 denotes equilibrium level after policy shock; subscripts i and j are sets and aliases that denote sectors of the economy (1, 2… 11).

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VITA

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