

# Exploring the Interaction of Forest Management and Climate in the Community Land Model

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(ABSTRACT)

Forests perform many important ecological functions and provide numerous environmental services to humanity. Currently forests are under ever increasing pressures from humans through deforestation, changes in land use, and anthropogenic climate change. Managed forests play an important role in supplying forest products to the global population, necessitating the need to predict how forests will respond to climate change and how this will influence future wood product supplies. In this dissertation I used loblolly pine (*Pinus taeda*), the most extensively cultivated tree species in the United States, as a study system to simulate how climate change and forest management could alter the dynamics of managed forests in the future. Using the land component (the Community Land Model) of the widely used Community Earth System Model (CESM), I developed and validated a set of tools necessary to simulate the loblolly pine plantation system using the vegetation demography model embedded in CESM (FATES). This included developing a representation of loblolly pine using data from the literature, which was better able to capture forest growth and development observed in field studies than FATES's existing conifer tree representation. I added the ability to simulate several aspects of forest management not

previously supported in FATES by creating the Vegetation Management Module, which I showed was able to realistically reproduce the common management practice of stand thinning. I used these new tools to perform simulations of how loblolly pine will grow across the Southeastern United States until the end of the 21st century, under the high and low climate change scenarios developed by the scientific community in the Coupled Model Intercomparison Project Phase 6 (CMIP6). Our experiments show that loblolly pine productivity may as much as double by the end of the century, with total wood harvest over that period increasing by almost half. I also showed that different management activities had significant effects on loblolly plantation yields, with mid-rotation stand thinning having an effect under both climate scenarios on par with increases due to the extreme climate change scenario SSP5 RCP8.5. I showed that these changes in wood yields could decrease the forest area in the Southeast required to meet the wood product demands over the rest of the century. These changes in plantation productivity could interact with socioeconomic factors to drive changes in land use and carbon storage in the Southeastern U.S. This work increases our understanding of how managed forests in the U.S. will be affected by climate change and how our management choices modulate that response. The techniques and tools developed here open up new areas of research into the role of forest management in the climate system.

# Exploring the Interaction of Forest Management and Climate in the Community Land Model

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(GENERAL AUDIENCE ABSTRACT)

Forests benefit humans by regulating Earth's climate and by providing natural resources such as wood. In the Southeastern United States forestry is an important industry. Tree farms of southern pine trees produce a large percentage of the region's wood. Predicting how forests will grow in the future is important for planning and making investments. However, the burning of fossil fuels has increased carbon dioxide in the atmosphere and is changing Earth's climate. This is affecting how fast trees grow and how much wood can be harvested from forests. The methods that foresters have traditionally used to predict how trees will grow in the future do not account for climate change, and thus may not be as accurate in the future. An alternative is to use the computer models that scientists have developed to predict both how global climate will change in the future and how forests are influenced by climate. These computer programs can be used to predict how natural forests will grow in the future, but aren't set up to predict managed forests well. I made changes to one of these programs to make it possible to simulate the managed loblolly pine forests of the Southeastern United States. First, I tested these changes to make sure that simulated forests grew like real forests do today. Then I simulated how

pine forests in Southeastern United States could grow over the next century with climate change. I found that pine forests will grow faster and allow more wood to be harvested as carbon dioxide in the atmosphere increases. If climate changes are extreme, loblolly forests could produce 70% more wood than today by the end of the 21st century. I also showed that the manner in which forests were managed in simulations changes the amount of wood they produced, with some management practices increasing wood harvested by 50% over the rest of the century. Because climate change could increase the amount of wood that can be produced from a fixed area of forest, I investigated how this might change the area of forest plantation in the Southeastern United States. Based on projections of demand for wood for the rest of the century I calculated how much loblolly pine forest would be needed to produce this wood over the next century. I found that increases in forest productivity due to climate change and forest management could decrease the forest area required to grow the wood we need. This could change how we use forests in the Southeastern United States, which in turn could have impacts on the climate.

# Dedication

*For my family.*

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# Chapter 1

## Introduction

Forests are a natural resource that provide numerous direct and indirect benefits to humankind (e.g. economic, recreational, aesthetic, and cultural) (Mori et al., 2017). They are also important regulators of local and global climate (Bonan, 2008). Forest management is the set of activities and techniques that humans use to manipulate the production of these environmental services (Duncker et al., 2012). Historically, humans have managed forests mostly for direct and proximate benefits such as food, fuel, and wood products (Sharpe et al., 1976). Increasingly though, forests are being managed for less direct environmental benefits such as preservation of biodiversity and carbon sequestration (Becknell et al., 2015).

With the Paris Climate Agreement the global community of nations has reached a consensus on the importance of limiting global warming (Cornwall, 2015; Tollefson and Weiss, 2015). Forests play an important role in a number of the mitigation approaches that have been proposed to reduce atmospheric carbon dioxide (Canadell and Raupach, 2008; Jackson et al., 2008; Ruddell et al., 2007). These mitigation approaches employ forest management activities to achieve their climate goals. From a policy and planning perspective it is therefore essential to understand the ways in which management alters forests' climate functions. Despite this many forest management practices are not well understood from a climate perspective and are not represented in Earth System Models (ESMs) (Pongratz et al., 2018).

Earth System Models are critical tools for understanding the interaction between forests and climate because forests both influence and respond to climate (Bonan and Doney, 2018). Smaller scale ecosystem models may be able to predict some effects of forest on local weather but will not be able to capture the feedbacks of these weather

processes back onto forests on a global scale. The land surface components of earth system models contain representations of the biophysical (e.g. evapotranspiration and forest albedo) and biogeochemical (e.g. carbon sequestration and storage) processes that link forest structures and functions to climate (Bonan, 2008; Bonan and Doney, 2018). By and large these models do not make a distinction between managed and unmanaged forests, despite differences that may be climate relevant (Pongratz et al., 2018), such as differences in carbon density, albedo, and fire regimes.

There is an opportunity to improve ESMs for multiple stakeholder groups by better representing forest management. Adding more realistic forest management to ESMs will help us better understand how forests influence climate (accuracy), understand how climate change will affect forest services including timber yields (impacts), and explore and plan mitigation strategies (planning and policy assessment). Modeling also has the potential to identify gaps in knowledge and areas of the greatest potential mitigation benefits. This in turn will inform appropriate manipulative research experiments, which due to their high costs and long timescales must be carefully selected and designed.

## 1.1 Forests and Climate

Forests are central to the carbon cycle, by removing the greenhouse gas carbon dioxide from the atmosphere. They are responsible for approximately half of terrestrial primary production (39-52% of GPP / NPP) (Beer et al., 2010; Field et al., 1998; Prentice et al., 2001) and represent 65-82% of the above ground terrestrial carbon

stock (Liu et al., 2015; Pan et al., 2011; Prentice et al., 2001).

Forests account for the most (if not all) of the terrestrial carbon sink (Liu et al., 2015; Pan et al., 2011). Globally forests absorb the equivalent of 30% of fossil fuel emissions, 50% if deforestation losses are excluded (Pan et al., 2011). In just the United States alone forests sequester 10% of national emissions (Ruddell et al., 2007).

In addition to carbon sequestration, trees influence the climate through other biophysical and biogeochemical mechanisms. About half of precipitation is returned to the atmosphere by transpiration with another 20% evaporating from plant surfaces (Good et al., 2015; Jasechko et al., 2013; Lian et al., 2018). In addition to modifying hydrology this vapor flux causes cooling via latent heat and increased albedo through cloud formation (Bonan, 2008; Penuelas and Staudt, 2010). Forests further effect cloud formation, atmospheric optical properties, and atmospheric chemistry by generation of biogenic volatile organic compounds (BVOCs) (Kulmala et al., 2004; Penuelas and Staudt, 2010; Unger, 2014). Forests decrease albedo by shielding lower albedo land surfaces, soil and snow, with highly absorbent photosynthetic tissues. By increasing surface roughness trees increase turbulent mixing in the lower atmosphere which alters the vertical profile of energy, moisture, and aerosols in the atmosphere (Bonan, 2008; Burakowski et al., 2018).

## 1.2 What is Forest Management?

As with many terms in the scientific literature ‘forest management’ does not have an universally accepted definition. Forest management can mean different things in different contexts and in different fields of research. We can divide these into two categories of use that reflect different scales and capture complementary aspects of human control over forests. The first is at the landscape to global scale and deals with the control of where forests are. The second context is at the stand to forest scale and deals with the control of forest attributes such as species composition, structure, and function. Both these contextual meanings are useful and describe activities that influence the services provided by forests and affect the earth’s climate. They are described further below.

### 1.2.1 Management Decisions About where Forest Should Be

For millennia humans have been changing the pattern of forest on the landscape ([Perlin, 2005](#); [Sharpe et al., 1976](#)). Humans have cleared land for agriculture, harvested forests for fuel and timber, and altered fire regimes.

‘Forest management’ is used in some contexts to describe human decisions and actions that change the pattern of forest on the landscape. This use of the term forest management occurs in the conservation, policy, remote sensing, and climate change literature, although not consistently. This use is related to, but not synonymous

with<sup>1</sup>, the concept of Land Use, Land Cover Change (LULCC) (also Land Use, Land-Use Change and Forestry (LULUCF) (Watson et al., 2000) or Land Use / Cover Change (LUCC) (Lambin and Geist, 2006)).

Land cover change describes the conversion of fragments of the landscape between different broad classes of land cover type (e.g. grassland, wetland, urban, forest, etc). Land-use change describes changes over time in human uses of land that may or may not change the general class of land cover, e.g. land-use change without land cover change: converting a native grassland to sheep grazing, land-use change with land cover change: converting a native grassland to crop production (Pongratz et al., 2018).

Forest management may include both land cover and / or land-use change. When ‘forest management’ is used to describe changes in the pattern of forest this is an example of land cover change. Forest management as land-use change is discussed in the next section (1.2.2).

Forest management activities related to land cover change include reforestation, afforestation, forest preservation, and conservation. Reforestation and afforestation are management activities that necessarily change land cover, to forest from something other than forest, and may change land use, as when pastureland is replaced with forest.

Forest preservation is an interesting special case where avoiding land cover change

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<sup>1</sup>Some who use the term LU(L)CC think ‘management’ occurs below the level of land use consisting of the activities used to implement a given land use (Lambin and Geist, 2006). By this logic forestry is an example of land use while silviculture is an example of forest management.

is often part of the management goal. This may be accomplished by preventing incompatible land uses. Some human interventions may still take place, e.g. invasive species removal or fire control, but these activities are aimed at maintaining the land cover in a forested state rather than changing it. Thus, forest preservation is a type of forest management that aims to maintain some existing valued set of environmental services. These services may simply be existence value.

Deforestation is not considered forest management by most authors, who limit the term to describe a class of land cover change ([Birdsey and Pan, 2015](#)). Deforestation describes more-or-less permanent forest losses. For some ‘forest management’ connotes some level of sustainability in its practice, so that deforestation seems like an incompatible outcome. Therefore, when linked to management deforestation is often qualified as *unsustainable* forest management. ‘Sustainable forests management’ is the clarifying term which has been adopted by the FAO and other organizations ([MacDicken et al., 2016](#)).

### State of the Research

LULCC has become an organizing principle in modern ESMs as a way to represent changes to the earth surface over historical time and for projected futures. A standardized data set of surface cover and transitions was developed starting with CMIP5<sup>2</sup> ([Hurtt et al., 2011](#)). This provides ESM researchers with detailed land cover

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<sup>2</sup>The Coupled Model Intercomparison Project (CMIP) is an international program that coordinates global climate modeling efforts. There have been multiple phases of this project since 1995, with CMIP6 being the latest iteration ([Eyring et al., 2016](#)).

data to feed into models.

In most ESMs the terrestrial surface is represented by different surface types, e.g. ice, urban, and vegetation. Vegetation is further divided into Plant Functional Types (PFTs, see Section 1.4.4) (Bonan et al., 2002). The spatial pattern of PFTs may be prescribed or dynamic depending on the model. By running simulations with the land surface data mapped to corresponding surface types and PFTs the influence of LULCC on biogeochemistry and biophysics can be examined.

There are a multitude of papers exploring the influence of land cover on climate using observational and modeling approaches. The earth system modeling research in this area is robust and very active. For forests deforestation and reforestation effects have been studied both for historical (Lejeune et al., 2017) and the potential future using different CMIP scenarios with very different land cover change trajectories (Moss et al., 2010).

However, the results of these studies rely on the representations of the land cover types in the models, which are limited. Most models only have a handful of PFTs to represent the diversity of forest types found in nature. The next section describes how these models do not capture many aspects of management. Experiments have shown that models capture only some of the climate changes observed with changes in forested status. Additionally there is high variability in model results (Lejeune et al., 2017). It is possible that that by representing more fully the heterogeneity that exists within forests that we will be able to better capture the aggregate behavior of forests in ESMs.

## 1.2.2 Management Decisions that Control the Structure and Function of Forests

In other contexts, ‘forest management’ is used to describe the decision making about techniques and practices used to change the structure and functions of forests in order to achieve certain desired benefits. In other words, forest management is often synonymous with the concept of forestry<sup>3</sup>. Such management occurs at a finer spatial scale than that described in the previous section, from the individual tree up to the stand and forest. Management activities at this scale (forest and non-forest) are pervasive affecting about half of the land surface of earth (42-58%) (Luyssaert et al., 2014).

It is important to understand how this sense of forest management relates to other terminology in the literature. From a LULCC perspective altering the structure and function of existing forest is a form of land-use change. However, not all users use LULCC terminology consistently. Some authors have tried to clarify things by separating land-use change further. They term land-use changes that change land-use type ‘land-use *conversions*’. land-use activities within a given land-use type they call ‘land management’ or ‘land management change’ (LMC) (Luyssaert et al., 2014; Pongratz et al., 2018). Using this scheme land-use conversions to and from forest aligns with the meaning of forest management (“where” sense) in the previous

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<sup>3</sup>It should be noted however that use is highly variable with some using forest management to refer only to the planning side of forestry. To foresters themselves forest management may mean business operations, monitoring, and regulation (Sharpe et al., 1976). Others use it exclusively for the physical practices of forestry such as site preparation, planting, fertilization, harvest, etc., i.e. silviculture (Lambin and Geist, 2006).

section. This definition of land management is consistent with the silviculture sense of forest management<sup>4</sup>.

Other groups have developed different ways of classifying these activities that are relevant to the environmental services that are prioritized. [Becknell et al. \(2015\)](#) provide a classification of forest management types (functional types) based on the environmental services they yield.

[Duncker et al. \(2012\)](#) developed a classification system that organizes management schemes along a spectrum of intervention intensity with detailed associated silvicultural practices. Their system is of interest because it ties specific operational forestry activities to environmental services via decisions linked to changes in ecosystem structure and functions.

## State of the Research

Forest management activities at this scale are not well represented in current earth system models. There are multiple reasons for this that include:

- Scale issues: Silviculture activities occur at a scale well below that of a grid cell, the fundamental spatial scale of ESMs.
- Model Dependencies: Representing management activities in a model requires more fundamental processes. For example, you cannot model selective har-

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<sup>4</sup>A subtlety of this perspective is that forest is a land cover type while forestry is a land-use type. As a land-use type forestry can have land management that comes without land cover conversions (fertilization, thinning, etc.) but can also have land cover conversions, albeit temporary, with clear cutting ([Pongratz et al., 2018](#)).

vesting of trees without a model that represents the size structure of trees in a forest.

- Lack of spatial information: We have a much less detailed understanding of where land-use practices occur than we have of land cover.
- Lack of process understanding.

[Pongratz et al. \(2018\)](#) provides a detailed discussion of these issues.

The deficiency of models in this area has been recognized by several groups with calls to incorporate further aspects of management into modeling. Using flux tower and remote sensing data [Luyssaert et al. \(2014\)](#) found that changes in land use can cause changes in surface temperature that are similar to those caused by changes between land cover types. This stresses the need to represent these processes, including forest management, in climate models. [Becknell et al. \(2015\)](#) suggest that management at the landscape scale could be represented in models as ‘management functional types’. [Pongratz et al. \(2018\)](#) recently published a detailed roadmap of steps needed to represent several globally important land management practices.

In ESMs there are a number of barriers to exploring the importance of forest management. Generally, ESMs do not distinguish natural from intensively managed forest plantations. Areas of natural and managed forest in the real world are represented by the same PFTs. The limited number of PFTs also make it impossible to assess the impact of climate on commercially important tree species in more than an approximate manner. Harvest rotations, which occur below the resolution of a grid

cell, are generally not represented in ESMs. I have only identified two papers that implement a harvest rotation using a modified version of the ORCHIDEE model<sup>5</sup> (Li et al., 2018; Yue et al., 2018) and a third using LPJ-GUESS<sup>6</sup> (Lindeskog et al., 2021).

### 1.2.3 Forest Management Summary

Definitions of ‘forest management’ in the scientific literature vary but fall into two main categories used to describe:

- Control of the *large-scale* patterns of forest distribution across the globe (*where*).
- Control of forest composition, attributes, and flow of environmental services at the *small-scale* (*what*).

I consider these different definitions valid, useful, and complementary. They describe closely related concepts that together make up a nested hierarchy. For example: A country might *manage its forests nationally* by maintaining a network of national forest lands, while each forest in the network is *managed at the forest level* to provide a unique mix of recreation, wood production, and biodiversity services. I will use a broad definition that encompasses both of these uses described above:

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<sup>5</sup>ORCHIDEE (Organizing Carbon and Hydrology In Dynamic EcosystEms) is a Dynamic Global Vegetation Model (DGVM) that is part of the IPSL ESM. The variant ORCHIDEE-MICT has a secondary forest cohort that was used to implement harvest rotations.

<sup>6</sup>LPJ-GUESS (Lund-Potsdam-Jena General Ecosystem Simulator) is a DGVM that is part of the EC-EARTH ESM.

*Forest management is the control and manipulation of forest ecosystems by humans to achieve a desired set of environmental services.*

Within this definition the two levels of forest management I have described, which I will term the ‘large’ or ‘where’ and ‘small’ or ‘what’ senses, remain useful. The distinction between these two levels of forest management aligns with distinctions in the way models represent the world.

All the forest management activities described above are climate relevant but they are not equally understood. Management at larger scales has been explored in ESMs through integration of LULCC concepts of land cover. For historic and technical reasons management activities occurring at finer scales are largely unexplored within the ESM literature.

### **1.3 Climate Mitigation Approaches that Utilize Forest**

Given the many ways they influence the climate it is not surprising that forests play a significant role in many proposed approaches to mitigate anthropogenic climate change. Analysis of the national commitments in the Paris Accords of 2015 by [Grassi et al. \(2017\)](#) indicate that approximately 25% of the emissions reductions would come from forest related mitigation. Climate mitigation approaches that utilize forests can

be classified into four categories: forest preservation, afforestation / reforestation, carbon storage, and bioenergy approaches ([Canadell and Raupach, 2008](#)).

While the importance of forests in global carbon sequestration and storage is well appreciated, mitigation using forests is actually rather poorly understood. A number of mitigation approaches have been proposed. The expected climate benefits from these approaches are based on a number of assumptions. It is often taken for granted that planting trees always has a cooling effect on climate. However, research indicates the interaction of the forest properties makes the climate benefit of forests context dependent ([Bala et al., 2007](#); [Bonan, 2008](#); [Jackson et al., 2008](#)). The uncertainties surrounding this issue must be constrained in order to develop effective climate mitigation strategies ([Bonan, 2008](#)).

The appropriate mitigation strategies for forests critically depend on whether they remain carbon sinks into the future ([Bellassen and Luyssaert, 2014](#)). If current forest management practices are responsible for part of the forest sink the continuation of these practices may be able to maintain or enhance the sink. However, the influence of management on the carbon sink is not well known. [Birdsey and Pan \(2015\)](#) conclude that forest management (in the broad sense) may account for 29% of the terrestrial carbon sink. However, they admit that it is not fully possible to separate management influences from other factors that also drive the sink such as disturbance, atmospheric nitrogen deposition, and fertilization of vegetation growth by increasing atmospheric CO<sub>2</sub>.

Modeling approaches provide an opportunity to address this uncertainty ([Bonan](#)

and Doney, 2018). Stocks and fluxes can be known precisely in a model setting. Additionally, ESMs are uniquely able to integrate the potentially counterbalancing biogeochemical and biophysical effects in forest.

### 1.3.1 Forest Preservation

Forest preservation mitigation aims to decrease the rate of atmospheric carbon dioxide growth by decreasing land cover change carbon fluxes, estimated to be  $\sim 1$  Pg / year (Ciais et al., 2013; van der Werf et al., 2009). In addition to maintaining forest stocks preservation maintains the sinks associated with any growing forest within the area protected.

Historic deforestation has decreased global forest (number of trees) by 46% (Crowther et al., 2015). In the northern hemisphere deforestation on balance has stopped and has reversed in some areas (Smith et al., 2014). Deforestation remains a major issue in the tropics (Pan et al., 2011). However, the trend is uncertain with some studies showing a decreasing rate of deforestation in the tropics (MacDicken et al., 2016) and others showing it increasing (Pan et al., 2011).

### 1.3.2 Afforestation and Reforestation

Afforestation and reforestation<sup>7</sup> (hereafter reforestation) are a component of almost every comprehensive mitigation strategy proposed (Moss et al., 2010). Historical losses from LULCC are estimated to be approximately 180 PgC since 1750, mainly from deforestation (Ciais et al., 2013). The implication is that a recovery of the same magnitude is possible with reforestation, but the reality is potentially more complicated.

Depending on where it occurs reforestation can either mitigate or exacerbate climate warming. The climate impact of reforestation depends on a combination of carbon sequestration, latitudinally variable radiative and water cycle effects, and the vegetation it replaces. Expansion of forest area is generally thought to have a cooling effect on climate in the tropics, and to a lesser degree in the temperate zone, while it has a net warming effect in the boreal forest (Arora and Montenegro, 2011; Bonan, 2008; Canadell and Raupach, 2008; Jackson et al., 2008).

Reforestation in areas which were historically peatlands can lead to large losses of soil carbon to the atmosphere, far larger than any gains made from the forest growth (Leifeld and Menichetti, 2018). Reforesting previously cultivated lands, on the other hand, increases soil carbon stocks as well as above ground stocks (Nave et al., 2018).

The impact of reforestation also depends on the management of these new forests. Species selection and harvest can change the sign of a forest's impact on climate.

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<sup>7</sup>Both afforestation and reforestation are the establishment of new forest. The distinction being that reforestation is planting of trees where deforestation has occurred in the recent past and afforestation is the establishment of forest where it has not been present in historic time.

The later 20th century saw forest expansion in the midlatitudes of North America and Europe (Hurt et al., 2002). A study showed that while the conversion of agricultural land to forest in Europe resulted in a large carbon sink the accompanying decrease in albedo caused by the shift to a managed evergreen forest system more than counteracted the climate benefits, resulting in a net warming effect (Naudts et al., 2016).

In the managed boreal forest of the Scandinavia allowing early successional regrowth of native deciduous trees following timber harvest, something normally prevented by local management practices, is predicted to have a local and global cooling effect though decreased albedo (Bright et al., 2014). Harvest of timber from forests may increase carbon sequestration rates by keeping more of the forested landscape in a younger fast growing state (Paquette and Messier, 2010). However, these increases will have little climate benefit if the wood products generated are short lived.

There is also a longstanding concern among researchers that the benefits of reforestation could be short-lived (Schroeder and Ladd, 1991) or that any gains could subsequently be lost (Canadell and Raupach, 2008). Recovering forests are a carbon sink but the strength of the sink may decrease as forests mature and approach a quasi-equilibrium state. Fluxes of carbon from forest into soil, the major store of terrestrial carbon, may equilibrate on a different time scale (van Groenigen et al., 2017). Increased atmospheric carbon dioxide has a fertilizing effect on plants (Zhu et al., 2016), but the future of this effect is made complicated by the potential interacting effects of nutrient limitation (Kolby Smith et al., 2015) and acclimation to elevated CO<sub>2</sub> (Rogers and Ellsworth, 2002). These factors combine to make the

future of the forest carbon sink very uncertain. The mitigation approaches that will be effective will be different depending on the fate of the carbon sink (Bellassen and Luysaert, 2014). Carbon sequestered by reforestation is also vulnerable to subsequent loss in natural or human induced disturbances such as windthrow, fire, or insect outbreaks, some of which may become more common with climate change (Canadell and Raupach, 2008; Williams et al., 2016).

### 1.3.3 Increased Carbon Storage/Density

While reforestation increases carbon sequestration and other climate services by increasing forest area an alternative approach is increasing the density of carbon within forests (Canadell and Raupach, 2008). There are a number of approaches that may be employed to achieve this goal. Decreasing disturbances or increasing recovery following disturbance, i.e. through planting of trees, would increase average biomass density. Relieving limitations can accelerate a forest's growth to climax and increasing its maximum biomass potential (e.g. fertilization and irrigation). Moving to longer rotations could increase the average biomass of forests (Nabuurs et al., 2007; Smith et al., 2014).

In other words, the modeling of carbon density mitigation is a matter of modeling the standard silvicultural practices of modern forestry. Some models include nitrogen fertilization and irrigation but in the CLM (Section 1.4.3) these management practices can only be applied to managed crops, not forests (Lawrence et al., 2018; Pongratz et al., 2018). As will be discussed later, harvest rotations are not currently

represented in most models.

### 1.3.4 Mitigation Summary

Mitigation is the application of management to control the climate services of forests in order to reduce anthropogenic climate change. Understanding the impact of mitigation through forest preservation and reforestation is possible to some degree with current earth system models since they can be represented using land cover conversion. However, if reforestation uses modern silviculture techniques to accelerate growth or to harvest forest products ESMS will not capture any differences from an unmanaged state. Furthermore, managing forests for bioenergy or increased carbon storage is problematic to model since representations of the interventions used to achieve these ends are largely not present in ESMS.

In short, the current mitigation research has dealt mainly with the ‘where’ aspect of forest management and not the ‘what’ aspect. Most studies performed in ESMS have looked exclusively at bioenergy through the lens of LCC using the limited set of existing PFTs in these models. Few have examined the realistic effect on climate of land-use changes.

Even with the skepticism surrounding bioenergy and BECCS (bioenergy with carbon capture and storage) it is important to get this right. It will be very difficult to achieve the Paris targets (well under 2.0°C with a goal of 1.5°C max temperature increase) without some amount of bioenergy and BECCS (Fuss et al., 2014; van Vuuren et al., 2018). Improving the representation of specific management practices such

as planting, rotations, and fertilization along with species important to mitigation strategies is an opportunity to greatly improve our understanding of the tradeoffs associated with them.

## **1.4 The Community Earth System Model and the Community Land Model**

### **1.4.1 Overview**

The Community Earth System Model (CESM) is a mature, influential, and open-source earth system model developed by the National Center for Atmospheric Research (NCAR) that I used to examine forest management in this dissertation. The CESM is a hierarchical software system that attempts to divide the complexity earth system into a manageable form. In the sections above several issues related to how forest management is represented in the CESM/CLM are mentioned. Here I give a brief overview and summary of the model to help contextualize these issues.

### **1.4.2 Component Model**

The CESM simulates the earth by dividing its parts and processes into a series of components. These include atmosphere, ocean, land, river, sea and land ice, and in CLM 5, wave components. When simulations are performed the components are coordinated by a central coupler component.

This component model has multiple advantages. First, it simplifies the ongoing development and maintenance of the software code. The different components communicate with the coupler using a standard interface. This means that changes in one component will not require other components to be modified. Second, the components divide the earth system into parts that align with conceptual and disciplinary divisions. Earth system scientists often divide earth processes into ‘spheres’, conceptual groupings of related physical elements and processes (e.g. atmosphere, cryosphere, biosphere) (Bonan, 2015). The component model similarly isolates simulated states and processes. Meteorologists and atmospheric scientists can work within the atmosphere component without needing to concern themselves with the particulars of how the sea ice component works. Third, components allow modularity and efficiency. The settings of and resolutions of an individual component do not matter to the other components. The coupler handles the translation of outputs and inputs between components. Simulations can be specified with different versions or implementations of individual components or with specific components turned off. This can dramatically decrease the computer overhead needed to run a simulation. Several international modeling groups have started their own modeling efforts by taking the CESM and replacing one or more of its components with their own, e.g. BNU-ESM (Ji et al., 2014) and NorESM (Bentsen et al., 2013).

### 1.4.3 Terrestrial Component Representation

The land model component of the CESM is the Community Land Model (CLM)<sup>8</sup>. The CLM represents the terrestrial surface as a spatial grid. Land cover heterogeneity within in grid cells is represented with a non-spatial sub-grid hierarchy (Figure 1.1). Land cover is divided into glacier, lake, urban, natural vegetation, and crop surface types. All areas of a given type within in a grid cell is managed in what is called a ‘land unit’. Each land unit has a fractional coverage for each grid cell but the spatial arrangement of these land units or their components is not specified. Each land unit has additional structure according to its needs (Lawrence et al., 2018). Only the vegetated land units will be further discussed.

The natural vegetated land unit is divided into fractions of bare ground and plant functional types (PFTs). These share a single multi-layer soil column. PFTs are discussed further in the next section (1.4.4).

The crop land unit is structurally similar to the natural vegetated land unit but has a number of crop PFTs (CFTs) in irrigated and unirrigated varieties and a number of unique properties and behaviors. Each CFT has its own soil column and can be fertilized or irrigated. There is also some unique surface roughness physics which will not be further discussed.

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<sup>8</sup>The CLM and another NCAR model Noah MP are currently being integrated into new combined model called the Community Terrestrial Systems Model (CTSM) (Land Model Working Group Meeting, Boulder Colorado, February 2019).

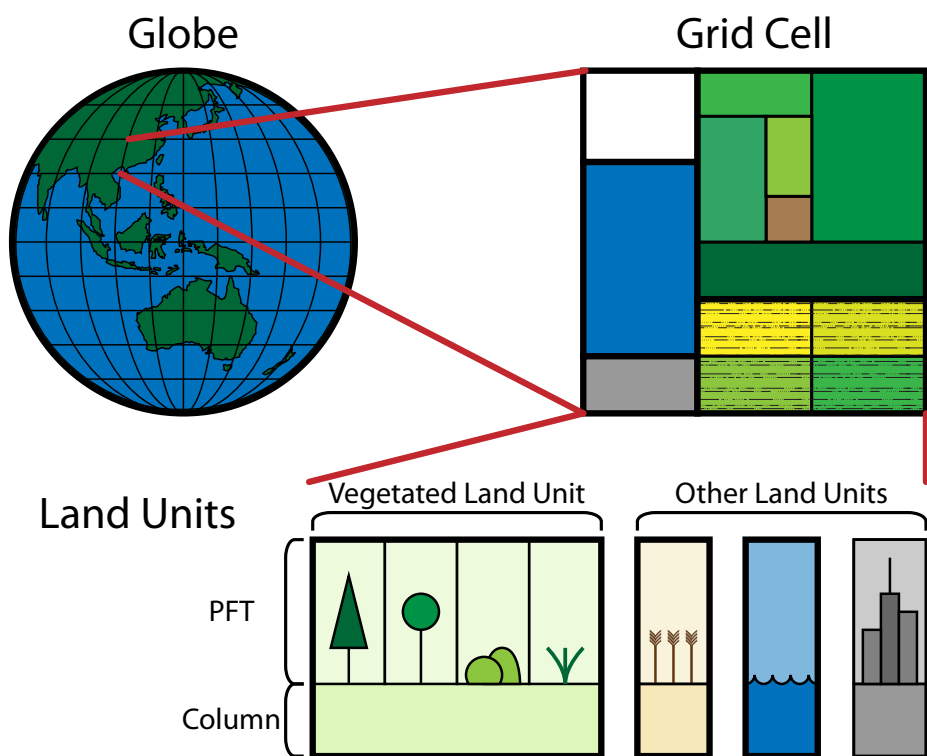


Figure 1.1: The CLM Subgrid Structure

### 1.4.4 Plant Functional Types

Vegetation is modeled in the CLM using functions in the code that represent various aspects of plant physiology, biophysics, and biogeochemistry. Individual vegetation types are specified through unique parameter sets supplied to these functions. These parameter sets define the model’s plant functional types (Lawrence et al., 2018).

Plant function types were adopted out of necessity when the carbon cycle was added to NCAR’s Land Surface Model (LSM) to create the first version of the Community

Land Model (Bonan et al., 2002). Prior to this the LSM model represented vegetation as various biomes. Once the carbon cycle was introduced it was necessary to simulate photosynthesis, a process that differs among the plants that make up biomes. Simulating the vast diversity of plant species on earth was beyond impractical. The solution that became popular in the 1990s was the plant functional type (Woodward and Cramer, 1996). Plant functional types represent collections of species that share significant structural and functional similarities. This simplifying assumption reduces the number of vegetation types that need to be parameterized to represent global vegetation. Different models use different numbers of PFTs, approximately 5-16 (Poulter et al., 2015). The CLM uses 16 (Lawrence et al., 2018). The use of these small numbers of PFTs has allowed ESMs to capture the major characteristics of the global carbon cycle (Collier et al., 2018).

All plant functional types represent the basic structure and physiological processes of plants. They have carbon pools that represent the major plant tissues that grow based on incoming NPP and allocation rules. Water and nutrient uptake by roots from a multi-layer soil are simulated. Photosynthesis is simulated using a single layer big leaf representation. Photosynthesis responds to light, atmospheric carbon dioxide, and nitrogen availability. In the newest version, water moves from the soil to leaves according to a resistor-based plant hydrologic model.

While useful in many contexts PFTs also make the assumption that the differences between species within a PFT are not of great, or at least relevant, importance. This assumption does not always hold. For some species it may be worth it to develop a species-specific representation, either because they are economically or

environmentally important or because creating such a representation allows new questions to be explored.

Crops are a good example. In earlier versions of the CLM crops areas were represented by grasses. As the model matured and better land surface data became available a crop model was integrated into the CLM and crop plant functional types were developed to use with it in version 4.5 (Levis et al., 2012; Oleson et al., 2013). The initial set of CFTs has grown in version 5 with CFTs representing several crop species or crop species groups with more under development. Crops can also be irrigated and fertilized (nitrogen only) (Lawrence et al., 2018).

Despite far greater diversity trees globally are represented by eight PFTs (and 3 shrubs) in the CLM (Lawrence et al., 2018). While these PFTs capture the general growth patterns of broad forest types their predictive value for specific species is limited. What if any tree species might deserve their own species representation? Loblolly pine (*Pinus taeda*) meets many qualifications. It is an economically important species representing a large area (~13 million hectares) in the Southeastern U.S. (Chen et al., 2017; Schultz, 1997). It is fast growing and may play a potential role in climate change mitigation (Kline and Coleman, 2010; Oswalt et al., 2014).

### 1.4.5 Forest Management in the CLM

The only management process that is represented *within* grid cells is wood harvest and it is highly simplified. The harvest data currently used to drive the model contains information about how much wood comes from forests of different age and

disturbance classes but currently this data is not used because the model does not represent forest age or history (Lawrence et al., 2018). Unlike crops, forests can be neither fertilized nor irrigated in the model.

#### 1.4.6 How are Distribution of Trees Determined?

In the standard CLM vegetation implementation the location of trees (PFTs) over space and time is prescribed. The prescribed areas are specified from input files (Lawrence et al., 2018) which are based on the Land-Use Harmonization database (LUH1/LUH2) (Hurtt et al., 2011, 2020).

Within the prescribed areas PFTs grow in response to the model meteorology, water, and nutrients obtained from the soil column, for which they compete with the other PFTs. In this way PFTs can impact the growth of other PFTs but do not change the area they occupy within the grid cell.

In previous versions of the CLM there was an extension that allow the vegetation coverage to be determined dynamically. Rather than specifying the areas PFTs occupy, PFTs are seeded and allowed to compete with each other for light. Competition and environmental limitations for the PFTs results in a dynamic pattern of vegetation coverage that changes with climate. This CLM-DGVM version had several limitations that prevented it from gaining widescale use and it is no longer being developed or supported (Lawrence et al., 2018).

In CLM 5 there a new vegetation demographic model called FATES, formerly CLM-

ED ([Fisher et al., 2015](#)). It was recently announced that the CLM will adopt FATES as the standard vegetation model in future versions (Dr. David Lawrence NCAR, CESM Workshop June 2019). FATES is discussed further in the next section.

### 1.4.7 The FATES Demographic Vegetation Model

In an effort to address some of the limitations of the ‘big leaf’ approach to vegetation used in the CLM an alternative vegetation sub-model has been developed. Termed the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) this model interfaces with a host land model, either CLM for CESM and NorESM or ELM for the related E3SM model, replacing their default vegetation representation. FATES is based on the popular Ecosystem Demography Model or ED ([Moorcroft et al., 2001](#)). While it shares the plant functional type concept with the CLM FATES otherwise represents vegetation very differently.

FATES attempts to capture a greater degree of the heterogeneity within forests by approximating the variation in tree age and size without simulating every tree. Within a grid cell the vegetated fraction is divided into patches but unlike in the CLM patches do not contain single PFTs. Instead each patch represents a segment of forest that shares a common age or alternatively disturbance history. Each patch can contain multiple PFTs. Within a patch there can also be multiple size classes, or cohorts, of each PFT ([Fisher et al., 2018](#)).

The areas occupied by each PFT are not fixed over time. As vegetation grows within a patch PFTs compete with each other for light and water and through growth and

mortality can change their fraction of the vegetated grid cell. PFTs can also change their geographic range in response to changing climate. Intraspecific competition (between PFTs) likewise occurs between cohorts. When disturbances like mortality or fire occur, new patches are created to represent the disturbed areas. To preserve computational resources, patches or cohorts that become substantially similar are merged.

FATES also represents more of a forest stand's structural complexity. The canopy has distinct overstory and understory layers. Cohorts explicitly represent the diameter, height, and spacing density of the trees they model. In addition to adding increased realism this can make comparison to observations more straightforward. Currently CLM-FATES does not model nutrient limitation but nitrogen and phosphorous pools have recently been added to the model and testing of nutrient limitation behavior is underway in ELM-FATES (Dr. Ryan Knox LBNL, FATES teleconferences).

### **FATES Selective Logging Module**

FATES also has a selective logging module that allows for the specification of harvest events during a simulation ([Huang et al., 2019](#)). The module provides a method for specifying the time of harvest events, the size of trees to harvest, and damage caused by logging infrastructure. It handles the transfer of wood and harvest slash to appropriate model pools.

As with many areas of FATES development this module was designed for the tropics. Its mode of harvest is consistent with the practices of that region and less so with the

practices of the temperate forests. It doesn't currently include rotational harvesting or thinning. It will be necessary to implement harvest rotations in FATES ourselves. Recently FATES has started to record the date since the last anthropogenic disturbance for each patch (Dr. Charlie Koven LBNL, FATES teleconferences). This should make processes such as rotations easier to implement in the model.

### 1.4.8 Simulating the Future of Southern Pine Forestry

CLM-FATES provides a great platform for examining the role of forests in the climate system but the selective logging module does not provide all the behaviors needed to simulate the managed pine systems of the Southeastern United States (see Section 2.3.3). To simulate a full management cycle for a loblolly pine plantation I need to be able specify the timing and density of planting, intermediate operations like competition control and thinning, as well as better control over the timing of wood harvests. Implementing these features is beyond just a simple modification of the logging module. It requires the development of a new module that more comprehensively represents vegetation management processes used around the globe.

In this dissertation I set out to develop a new more comprehensive management module for FATES, along with a loblolly pine plant functional type. Together these developments enabled me to perform simulations that were directly comparable to field data. Comparison to field data allowed me to validate the model's performance for growth, competition, and management behavior. Validating the accuracy of the model under present climate conditions is a necessary step prior to moving on to

simulations under projected future climate.

I first set out to answer the fundamental question of how climate change will affect managed forests in the future. Managed forests are dynamic, being shaped both by their environment and the interventions of managers. Therefore, I simultaneously asked how management would modulate and interact with climate effects to shape the forests of the future. Management practices have varied over history (Fox et al., 2007), and vary today by region, and with changes in managers' goals. Variability in management practices must be examined to see if it changes the effect of climate on forests. Additionally, I expect that managers will also respond to changes in climate, adjusting their practices in response to forest growth and mortality. In this work I attempted to anticipate how managers might react to changes in their forests and estimated the possible effect on the management cycle.

Answering these initial questions about how managed forests may change over the next century prepared me to look at the potential implications of these changes. Longer growing seasons and elevated CO<sub>2</sub> have the potential to increase loblolly productivity while temperature extremes and water stress could reduce yields. I asked how such changes to forests could drive changes in the area occupied by forest plantations in the region by the end of the century.

## Chapter 2

# Simulating Comprehensive Forest Management in FATES with the Vegetation Management Module

## 2.1 Abstract

An important challenge for the terrestrial component of Earth System Models is capturing the behavior of vegetation realistically. Vegetation has a strong influence on climate through both the carbon cycle and the surface energy balance. In an attempt to capture vegetation more accurately some ESMs have started using demographic vegetative models. These vegetation models use simulated competition to dictate the composition, structure, and distribution of vegetation on the land surface. However, competition is a complex process and it can be difficult to validate in these models. We used data from several forest manipulation experiments conducted in the managed forests of the Southeastern United States to assess the ability of the Functionally Assembled Terrestrial Ecosystem Simulator (FATES), a Vegetation Demography Model used with the Community Land Model (CLM) version 5, to accurately simulate competition. To capture the growth and development of Southeastern U.S. managed forest stands we found that the behaviors of simulated trees, stand behaviors, and human manipulations of these stands all had to be taken into account. In the process we developed two complementary modifications to the FATES model. The first is a new Plant Functional Type (PFT) designed to capture the behavior of loblolly pine (*Pinus taeda*). This new loblolly representation increased the accuracy of simulations based on multiple metrics. The second modification is the Vegetation Management Module that adds the ability to simulate a broad set of human forest management activities within FATES. This module was used to simulate stands where mid-rotation stand thinning was performed. This

work showed that we were able realistically reproduce the demographic transitions that occur during thinning. Together these model extensions demonstrate the ability to simulate the most ubiquitous managed forest system in North America with reasonable realism, opening up a new class of forests management experiments within CLM-FATES.

## 2.2 Introduction

Earth System Models (ESMs) have historically used highly simplified representations of terrestrial vegetation in their land surface components. When ESMs began to represent vegetation they did so first at the biome level and later with plant functional types (PFTs), both of which abstracted whole ecosystems or species assemblages respectively using so called big-leaf representations ([Bonan et al., 2002](#)). While this approach has been very useful, big-leaf representation have their limitations. For example, big-leaf models are unable to represent some competitive processes and do not capture the structural complexities of ecosystems because all individuals within a functional type, regardless of age and size, are represented as a single unit.

Vegetation demographic models (VDMs) have the potential to overcome some of these limitations ([Fisher et al., 2018](#)). These models represent an intermediate position between big-leaf and individual based models. They continue to use PFTs, but rather than representing them as monolithic units they model PFTs with multiple ‘cohorts’ that represent different size and age classes within a population. Since cohorts have different sizes competition for light can be explicitly resolved by modeling

a structured canopy. Also since competition is explicitly represented, these models hold the promise to represent the temporal evolution of forests through processes such as succession and disturbance. The ability of such models to capture the structural and demographic characteristics of vegetated ecosystems allows comparison to observations in a way that can assess the realism of model simulations in a manner not possible with big-leaf models. In particular, the Community Earth System Model (CESM), a widely used, open-source ESM, has adopted a vegetation demography model known as the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) ([Lawrence et al., 2019](#)).

Despite their many potential advantages there are also significant challenges to testing demographic models. Competition, while central to how these models work, is often not directly observed and needs to be inferred. It can be challenging to disentangle the effect of competition on growth and mortality from other factors. Forest manipulation experiments used in pine plantation forestry research provide controlled conditions that we can take advantage of for model comparison. Pine plantations are primarily single species and single aged and this homogeneity simplifies the competitive environment. Spacing trial experiments have been conducted that isolate the effect of tree density from all other variables, providing different levels of competition, in a manner that is ideal for model validation.

Here we use observations from experimental loblolly pine forests from across the Southeastern United States (SEUS) to evaluate the FATES model and improve it by developing a new module for simulating active management of vegetation. First, we examined the ability of the CLM-FATES model to capture intraspecific competition

under rigorously controlled conditions in a loblolly spacing trial. Second, we examine the ability of FATES to reproduce mid-rotation stand thinning, a common management activity that alters the competitive environment. We set out to answer four questions. 1. How well does FATES simulate single age stands of loblolly pine with its existing plant functional types? 2. Do we improve model accuracy by using loblolly specific model parameters and behaviors? 3. Can we simulate mid-rotation stand thinning practices in the model? 4. Can we capture the demographics of thinning accurately and does this affect simulated stand recovery after thinning?

## 2.3 Methods

### 2.3.1 Study System

The dominant form of pine cultivation in the SEUS is in pine plantations. This system's typical management cycle begins with site preparation followed by planting of genetically improved nursery grown seedlings in a regular spacing. Competition control or fertilization may follow depending on site conditions. Best practices recommend a least one stand thinning to remove the smaller slower growing, or damaged individuals (a so-called low thinning) around mid-rotation. The remaining trees are harvested by clear-cutting when they reach commercial size around 25-40 years. This regime can thus be characterized as a single age, single species, clear-cut rotation based system.

### 2.3.2 The FATES Model

In brief, the Functionally Assembled Terrestrial Ecosystem Simulator is a Vegetation Demography Model (VDM) descended from the ED model (Fisher et al., 2015; Moorcroft et al., 2001) designed as a modular replacement for the natural vegetation in Earth System Models (ESMs). Currently it can be used with the Community Land Model (CLM) version 5 (Lawrence et al., 2019), the land surface component of CESM2, or with the E3SM Land Model (ELM), the terrestrial model for E3SM version 1 (Golaz et al., 2019). The land surface model used in conjunction with FATES is termed the host land model and provides FATES with climatological forcings and handles the calculations of fluxes outside the domain of the FATES vegetation.

FATES conceptualizes vegetation within a grid cell as having a hierarchical structure. The grid cell is divided into patches that represent areas with a common time since disturbance. Within patches multiple Plant Functional Types (PFTs) may be present and for each PFT multiple cohorts are used to represent different size classes of the vegetation. Within patches, cohorts compete for light in a canopy scheme with two layers. Belowground competition, currently only for water, occurs across patches as they share a common soil column from the host land model.

FATES PFTs are parameterized with values that are largely observable and should in principle be parameterizable from the literature. Out of the box, the model provides twelve PFTs, six of them tree PFTs, parameterized from the TRY database (Kattge et al., 2011) to simulate global vegetation. The FATES model is described in greater detail elsewhere (Fisher et al., 2015).

Here we use FATES within the host land model CLM5 (modified CLM doi:10.5281/zenodo.7335082, modified FATES doi:10.5281/zenodo.7335554), hereafter called CLM-FATES.

### 2.3.3 The Vegetation Management Module

FATES has a selective logging module that allows for simulation of harvest of wood from forests (Huang et al., 2019). However, the module has some limitations both in what kind of activities it can perform and how simulations are run.

- Harvests occur from all woody PFTs (trees and shrubs). Harvesting from specific PFTs is not possible.
- The module only allows harvest from woody PFTS. Other forms of management induced mortalities, planting, and alterations to understory are not implemented.
- Logging events can be scheduled on a periodic basis or at one specific date. Events cannot be scheduled to occur at an arbitrary sequence of dates or when certain conditions are met.
- Wood is harvested from all patches and grid cells. Harvest cannot be targeted at specific locations or patches.
- Logging occurs as a fraction of plants present. Harvest cannot be specified by amount or goal, e.g. by a specific biomass removal.

- A minimum diameter at breast height (DBH) can be set but no other size controls are provided for harvest. This prevents simulation of management activities that target small or mid-sized trees.
- The only mode of harvest mortality is a bole harvest (harvest of the trunk wood).

In order to expand the range of management activities that can be simulated in FATES we developed the Vegetation Management (VM) Module. While used here to simulate forestry the module's tools can be used to alter any vegetation in ecosystems simulated by FATES. It provides backwards compatibility with the logging module.

## Overview

The VM module uses a hierarchical approach to simulate management. It implements low level routines that interface with the model structure to introduce plants and induce targeted mortality. Higher level routines use these to build abstractions of specific real world management operations, which can be initiated via an input file. In turn these operations can be combined in a sequence to simulate a management cycle.

## Management Operations

The VM module implements a number of behaviors that simulate real world management activities, which we term operations. Operations are the building blocks

that can be combined to simulate the stages of different forest management cycles. The scheduling of an operation at a place and time is an ‘event’, and these events can be prescribed via a driver file as described below.

Operations include generative events, such as planting, and mortality events such as understory removal, stand thinning (see section 2.3.3 below), and harvest. Several harvest routines have been implemented. These routines allow a fine level of control to specify the PFTs to be harvested, allowing size ranges with minimums and/or maximums, and allowing sizes to be specified by height as well as by DBH. Routines include methods that specify harvest amounts by mass as well by a fraction of plants. Like the logging module, the VM harvest routines perform bole harvests (which gives identical results to the logging module if appropriate settings are used). Alternative methods of harvest can be developed using flux profiles.

### **Flux Profiles**

When management induced mortality occurs, the VM module controls the partitioning of necromass to different model biomass pools through what we call flux profiles. For example, when removing competing understory vegetation all biomass components move to the appropriate soil and litter pools. On the other hand, when a tree harvest occurs the bole components (trunk sapwood and heartwood) are moved to the harvest pools while the foliage, branches, etc. (i.e. slash) are left on site and enter the litter pools. These different fates for necromass are represented as in-place and bole harvest flux profiles respectively.

## Events

Events for the logging module are specified using a set of values in the parameter file. Harvest events can be scheduled on a recurring basis or a single point in time. If recurring, all logging events will have the same settings and will occur simultaneously in all patches and grid cells within the simulations. While this has allowed for useful studies of logging impacts at point and regional scales where natural recruitment follows harvest, this does not lend itself to more complex forest management modalities and simulations where different events occur at different locations.

The VM module provides a different approach for scheduling of events. VM events can be scheduled prognostically using a human readable driver file. The event driver file is specified by two name list parameters that have been added to the CLM model, one notifying the model to look for a driver file, the second specifying the location of the file. Each event is specified by the date of occurrence, a location (either a latitude longitude pair, or everywhere) and an event specification. The event specification provides the management operation (see above) to occur along with operation specific parameters (settings). The event driver file can specify an arbitrary number of events occurring at different dates and locations within the simulation.

The event driver file is intended for use in point to regional scale studies where a specific series of events to simulate need to be specified manually. To meet this use case the file format is designed to be human readable. Work to allow more dynamic behavior at a global gridded level is ongoing and may be added in future versions.

Logging module events scheduled via the parameter file will occur without alteration.

Logging module and VM events can both be scheduled as long as only one event occurs for a given grid cell per timestep. This is provided primarily for backward compatibility since VM events can reproduce most logging module behaviors.

### **Disturbance**

While prognostic logging module events always target full patches, the VM module allows management activities to be targeted at a fraction of a patch, leading to patch splitting. This is an important prerequisite for being able to simulate management in cases where grid cells represent heterogeneous landscapes.

### **Thinning Operation Events**

Thinning is a management practice in which some trees are harvested with the goal of reducing competition induced mortality while improving the growth and form of the remaining individuals ([Sharpe et al., 1976](#)). Less desirable small trees and those with poor form may be removed in what is termed a low thinning (or thinning from below). The opposite extreme is where some of largest trees are removed in what may be called a high thinning (thinning from above).

Low thinning is the common approach used in SEUS pine forestry. In these forests thinning is conducted around the time of canopy closure, or when stocking exceeds 100 percent. The thinning specification may be to remove a fraction of trees or to thin until a goal stem density, stocking percent, or basal area (BA) is achieved.

We can place these thinning approaches on a continuum (Figure 2.1). We define one extreme as what we will call a perfect low thinning, where only the minimum number of the smallest trees are removed to achieve the goal density. Similarly a perfect high thinning only removes the largest trees. In the middle is what we will call a proportional thinning, where an equal fraction of all size classes are removed to achieve the final goal (row thinning may approximate this). High thinning is rare in our study region and will not be considered further.

In reality low thinnings are rarely ever ‘perfect’ because the spacing of trees must be balanced with the trees’ other qualities. For this reason some larger trees are often taken either because failing to do so would leave a clumpy stand structure, leave trees of poor form, or because of limitations imposed by equipment (not all trees are equally easy to remove without damaging others).

The FATES selective logging module can perform partial harvests and in principle could be used to simulate a thinning. However, as mentioned above the logging module can only specify trees to be harvested based on a minimum DBH. Therefore, the logging module can only simulate thinnings either where trees across all size classes are thinned (proportional thinning) or the larger trees are preferentially thinned (perfect high thinning). The logging module cannot simulate low thinnings. Additionally, all harvests with the logging module must be specified as a fraction of the existing stems.

We implemented improved thinning operations in the Vegetation Management Module. We implemented two of the idealized thinning methods described above: a

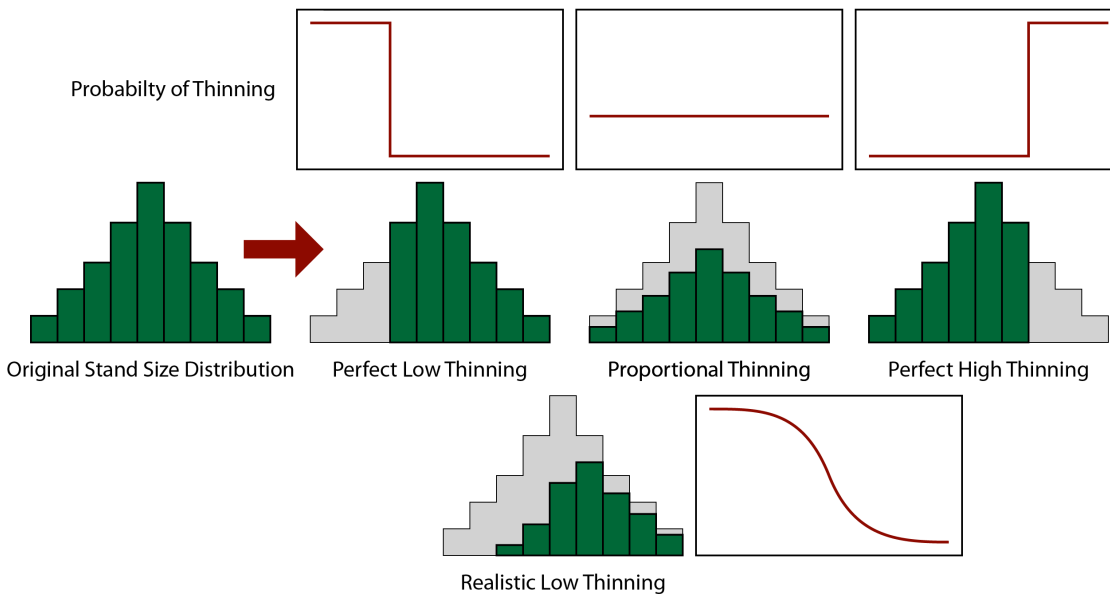


Figure 2.1: Thinning Types: An idealized representation of the continuum of thinning practices. For each thinning type the original tree size distribution is shown in gray and the trees that remain after thinning are shown in green. The probability of thinning by tree size is shown for each type as a red probability curve. Real world thinned stands similar to three of these thinning types are shown in Figure 2.2

proportional thinning and a perfect low thinning. Additionally, we developed a third method that mimics low thinning as it is actually performed in practice, which we call probabilistic low thinning. Thinning with all three methods can be specified as a fraction of all stems, or as a final stand stem density or basal area.

While there is notable variation, the pattern for most of the observed thinnings is that the majority of the smallest trees are removed while the fraction of the larger trees removed declines with increasing size. To model this behavior we developed an algorithm that applies a decreasing probability of thinning to cohorts of increasing size according to a logistic relationship fit from observations.

The probability of thinning is not strictly related to the size of a tree, rather it is related to the relative size of the tree within the size distribution of its stand. For example a tree of 15 cm DBH might be very likely to be thinned if it were the smallest tree in its stand but would be very unlikely to be thinned if it were the second largest. To build a relationship across stands with varied population characteristics we normalized our parameterization thinning plot inventories (section 2.3.5). We took the tree size inventory for the thinning year for each plot and subtracted the mean DBH from all values (mean-adjusted DBH). This centered each size distribution on zero, with each tree coded as thinned or unthinned. We also calculated the fraction of trees thinned for each plot. We then fit a logistic regression using R's `glm()` function to relate the probability of thinning to mean-adjusted DBH for each plot.

The logistic form fit by R's regression yield's two parameters, a exponent slope and intercept term. We rearrange the terms to give a form with parameters that are more intuitively useful. The slope is now a steepness parameter, which relates how quickly the probability of thinning decreases with size. The second parameter is now the logistic functions midpoint, the mean-centered DBH value where 50% of stems are thinned (Equation 2.1).

$$Probability\ of\ Thinning = \frac{1}{(1 + e^{-k(DBH_{trans} - DBH_0)})} \quad (2.1)$$

Where  $k$  is the steepness parameter,  $DBH_0$  is the midpoint parameter, and  $DBH_{trans}$  is the transformed diameter at breast height.

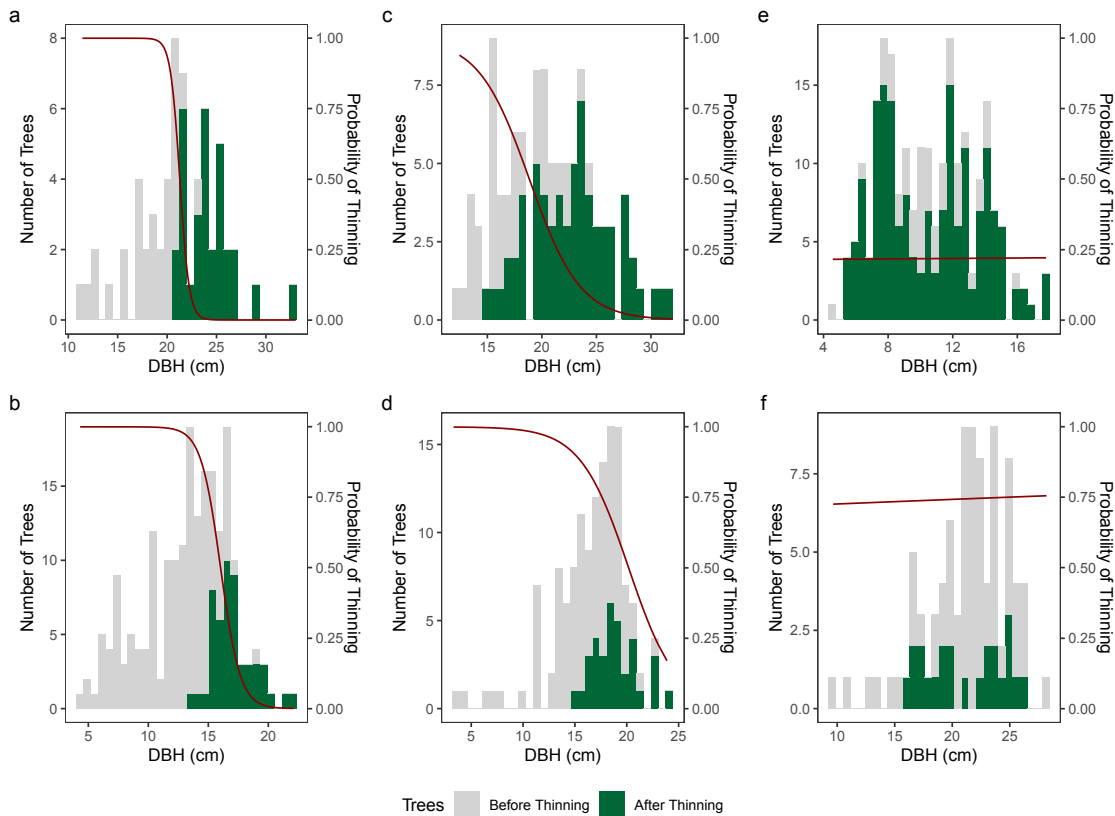


Figure 2.2: Real World Thinning Demography: Shown are histograms of tree diameters from forest plots that have undergone thinning. The trees prior to thinning are shown in gray and the trees that remain after thinning are show in green. The red line shows the logistic regression expressing the the probability of thinning at a given diameter. The panels illustrate real world examples of (a-b) near-perfect low thinning, (c-d) typical low thinning, and (e-f) proportional thinning.

We sought to identify patterns in these parameters across thinning events We found that the steepness parameter had a strong central tendency. The range of parameter values reflects variation in the parameterization plots. As the steepness value approaches zero the thinning probability converges on a proportional thinning (Figure 2.2e,f) while at very large negative values it approaches a perfect low thinning

(Figure 2.2a,b).

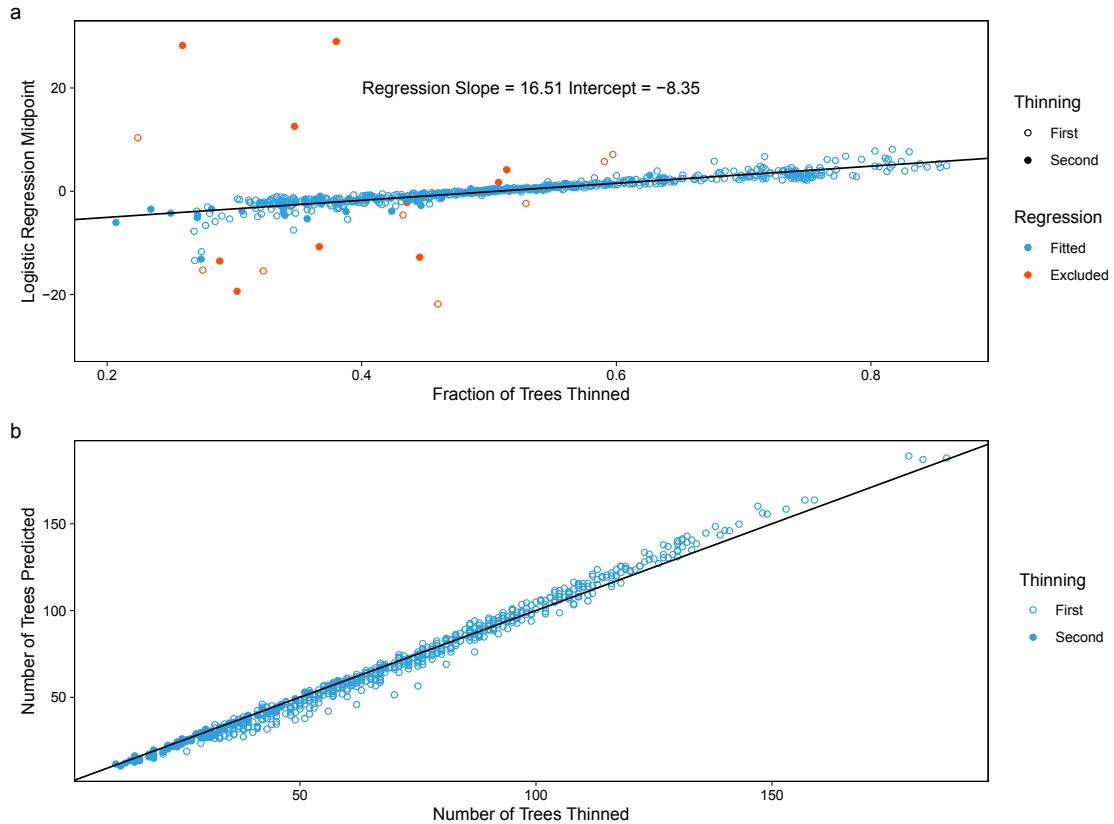


Figure 2.3: Fitting of Thinning Parameters: (a) The linear regression used to derive the equation to calculate the starting midpoint value for the probabilistic low thinning algorithm. (b) A comparison of the number of trees removed in field study thinnings versus the number of trees predicted using the probabilistic low thinning algorithm.

There was a strong relationship between the thinning fraction and the midpoint value (Figure 2.3a). This is consistent with the fact that as more trees are thinned the midpoint of the thinning probability curve will move to the right. We found that the majority of plots that deviated strongly from the linear trend had steepness

values close to zero, that is they were thinned proportionally. We excluded plots with steepnesses above -0.075.

For our thinning algorithm we chose to use a fixed value for the steepness parameter based on the mean across all parameterization plots and to derive only the midpoint value. Using the remaining thinning observations we fit a linear equation for the thinning algorithm to derive an initial midpoint value based on a specified thinning fraction (Figure 2.3a). Starting from this initial midpoint value estimate the algorithm solves for a midpoint value that will thin the stand precisely to the requested fraction of stems, stem density, or basal area. To confirm that a fixed steepness parameter would not unduly bias our results we used the revised function to predict the thinning probabilities of the original values. The use of a fixed value still allowed good prediction of the probability of thinning (Figure 2.3b).

### 2.3.4 Loblolly PFT Parameters and Model Modifications

All conifers of the temperate and boreal zone are represented by default in FATES by a single (extratropical needleleaf tree) PFT. We set out to see if we could improve the accuracy of simulations of loblolly stands by developing a specific loblolly PFT. To do this we obtained PFT trait parameters from the literature and estimated others from reserved observation data (described below). Several new allometric relationships and an alteration to the response of crown area to canopy closure were implemented in the code. Parameter estimates are described in the following sections and are summarized in Table 2.5.

## Wood Density

Jordan et al. (2008) report a whole wood core (across all ring ages) species range wide average wood density/specific gravity of 0.46. This value is compatible with other values reported in the recent literature (Jenkins et al., 2004; Jokela et al., 2004).

## Background Mortality

FATES's background mortality parameter attempts to approximate the remaining mortality not simulated by the model's explicit mortality processes. We adjusted this parameter by examining the slope of declining stem density in the observations prior to canopy closure. Data from the reserved spacing trial location (Table 2.1) was used. It was determined visually from crown area plots that no density at this location had closed its canopy prior to 10 years, so observations below this age were used. The number of stems for each planting density were normalized to the number of stems at the initial (year one) time point such that all curves started at a value of 1. A linear regression was performed on the normalized data across all densities (Figure 2.4). The resulting slope of the regression yields the background mortality rate through a reversal of sign. In fitting the regression the intercept was allowed to be free and the fitted value passes close to the expected value at the planting date of 1984.

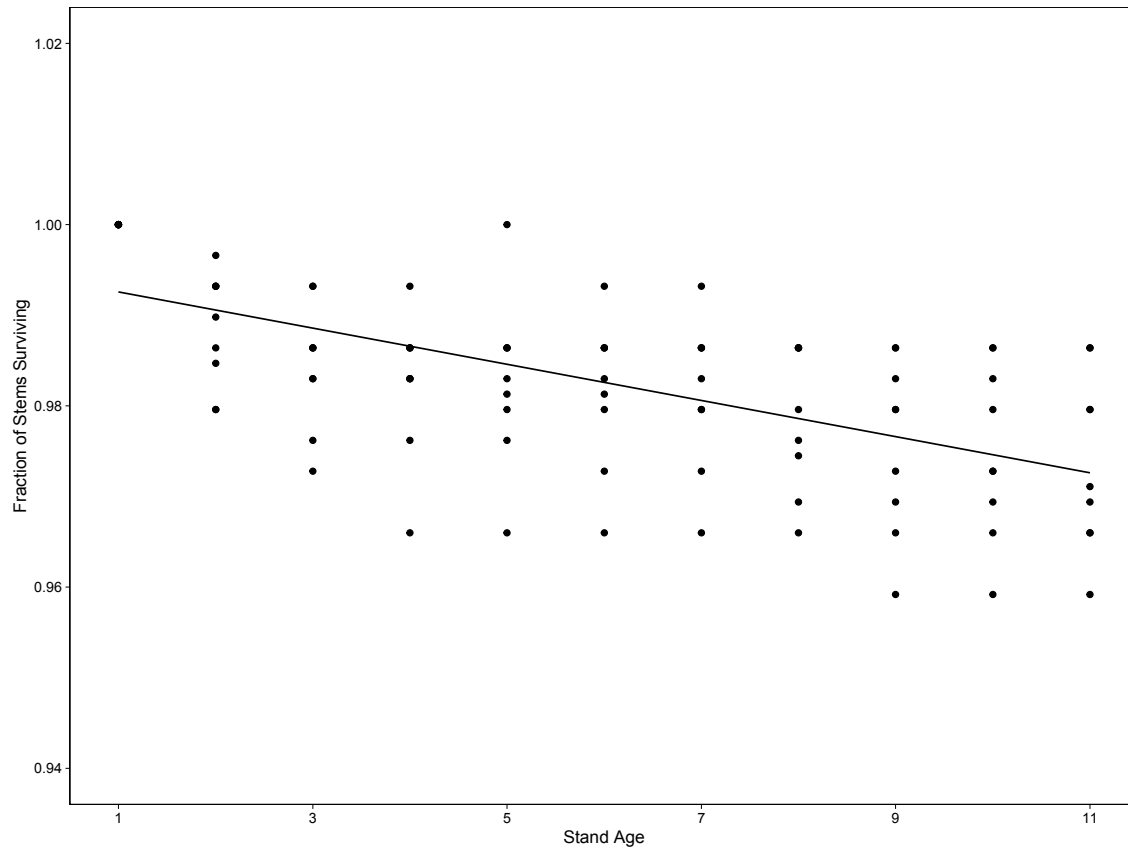


Figure 2.4: Background Mortality Fitting: The background mortality parameter was fit using a linear regression against fractional survival of trees prior to canopy closure.

### Photosynthesis Parameters

Values for  $V_{c_{\max 25\text{Top}}}$  (the maximum carboxylation rate of RuBisCO at 25°C at the top of the canopy), the activation energy of  $V_{c_{\max}}$ , and the activation energy of  $J_{\max}$  were obtained from Ellsworth et al. 2012 [Ellsworth et al. \(2012\)](#). FATES calculates  $J_{\max}$  from  $V_{c_{\max}}$  in the model code using a fixed  $J_{\max}:V_{c_{\max}}$  ratio of 1.67 based on [Medlyn et al. \(2002\)](#). The calculated value of  $121.91 \mu\text{mol m}^{-2} \text{s}^{-2}$  is higher than the values reported in [Ellsworth et al.](#) ( $100 \pm 2 \mu\text{mol m}^{-2} \text{s}^{-2}$  for new needles and  $109 \pm$

8  $\mu\text{mol m}^{-2} \text{s}^{-2}$  for overwintering old needles). The paper does not give deactivation energies for  $V_{c_{\max}}$  or  $J_{\max}$  and cites [Medlyn et al.](#) for the remaining parameters ([Ellsworth et al., 2012](#)). We followed [Medlyn et al.](#) in using a fixed deactivation of 200 kJ/mol for  $V_{c_{\max}}$  (all species) and for  $J_{\max}$  (the majority of tree species). The [Medlyn et al.](#) Farquhar formulation does not contain an entropy terms ( $\Delta S/S_v$ ), so we maintained the default values for this FATES parameter (Table 2.5).

### Needle Longevity

Studies that have closely examined the phenology of loblolly pine have showed that it is more complex than may be commonly appreciated. Needles accrue over the full growing season with most falling in the first 24 months, although some may last up to three years ([Sampson et al., 2003](#)). Most sources give a needle longevity of 1.5-2 years ([Schoettle et al., 1994](#); [Schultz, 1997](#)). FATES does not attempt to capture the full complexity of evergreen phenology and foliage longevity is a fixed rate constant. We changed the parameter value to 2 years (Table 2.5). With more information about the distribution of needle ages this value could be estimated with higher confidence.

### SLA Top

[Baldwin et al. \(1997\)](#) developed equations to predict specific leaf area (SLA) for both new and old loblolly needles as a function of depth in the canopy and tree age. These equations yield SLA in  $\text{cm}^2/\text{g}$  dry biomass while FATES uses  $\text{m}^2/\text{g}$  carbon.

Baldwin et al. also measured needle area using a geometric approach, which gives the area for the full needle surface. For simplicity we converted to a single sided value by assuming that only half the needle is surface is illuminated. Future work should examine alternate conversions. The carbon to biomass ratio and the one sided conversion factor cancel out. With rearrangement we get:

$$SLA_{New}(D, Y) = \exp(4.8852 + 0.3732 \times D - 0.1175 \times \ln(Y)) \div 10,000 \quad (2.2)$$

$$SLA_{Old}(D, Y) = \exp(4.6052 + 0.3721 \times D - 0.0910 \times \ln(Y)) \div 10,000 \quad (2.3)$$

Where D is the relative depth in the canopy (0-1: top to bottom) and Y is the tree age in years.

FATES uses a single parameter SLA at the top of the canopy (SLATop) and then computes a full SLA profile for the canopy. It does not vary SLA with foliage age. To obtain a single average parameter value we used the equations of Baldwin et al. to calculate SLATop for new and old needles across the approximate tree age range over which their model was parameterized (9-35 years) and then computed the mean, which gave 0.00845 m<sup>2</sup>/gC.

$$SLA_{top} = \frac{1}{54} \left( \sum_{y=9}^{35} SLA_{New}(0, Y) + SLA_{Old}(0, Y) \right) \quad (2.4)$$

## DBH to Height Allometry

The default O'Brien DBH to Height allometry equation (O'Brien et al., 1995) was refit using observations for loblolly pine. This allometry is a linear function of the log transformed data and we got a good fit to our plantation tree observations, which included trees up to  $\sim 50$ cm DBH (Table 2.2). Our large tree dataset made it clear that at larger sizes the equation fails to give an accurate prediction (Figure 2.5). FATES provides a parameter for a DBH corresponding to a maximum height that, if provided, caps height growth for an allometry. This approach is not ideal because it causes an abrupt and unrealistic transition when used (Figure 2.5). While this allometry would have probably been sufficient for our experiments because trees do not grow to very large DBHs in the course of our simulations, we decided to revise the allometry for the PFT to make it more realistic over a wider range of conditions.

We chose the Chapman-Richards equation for our new DBH-height allometry. The Chapman-Richards equation is a flexible generalized logistic function . A number of variant formulations are available in the literature. For consistency and compatibility with the existing FATES allometry parameters we used a four parameter form that includes a intercept term (P1) but this was set to 0 in our fitting.

$$Height (m) = DBH_{max} \times (1 - \exp(-P2 \times DBH))^{P3} + P1 \quad (2.5)$$

The interpretation of FATES's DBH at maximum height parameter was changed for this allometry and was used to represent the maximum height asymptote (DBHmax).

We chose a maximum height of 50 meters based on our large tree data set but these values were not used for fitting. We fit the equation against observed measurement with the rate (P2) and shape (P3) parameters free. The resulting fit is shown in Figure 2.5.

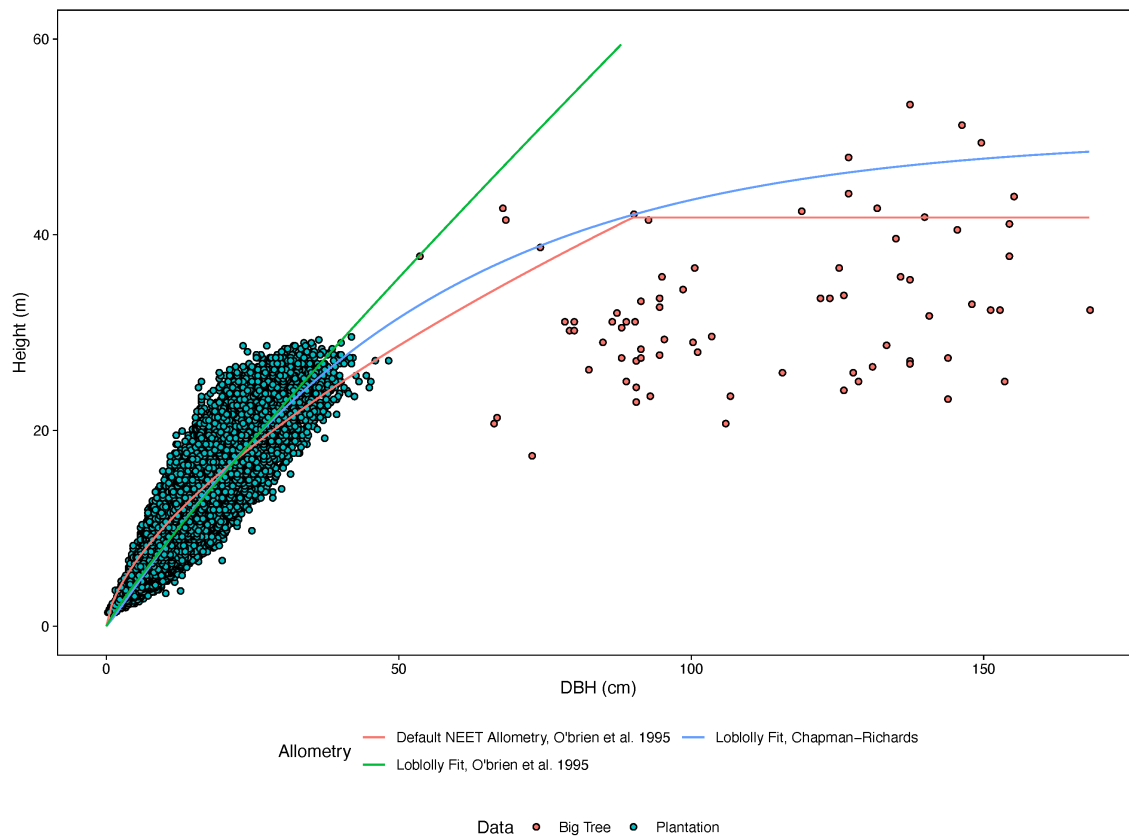


Figure 2.5: DBH to Height Allometry: The default NEET PFT DBH to height allometry is show in red. The default O'Brien allometry equation fit against the loblolly plantation observations is show in green. Our selected Chapman-Richards allometry fit to the loblolly plantation observations is shown in blue. Sources for the observations (dots) can be found in Tables 2.2 and 2.3.

### Aboveground Biomass Allometry

A new function for above ground biomass (AGB) was added to the code based on that presented in [Gonzalez-Benecke et al. \(2014\)](#) loblolly Equation T1. The original equation gives the biomass in terms of total kg dry weight. We add a term to convert the model currency units of kg carbon.

$$AGB \text{ (kg C)} = P1 \times DBH^{P2} / \text{Carbon to Biomass Ratio} \quad (2.6)$$

Parameters P1 and P2 were obtained from the same source ([Gonzalez-Benecke et al., 2014](#)). The carbon to biomass ratio is an existing model parameter that was left at its default value of 2. The fraction of woody biomass that is above ground was changed based on the analysis of [Albaugh et al. \(2005\)](#).

### Leaf Biomass Allometry

The diameter to maximum foliage biomass allometry required a choice between two alternatives, both of which had their own drawbacks. [Gonzalez-Benecke et al. \(2014\)](#) present multiple DBH to foliage allometric equations, two of which have appropriate arguments for use with FATES (Equation F1 uses DBH and F4 DBH and height). [Zhao et al. \(2015\)](#) present an alternative equation based on DBH and height (Equation Y7).

The two equations were parameterized against data from different size ranges of trees, [Gonzalez-Benecke et al.](#) with trees of DBH from 1.0 to 32.6 cm and the [Zhao](#)

et al. allometry with trees of DBH from 7.6 to 38.1 cm. One might therefore expect Gonzalez-Benecke et al. to be more accurate for smaller and Zhao et al. for larger trees. Moreover, the Gonzalez-Benecke et al. equations give non-zero foliage amounts even at very small DBHs, which is realistic since a tree with a DBH of just over zero is already 1.35 meters tall and will therefore have some amount of foliage. As with the model's default allometry the Zhao et al. allometry has a zero foliage biomass at zero DBH, which is unrealistic. Both equations yield similar values for midsize trees. The equation form use by Gonzalez-Benecke et al. yields values that drops rapidly to zero leaf biomass as DBH approaches zero. This is both unrealistic and was computationally problematic when tested with the FATES code. This led us to add the Zhao et al. allometry to FATES despite its lack of realism at small DBHs. The original equation gives the biomass in terms of total kg dry weight. We add a term to convert the model currency units of kg carbon. The leaf allometry remains an area where improvements could likely be made in future work.

$$\text{Maximum Foliage Biomass (kg C)} = \frac{P1 \times \text{DBH}^{P2} \times \text{Height}^{P3}}{\text{Carbon to Biomass Ratio}} \quad (2.7)$$

### Crown Area Allometry

Several groups have developed allometric relationships for the crowns of loblolly pines. Gering and May (1995) found a linear relationship between crown diameter and DBH for a combined sample of loblolly and shortleaf pine (Gering and May (1995)) converted to metric units: intercept = 0.9040368 m, slope = 0.168456 m/cm).

Leites et al. (2013) used the same linear model and obtained similar parameters ((Leites et al., 2013) Equation 4 / Table 4: intercept = 0.6146 m, slope = 0.1703 m/cm) for loblolly pine in Uruguay. The observational study used for this experiment was previously used to develop a linear model to predict crown diameter from DBH, height, and the row and column spacing (Sharma et al., 2002). This model was not considered as a candidate both because of self-prediction bias and the inclusion of the spacing terms which are incompatible with the FATES conceptual model. However, it is informative that the intercept and DBH terms are dominant in this linear model and if the other terms are ignored these parameters are very similar to those of the other models (intercept = 0.65810 m, DBH slope = 0.19190 m/cm).

A new function for DBH to crown area allometry was added to the code based on the equation and parameters of Gering and May (1995). They present an equation predicting canopy diameter from DBH (Equation 2.8). We made the simple assumption of a circular canopy to convert canopy diameter to canopy area (Equation 2.8).

$$Crown\ Diameter = P1 + P2 \times DBH \quad (2.8)$$

$$Crown\ Area = \pi \times \left( \frac{Crown\ Diameter}{2} \right)^2 \quad (2.9)$$

### Canopy Spread Modification

Some work was necessary in addition to the new crown allometry to make the canopy behave reasonably. The existing implementation includes a behavior designed to approximate crown plasticity at canopy closure. In short, a so called ‘spread factor’

from 1 to 0 is calculated once the total stand crown area fraction exceeds a certain threshold, currently 0.8. This spread factor is then used to reduce the crown area produced for a given DBH using a spread term multiplier. This is meant to approximate the way in which real world trees adjust their crowns as they begin to interact with and compete with their neighbors for light.

However, it was not clear that the existing model behavior was having its intended effect. In our default NEET PFT simulations we observed that once canopy area exceeds the spread threshold it forms a flat shelf (Figure 2.13a). This is a consequence of the use of a fixed threshold in the code. Any increase in the crown area above the threshold decreases the spread factor, which decreases the canopy area marginally below the threshold and the process repeats. The result is a shelf of nearly constant area between the threshold and a canopy fraction of 1. After canopy closure crown area again begins to increase. This is clearly not realistic. Modifying this behavior required changes to the model code.

In revising the crown allometry plasticity we wanted to achieve a more gradual adjustment of the crown allometry during canopy closure. We maintained the model's basic formulation of using a spread calculation to drive an adjustment of an underlying fixed allometry. However, we changed the manner in which the 'spread' calculation was performed. We changed the interpretation of the canopy closure threshold parameter from a fixed threshold to a starting value for allometry adjustment. Between the starting threshold and canopy closure at a value of 1 we transition the spread value from 1 to 0 linearly. This is accomplished by calculating a moving triggering threshold at each timestep based on the current spread value. Only when

the canopy area increased enough to exceed the triggering threshold is the spread incremented or decremented again.

The spread increment step size is currently specified in the code. While it has little visible influence on the pattern of canopy area during canopy closure it does affect the rate at which canopy area contracts. We decreased the step size to smooth the canopy closure transition and to make the canopy contraction rate more similar to the default allometry.

### Modified Crown Area Response to Canopy Spread

Next we had to convert the canopy spread to a crown adjustment. As with the default allometry we use the spread value to calculate a spread term multiplier. We modify that calculation such that the unmodified literature allometry occurs at a spread value of 0.5, with larger crown areas when the canopy is more open and smaller when it is more closed (Equation 2.10).

$$Spread\ Term = (Spread \times Multiplier_{max} + (1 - Spread \times Multiplier_{min}) \times 2 \quad (2.10)$$

Unlike the default crown allometry our allometry based on [Gering and May \(1995\)](#) has a non-zero intercept. We therefore modified Equation 8 so the spread factor only adjusts the crown area growth rate term of the equation (equations 2.11 & 2.12).

$$\text{Nominal Crown Area} = \pi \times \left( \frac{\text{Crown Diameter}}{2} \right)^2 \quad (2.11)$$

$$\text{Crown Area} = \text{Spread Term} \times (\text{Nominal Crown Area} - \text{Area Intercept}) + \text{Area Intercept} \quad (2.12)$$

The area intercept term is the area calculated from Equation 2.8 when DBH is 0 (i.e. crown diameter = 0). The result of these changes can be seen in Figure 2.13 panel a vs. panel b.

### Roots Parameters

The root longevity/turnover parameter was changed from 2 to 5 years based on the average across all root size classes calculated by Matamala et al. (2003), rounded to the nearest year. Information about loblolly fine root to leaf carbon ratio was limited in the literature. King et al. (1999) report values from 0.27-0.5 but were not able to find other values. Given the dearth of estimates in the literature these values must be viewed as highly uncertain. We chose to select the fine root to leaf carbon ratio by parameter tuning. We tested values, on either side of the default value of 1.0, from 0.25 to 3.5 with all other parameter values held constant. A final value was chosen that yielded the best fit across all the densities as a whole for the majority of metrics.

### 2.3.5 Forest Manipulation Data

For this study we used observations from experimental forest plantation experiments conducted by the Virginia Tech Forest Modeling Research Cooperative (VT FMRC) to examine FATES's ability to model young single age loblolly forest stands (Figure 2.6).

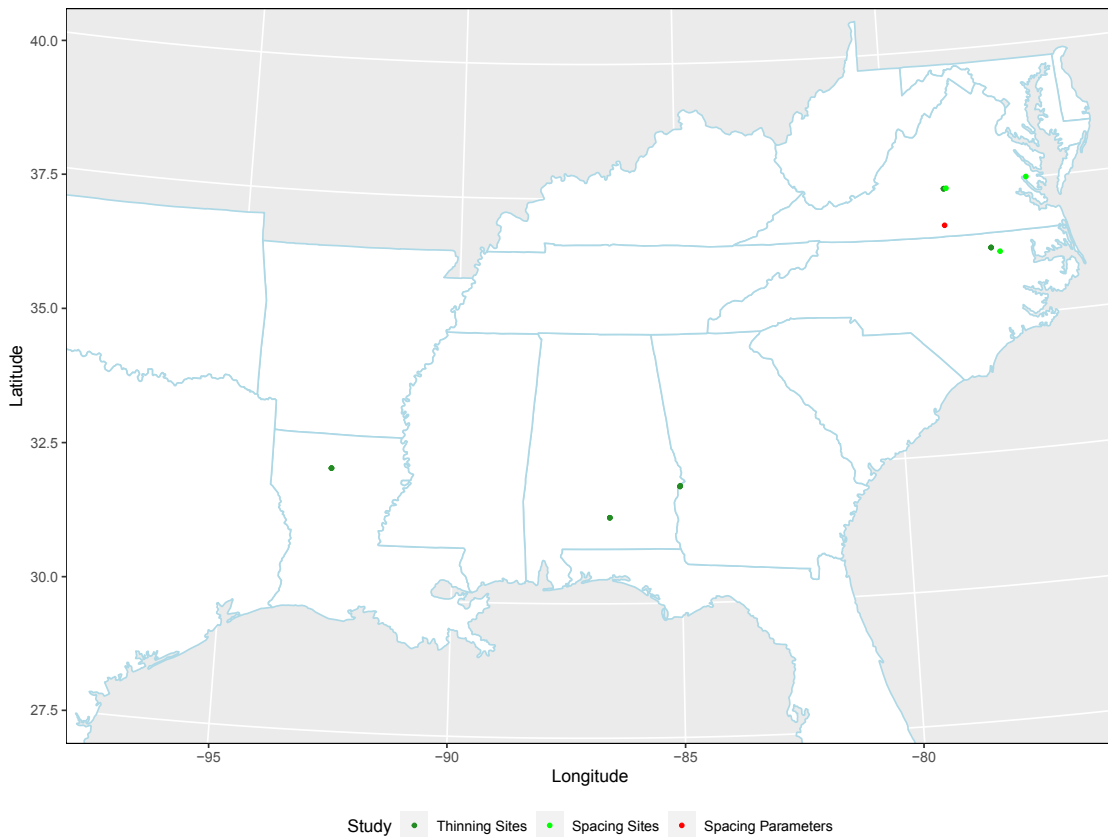


Figure 2.6: Study Sites: Locations of the spacing trial and thinning field experiments that we simulated in this study.

### Spacing Trial Observations

We used observations from a ‘spacing trial’ study to examine growth and competition in FATES. This study has been described in detail elsewhere ([Amateis and Burkhardt, 2012](#); [Sharma et al., 2002](#)). We provide the relevant details here. In 1983 experimental blocks of loblolly pine were established at four locations in Virginia and North Carolina, in the Southeastern United States of America (Table 2.1). Blocks contained plots with trees planted in varying configurations. Seedlings were planted in columns and rows of varying widths producing 14 different spacing arrangements. Each replication consisted of 7 rows by 7 columns for a total of 49 trees each. Each spacing was separated by unmeasured border trees. Each block was established in triplicate at each location ([Amateis and Burkhardt, 2012](#)).

Trees were measured every 1-2 years for height and diameter during the winter dormant season until the age of 25 years after planting. Measurements of crown diameter along two perpendicular axes were recorded until canopy closure and for two locations in the final year. The condition of trees (live, dead, damaged) were recorded at each observation. The first year success of newly planted seedlings is highly stochastic ([Amateis et al., 1997](#)). First year seedlings that died were replaced. Competing vegetation was suppressed with herbicide during the early years of the study ([Sharma et al., 2002](#)).

The Halifax County, VA location of the study was prematurely cut down at year 20. Data from this location was used to supplement other data sets with measurements of young trees, which are rare in most studies, and for other purposes in parameter-

ization (see below). This location was excluded from simulation comparisons. Some plots at the Buckingham County, VA location were damaged by an ice storm in year 11 and additional plots were lost due to southern pine beetle (*Dendroctonus frontalis*) infestation in year 20. While this reduces sample size at this location replication of blocks meant that no treatment conditions were lost.

FATES does not represent the spatial arrangement of trees in its simulations. Therefore, experimental plots that had the same number of trees planted per unit area were combined independent of the spatial arraignment of the trees, resulting in a total of 9 planting density conditions from 0.075 - 0.673 trees / m<sup>2</sup>. This decision is consistent with a conclusion of the original study that the rectangularity of spacing did not impact tree growth, only overall density did ([Amateis and Burkhart, 2012](#)). Likewise replicates for each location were combined by planting density. All observations were converted to metric units. Calculations for quantities derived from measurements can be found in the metrics section that follows.

### **Thinning Trial Observations**

Observations from a second VT FMRC study was used to test our ability to simulate stand thinning. This thinning study has been described elsewhere ([Amateis et al., 2006](#); [Russell et al., 2010](#)). Between the years of 1996-2007 young loblolly plantation stands from across the loblolly cultivation range were selected. For each site three plots were established, a control and two thinning plots. The species, height, and diameter (DBH), and status was recorded for each tree in the plot at the time of

enrollment in the study. Measurements were repeated every two years through the date of thinning. The remaining trees were remeasured two years after thinning and then every three years after that until harvest. Measurements were made in the dormant season. Exact dates of measurements were not recorded. At the time of this work some sites had yet to be harvested.

Forest managers were instructed that when the stands reached dominant height of 13.7 m (45 ft) and a minimum diameter of 15.2 cm (6 in) a low (from below) thinning would be performed. One plot would be thinned by half or to 617.7 trees / ha (250 trees / ac), whichever yielded a greater stand density (light thin plot). The other plot would be thinned by 75% or to 308.8 trees / ha (125 trees / ac), whichever was greater (heavy thin plot). Dead lower branches were pruned in the heavy thin plots. Trees were measured prior to thinning and the trees removed during thinned were recorded. The conditional thinning prescription combined with decisions made by managers based on field conditions meant that the actually fraction of stems thinned and the demographics of trees thinned varied (Figure 2.3a).

For comparison to CLM-FATES simulations we chose a five sites that were spread across the species range and included a mix of locations from the coastal and piedmont physiographic regions (Figure 2.6, Table 2.1). We included two sites that were located close to two of the spacing trial locations (no thinning location was located close to the King and Queen Co., VA spacing trial location). Sites were chosen that had predominant loblolly composition, had no missing data, and had at least two observations before and after the thinning date. Data from some sites that did not meet this criteria but had thinnings recorded were used for parameter estimation (see

Physiographic Region	State	County	Latitude (N)	Longitude (W)	Data Use	Year Planted	Years Simulated
Lower Piedmont	VA	Halifax	36.75	78.717	Parameterization	1983	1984-2008
Upper Piedmont	VA	Buckingham	37.433	78.617	PFT Validation	1983	1984-2008
Upper Coastal Plain	NC	Halifax	36.183	77.483	PFT Validation	1983	1985-2008
Lower Coastal Plain	VA	King & Queen	37.517	76.717	PFT Validation	1983	1986-2008
Coastal Plain	NC	Halifax	36.267	77.683	Thinning Validation	1994	2000-2009
Piedmont	VA	Buckingham	37.428	78.673	Thinning Validation	1992	1997-2019
Lower Coastal Plain	AL	Butler	31.597	86.567	Thinning Validation	1991	1998-2019
Coastal Plain	GA	Stewart	32.161	85.014	Thinning Validation	1993	1999-2018
Gulf Coastal Plain	LA	Jackson	32.383	92.733	Thinning Validation	1995	2000-2019

Table 2.1: Study Sites

below). Since only the season of measurements were recorded we standardized the dates of measurements to January 1 of the appropriate year for comparison purposes and the date of thinnings to February 1.

### 2.3.6 Other Tree Data for Parameter Estimation

Additional data to robustly parameterize the DBH to height relationship in the model was obtained from the VT FMRC. A selection of plots from sites across the species range were made and DBH and height measurement of trees from these plots were combined. Trees from multiple studies were included in order to represent trees of varying age, size, genetic background, and management intensity. The data sets included mid-20th century loblolly stands established by natural recruitment or plantings from nurseries as well late century stands employing more modern management practices (Table 2.2).

We had to look to alternative sources to obtain data to constrain the DBH to height relationship for large trees. Most studies in the forestry literature only measure trees to the end of a typical loblolly plantation harvest rotation, which is generally 25-40

Description	States	Trees	Measures	Obs	Tree Ages (years)	DBH Range	Source
Natural Recruitment	NC, VA	208	Single		13-77	11.7-35.8	<a href="#">Burkhart et al. (1972a)</a>
Old-field Plantation	DE, MA, NC, VA	427	Single		9-35	6.4-31.2	<a href="#">Burkhart et al. (1972b)</a>
Low Intensity Management Plantation	AL, GA, LA, MS, NC, SC, VA	6266	Repeated	22132	9-43	1.5-48.3	<a href="#">Burkhart et al. (1985)</a>
Spacing Trial	VA	2306	Repeated	22269	1-18	0.25-30.23	<a href="#">Amateis and Burkhart (2012)</a>

Table 2.2: Loblolly Plantation Tree Data

years. Measurements are also rarely made before 5 years of age in most forestry studies. For this reason data for very young, small trees and old, large trees is in short supply. As discussed above we reserved one location from our spacing study to fill in the low size ranges. To supplement the larger trees we collected data from multiple sources (Table 2.3). We compiled measurements of large trees listed on state and national champion and big tree lists and converted them to metric DBH and height. The Maryland database includes far more records that lists for other states so only the 25 largest records were included. The Maryland trees are all on the smaller end of those compiled (Figure 2.5).

Additionally the largest trees recorded for each state by the USDA Forest Service Forest Inventory and Analysis program (FIA) were obtained from [Oswalt et al. \(2010\)](#) and were included in our list. Perhaps because FIA plots represent a more random sample and very large trees are quite rare on the landscape the trees recorded are on the smaller end of the dataset, barely overlapping with the other trees compiled.

There are some caveats to this data. While the FIA program observes rigorous standards and its data is well trusted, data from big tree databases needs to be considered

State	Source	FIA (Oswalt et al., 2010)	Trees
Alabama	<a href="#">Alabama Forestry Commission (2017)</a>	✓	2
Arkansas	<a href="#">Arkansas Department of Agriculture (2019)</a>	✓	2
Florida	<a href="#">Florida Department of Agriculture and Consumer Services (2019)</a>	✓	4
Georgia	<a href="#">Georgia Forestry Commission (No Date)</a>	✓	7
Kentucky		✓	1
Louisiana	<a href="#">Louisiana Forestry Association (2019)</a>	✓	2
Maryland	<a href="#">Maryland Big Tree Program (No Date)</a>		25
Mississippi	<a href="#">Mississippi Forestry Commission (2009)</a>	✓	2
New Jersey	<a href="#">New Jersey Forest Service (2019)</a>		6
North Carolina	<a href="#">North Carolina Forest Service (No Date)</a>	✓	2
Pennsylvania	<a href="#">The Pennsylvania Forestry Association (No Date)</a>		2
South Carolina	<a href="#">American Forests (2019)</a>	✓	2
Tennessee	<a href="#">Tennessee Division of Forestry (2003)</a>	✓	3
Texas	<a href="#">Texas A and M Forest Service (No Date)</a>	✓	13
Virginia	<a href="#">Virginia Big Tree Program (2019)</a>	✓	6

Table 2.3: Large Loblolly Tree Data

more carefully. While measurements of some of these trees have been verified by researchers many individuals contributing data to big tree databases are hobbyists. Measurement techniques are rarely recorded. Trees recorded are in some cases atypical, probably because trees in open fields or more populated areas are more likely to be noticed. Also old trees are more likely to have suffered damage at some point so that heights may not strictly reflect biologically dictated allometry. While most are unique a few data points may represent repeated measures of several monumental trees in Congaree National Park over the course of several years. Perhaps most importantly the number of trees in our dataset is very limited compared to trees of smaller stature. Therefore these trees were used to help define the upper height limit for the species and for verification of the model rather than for model fitting (see DBH to height allometry section below).

### 2.3.7 Typical Planting Densities

To contextualize the planting densities used in our experiments we compiled estimates of what planting densities have been used over time for loblolly pine. We performed a literature search for estimates of current and historic planting densities. While journal articles often report the planting densities for experimental stands, it is not always clear that those represent typical conditions used in regular practice. We limited ourselves to collecting values that were explicitly descriptive of actual practices. We also collected both descriptive and prescriptive (recommended) values from state and federal planting guides, pamphlets, and books on southern pine management from the 1920s to today (Table 2.4). Most historic accounts did not give specific dates for practices so the dates presented represent our best interpretation of the text. For planting guidelines and contemporaneous accounts we use the year of publication as the date for those data points. In some sources, especially older ones, densities are for southern pines generally, and in one case all trees. Most of the more recent values are for loblolly pine specifically.

We also consulted four members of our department with expertise in loblolly forestry practices and obtained their professional estimates of the typical planting densities are currently in use. The combined results of this research are presented in Figure 2.7.

State or Region	Source
Alabama	<a href="#">Alabama Forestry Commission (2003)</a>
Arkansas	<a href="#">Cunningham et al. (2008)</a>
Georgia	<a href="#">Georgia Forestry Commission (No Date)</a>
Georgia	<a href="#">Georgia Forestry Commission (2011)</a>
Mississippi	<a href="#">Londo and Ezell (2011)</a>
Mississippi	<a href="#">Self and Ezell (2019)</a>
North Carolina	<a href="#">North Carolina Forest Service (2016)</a>
Virginia-Carolina Piedmont	<a href="#">Minckler and Chapman (1948)</a>
Virginia	<a href="#">Scrivani and Bowman (2004)</a>
Virginia	<a href="#">Bowman et al. (2008)</a>
Virginia	<a href="#">Virginia Department of Forestry (2017)</a>
Midsouth	<a href="#">Grano (1967)</a>
South Atlantic	<a href="#">Lotti (1956)</a>
Region Wide	<a href="#">Tillotson (1925)</a>
Region Wide	<a href="#">Van Lear et al. (2004)</a>
Region Wide	<a href="#">Wakeley (1954)</a>
Region Wide	<a href="#">Balmer and Williston (1974)</a>
Region Wide	<a href="#">Smith and Strub (1991)</a>
Region Wide	<a href="#">Schultz (1997)</a>

Table 2.4: Sources for Historical Planting Densities

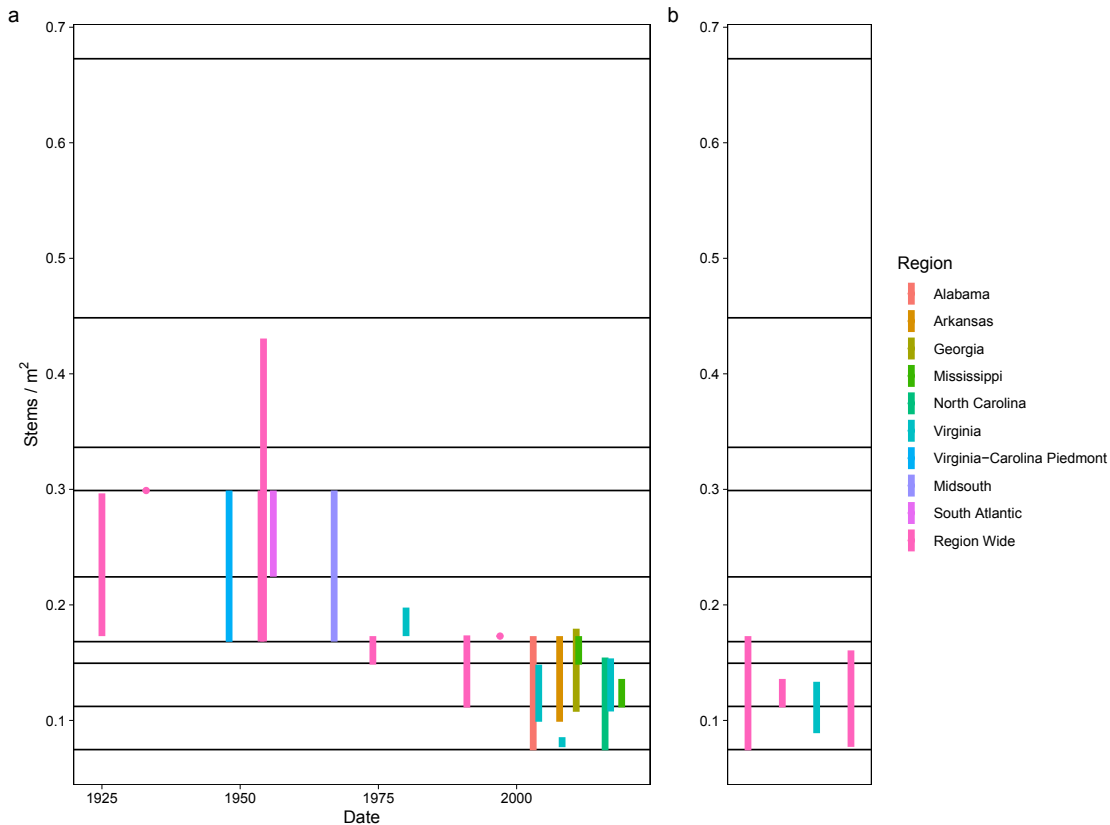


Figure 2.7: Historical Planting Densities: (a) Ranges of planting densities recorded in the literature and historical sources (Table 2.4). (b) Expert estimates of planting densities in use today. Black lines mark the planting densities of the spacing trial experiment.

### 2.3.8 CLM-FATES Simulations

#### Spacing Trial Simulation Configuration

CLM-FATES was run in single point mode for each location. The land surface data and forcing data were subsetted for the nearest grid cell to the locations' geographic coordinates (Table 2.1). The land surface file for each location was altered to consist

of 100% natural vegetation with 100% of the natural vegetation being a single PFT, PFT number 2, which is by default the Needleleaf Evergreen Extratropical Tree (NEET).

The model was run in offline, or uncoupled, mode with a prescribed data atmosphere, transient carbon dioxide, transient aerosols, and stub components for ice, glacier, river, ocean, and wave components. Simulations were run with forcings matched to the dates of the study. GSWP3 forcings for temperature, humidity, precipitation, wind, aerosols, and atmospheric CO<sub>2</sub> were used. Since the initial height of seedlings were not recorded at the time of planting simulations were initiated in 1984 at the time of the first measurement.

The model was initialized as a so-called cold start, that is without prior spin-up of the model. This is standard procedure with FATES since it does not currently have a nutrient cycle. All simulations were initialized with trees matching the approximated average height of the seedlings at the first year of measurement, which was 0.35 m. Nine simulations were performed with initial tree densities matching each experimental planting density. The resolution of the DBH bins output by the model were changed to match that of the observations (see section 2.3.9). Data was output monthly. Since observations were collected during the dormant season we used the simulation output for January 1 of each year to compare to the observations.

### Thinning Simulation Configuration

We performed simulations that reproduced the conditions of the real world thinning experiments described above. Simulation conditions were similar to the spacing trial experiments in most regards. Single point simulations were set up with grid cell locations matching the site coordinates. Pure PPA was used and our loblolly PFT was used for simulations except where noted below.

Since the plots in the thinning studies were established years after planting and there was limited information about planting conditions we began the simulations using FATES's inventory initialization mode. Simulations were initialized from two dates for each simulated plot as follows. A FATES model cohort was initialized for each tree in the inventory at the date of the simulation start according to its DBH and with a per-hectare density scaled from the plot size. The year of thinning was determined from the plot data and a matching thinning event was scheduled on February first of that year using the VM module's event driver file. Parallel simulations were performed for each of the experimental plots for the sites. Stand statistics for basal area, stem density, etc. were calculated for the observations and simulations as described above for the spacing trial.

The first set of simulations were initialized from inventory data at the earliest observation that had diameters for all the location's trees. For most locations this was the first observation. One location was enrolled in the study at three years after planting when not all trees had reached breast height, so the second observation was used in this case. These simulations starting from the initial observation were

treated as a ‘blind’ simulations, where only the thinning date and study thinning prescription were used to specify the thinning, without regard to the recorded thinning observations. The thinning prescription for the study was contingent, i.e. thin by a fraction or to a specific density depending on which left more trees. We calculated the appropriate final stem density for each plot based on its pre-thinning stem density according to Equations 2.13-2.14, and used these values to specify the thinning.

$$\textit{Light Thin } SD_{\textit{post-thin}} = \max(SD_{\textit{pre-thin}} \times 0.5, 617.7635) \quad (2.13)$$

$$\textit{Heavy Thin } SD_{\textit{post-thin}} = \max((SD_{\textit{pre-thin}} \times 0.25), 308.8817) \quad (2.14)$$

The second set of simulations were initialized on January 1 of the thinning year from the inventory immediately prior to thinning. These thinning date simulation were treated as an ‘informed’ simulations. The thinnings for these simulations were specified by calculating the actual basal area after thinning occurred in the corresponding observational plots.

For each initialization date parallel simulations were conducted for the thinned plots using the three thinning methodologies implemented. Finally, simulations from the initial observation date of the control plots were replicated with the default NEET PFT for comparison purposes.

The starting dates for the simulations were set to match those of the observations used to initialize them. The simulations were run past the last observation. GSWP3

climate forcing was used in the manner describe for the spacing trial simulations. The GSWP3 forcing data ends in 2014 while some of our sites recorded data into 2019. An alternative data set was not available that covered all the years of our simulations so we used cycled climate data after 2014. Table 2.1 summarizes the dates for each location.

For all simulations data was output monthly. As in the spacing simulations very fine size bins were used for output (see section 2.3.9), so that in most cases each simulated cohort will appear in its own size bin. To analyze the thinning state transition explicitly for the year in which thinning occurred the thinning date simulations were also simulated with daily output. The thinnings were scheduled for one month after initialization (on February 1) to allow the model behavior that follows initialization to play out and stabilize. For consistency this date was used for all simulations regardless of initialization date. It was verified that demographic did not changed significantly in this one month settling in period.

### **Shared Stand Parameter Changes**

We identified parameters that control the structure and development of the modeled forest stands that needed modification to reproduce our managed forest system. Theses ‘stand’ parameters were shared across our simulations.

By default FATES PFTs show high levels of recruitment of seedlings. The spacing trial stands lacked significant loblolly recruitment beyond the trees that were planted. We reproduced this by changing the two parameters that control the allocation to

seeds and seed rain from outside the grid cell (Table 2.5). An alternative approach would be to reduce the parameter that controls the germination of seeds to zero. The choice between the two alternatives does have a small effect on the results because turning off allocation to seed allows more carbon to be allocated to growth. We used the former option because the difference is small and we did not have good data to constrain seed allocation in any case.

With the default FATES parameter values individual tree mortality events results in a fraction of the area occupied by that tree/cohort being transferred to a new patch. This has the effect of decreasing the area occupied by the remaining trees. While this behavior can be desirable when simulating a heterogeneous landscape with disturbance, it can be unrealistic for simulating a small stand without large scale disturbance. For a homogeneous stand this behavior is conceptually equivalent to the surviving trees getting closer to each other. The spacing trial study was designed to isolate intraspecies competitive effects and the plots that experienced large scale disturbances were excluded from our analysis. Therefore, we changed the fraction of the patch area that forms a new patch after a 'natural' disturbance to 0, switching to so-called 'Pure PPA' disturbance behavior (Table 2.5). This retains the area occupied by trees that die in the current patch so that light and resources become available to surviving trees.

### 2.3.9 Experimental Metrics

Six metrics were selected to compare spacing trial simulations to observations. Mean DBH and mean tree height capture average tree structure, while total aboveground biomass, stem density, stand basal area, and total crown area were chosen to examine stand level properties.

#### DBH, Height, and Stand Basal Area

DBH and height were recorded for the observations but are not directly output by FATES. Internally FATES tracks the DBH of each simulated cohort. Height is determined directly from DBH to height allometry in the model. Currently in FATES cohort level data is not output as the number of cohorts varies with time and can grow very large, presenting challenges for an efficient output format. Instead output is aggregated into DBH (and height) size bins that are invariant with time. By default these size bins are quite wide (5-10 cm). To get data that is directly comparable to our observations we altered the DBH size bins so their width matched the measurement increment of the data (0.1 inches = 0.254 cm) with bin centers aligned with the measurement values. The corresponding height of each bin was calculated from the matching DBH to height allometric equation during post processing. To calculate mean DBH and height, values were weighted by the number of trees per size class.

$$\overline{\text{DBH}}(cm) = \left( \sum_{\text{bin}=1}^n \text{DBH}_{\text{bin}} \times \text{Trees}_{\text{bin}} \right) / n \quad (2.15)$$

$$\overline{\text{Height}}(m) = \left( \sum_{\text{bin}=1}^n \text{Height}_{\text{bin}} \times \text{Trees}_{\text{bin}} \right) / n \quad (2.16)$$

FATES outputs total basal area per hectare per size class. Summing it across all size bins yields the stand basal area.

$$\text{BA}(\text{m}^2/\text{ha}) = \sum_{\text{bin}=1}^n \text{BA}_{\text{bin}} \quad (2.17)$$

### Aboveground Biomass

Aboveground biomass was calculated for the observed stands using [Gonzalez-Benecke et al. \(2014\)](#) loblolly Equation T4. This equation is part of the set of equations used for the loblolly PFTs AGB calculation above. Therefore AGB estimates for observations and simulations are subject to consistent model assumptions and shared fitting data. Again, the original equation gives the biomass in terms of total kg dry weight. We add a term to convert to the model currency units of kg carbon.

$$\text{AGB}(\text{kg C}) = \frac{\text{P1} \times \text{DBH}^{\text{P2}} \times \text{Height}^{\text{P2}}}{\text{Carbon to Biomass Ratio}} \quad (2.18)$$

This calculation was applied to all living trees in each experimental condition (replicates were combined) to obtain a total stand biomass at each timepoint. This biomass was then divided by the total area of the combined plots to yield a per meter squared value.

FATES outputs simulated aboveground biomass by size class. We sum across all size

classes to obtain the total above ground biomass.

### Stem Density

The stem density of the observations was obtained by counting the number of live trees at each time point and dividing that by the total area of the experimental plots for each planting density. FATES reports the stem density in number of trees per meter squared.

### Canopy / Crown Area

The observations included measurements of tree canopy widths at time points until crown closure and again at the end of the study for two locations. The crowns were measured in two perpendicular dimensions. We made the simplifying assumption that crowns shapes were ellipses.

$$Crown\ Area\ (m^2) = \pi \times \frac{Crown\ Width_x}{2} \times \frac{Crown\ Width_y}{2} \quad (2.19)$$

This assumption is not entirely accurate. Observations included a maximum width and in some cases this was greater than the larger of the two standard axes. However, without an angle for this maximum width we cannot systematically adjust our ellipses.

FATES outputs canopy area binned by size class and canopy layer in the units of meter squared per hectare. We obtained the total canopy area by summing across

the all size classes and both canopy layers. We then converted to units of crown area over ground area by dividing the total by 10,000 m<sup>2</sup>/ha. Since there are two canopy layers the maximum value is 2, with a value of 1 corresponding to a ‘closed’ canopy.

## Statistics

Goodness of fit was determined by calculating the Root Mean Squared Error (RMSE) between the observations and simulation data for each metric across all common timepoints and across the three simulated locations. For some graphs RMSEs were also calculated for early (1-10 years) and late (11-25 years) periods of the simulations. It should be noted that the different locations had different data coverage. The number of locations and the number of plots per density varied with time, primarily at later time points (see section 2.3.5).

### 2.3.10 Loblolly Leaf Area Index Estimates

We lack measurements of leaf area index (LAI) for the experimental stands in this study. However, we determined an appropriate LAI range for mature loblolly stands using literature data and expert opinion to contextualize our simulated LAI results. One study that estimated LAI using LIDAR for our study region gave a maximum pine LAI value of 4.69 (Peduzzi et al., 2012). Recent work in our lab estimated a mean maximum LAI value of 2.6 and a 95th percentile estimate of 3.1 for loblolly pine plantations in Virginia (McCurdy, 2019) (assuming a winter to summer phenological amplitude of 1.2768 from Peduzzi et al. (2012)). For the whole species range values of

as high as 6.5 have been reported but are rare and are isolated to locales with optimal site condition in the southern part of the range (Jokela et al., 2004). The consensus opinion of experts in our department was that the peak loblolly plantation LAI for our spacing trial region of Virginia and North Carolina is between 1 and 4. Based on this information we categorize LAI values that fall in the range of 1-4 as most typical, 4-6.5 as possible but uncommon, and values of 6.5 and above as unlikely.

## 2.4 Results

### 2.4.1 Spacing Trial Experiment

#### Default PFT Performance

The default NEET PFT with stand parameters (hereafter default PFT) simulates trees with growth patterns that overlap the observations, but the modeled trees diverge from the observations increasingly as the stand ages, especially with regard to the stand level properties. The default PFT also exhibits unrealistic canopy growth behavior during stand development.

The mean DBH starts below the observations for the early years of the simulation but exceeds the observations by 25 years (Figure 2.8a). Simulated height agrees well with the observations (Figure 2.9a). Mean observed tree heights are similar across the planting densities. The simulated heights for the different densities diverge from each other earlier in the simulations than the observations. Aboveground biomass is

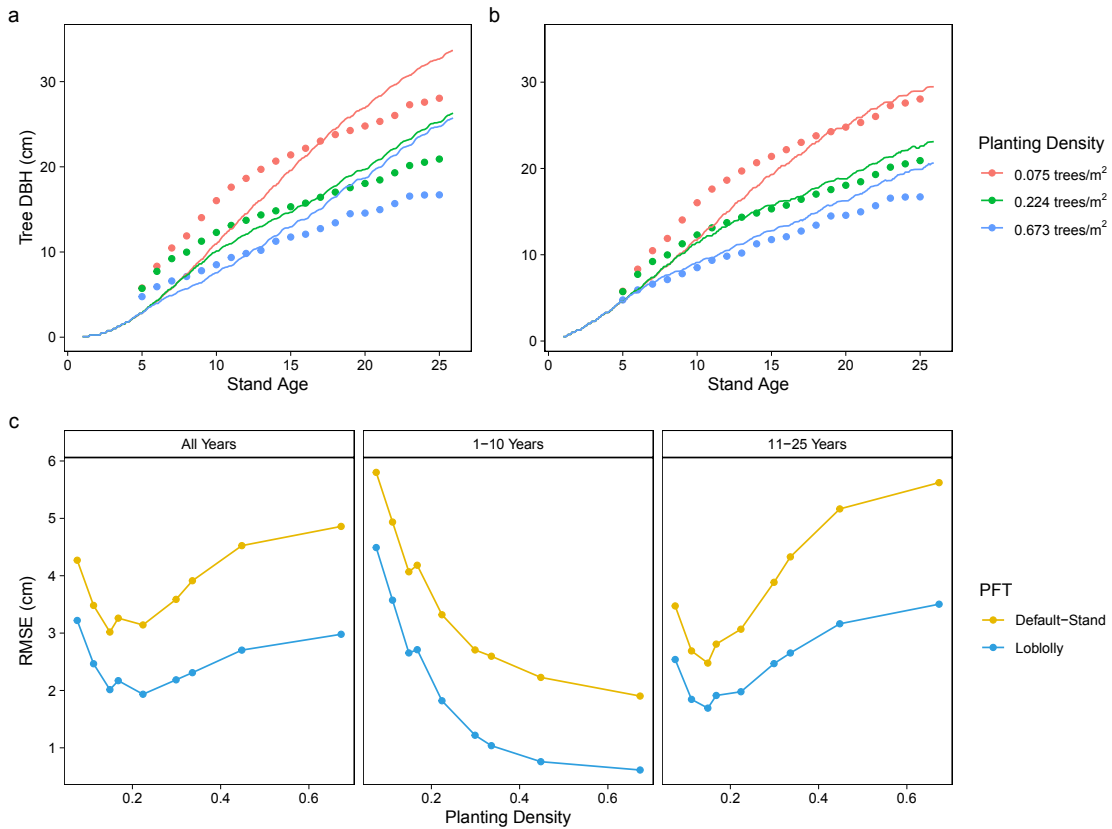


Figure 2.8: PFT Performance for Tree Diameter: Observed (dots) versus simulated (lines) mean DBH for (a) the default PFT and (b) our loblolly PFT. The high, middle, and low planting densities experiments are shown. (c) The RSMEs for all planting densities for all, early, and late years of the experiment.

similar to the observations in the early years but by 12-18 years it begins to exceed the observed values and gets worse as the stand age. At 25 years the AGB for the simulations have nearly converged, while the observations maintain variability across planting densities (Figure 2.10a).

The stem densities show that self-thinning begins around the same time in the simulation as in the observations. However, self-thinning mortality is too strong in the

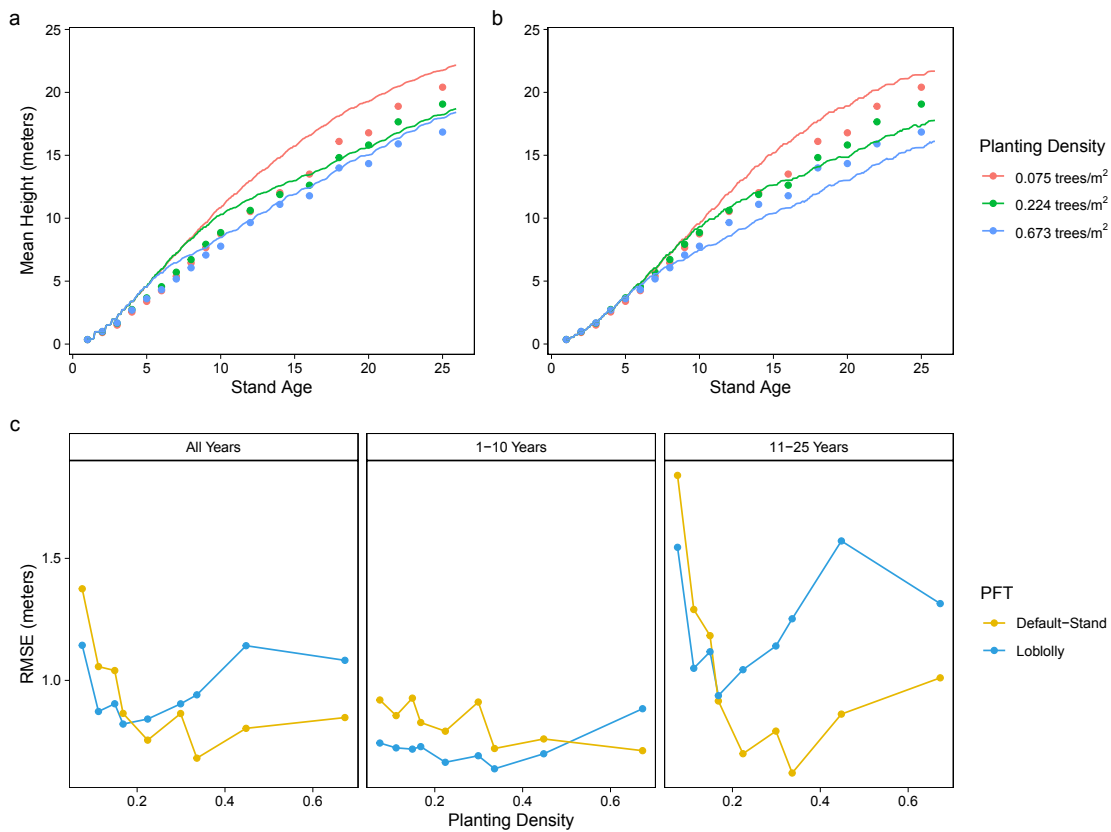


Figure 2.9: PFT Performance for Height: Observed (dots) versus simulated (lines) mean tree height for (a) the default PFT and (b) our loblolly PFT. The high, middle, and low planting densities experiments are shown. (c) The RSMEs for all planting densities for all, early, and late years of the experiment.

model and densities at the 25 years are far lower than those observed (Figure 2.11a). Basal area is lower than the observations in the early years of the simulations and doesn't show the plateauing, or peaking for the highest densities that is observed in the field data. Instead basal area is still increasing at the end of 25 years (Figure 2.12a). When considered along with the DBH data it is clear that the modeled stand is characterized by fewer and larger trees than the observed stands. Simulated

crown area is similar for the early years but levels off at a crown around 0.8, forming a step-like plateau, before increasing again. Stand level crown area greatly exceeds the observations in in the later years of the simulations, forming a full double layer canopy at the middle to high densities (Figure 2.13a).

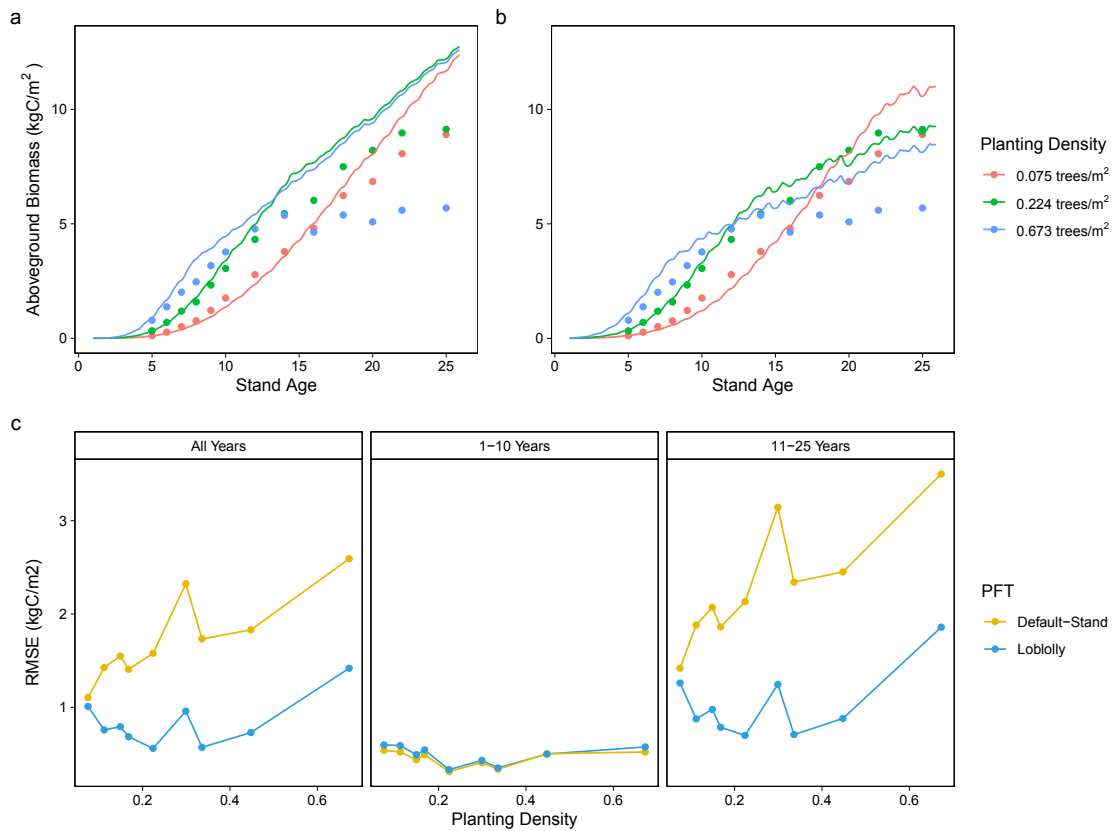


Figure 2.10: PFT Performance for Aboveground Biomass: Observed (dots) versus simulated (lines) aboveground biomass for (a) the default PFT and (b) our loblolly PFT. The high, middle, and low planting densities experiments are shown. (c) The RSMES for all planting densities for all, early, and late years of the experiment.

### Loblolly PFT Performance

The loblolly PFT performed better than the default PFT, matching observed tree and stand properties more closely. The loblolly PFT had lower RMSEs for all metrics except for height at the higher densities and crown area at the lowest densities.

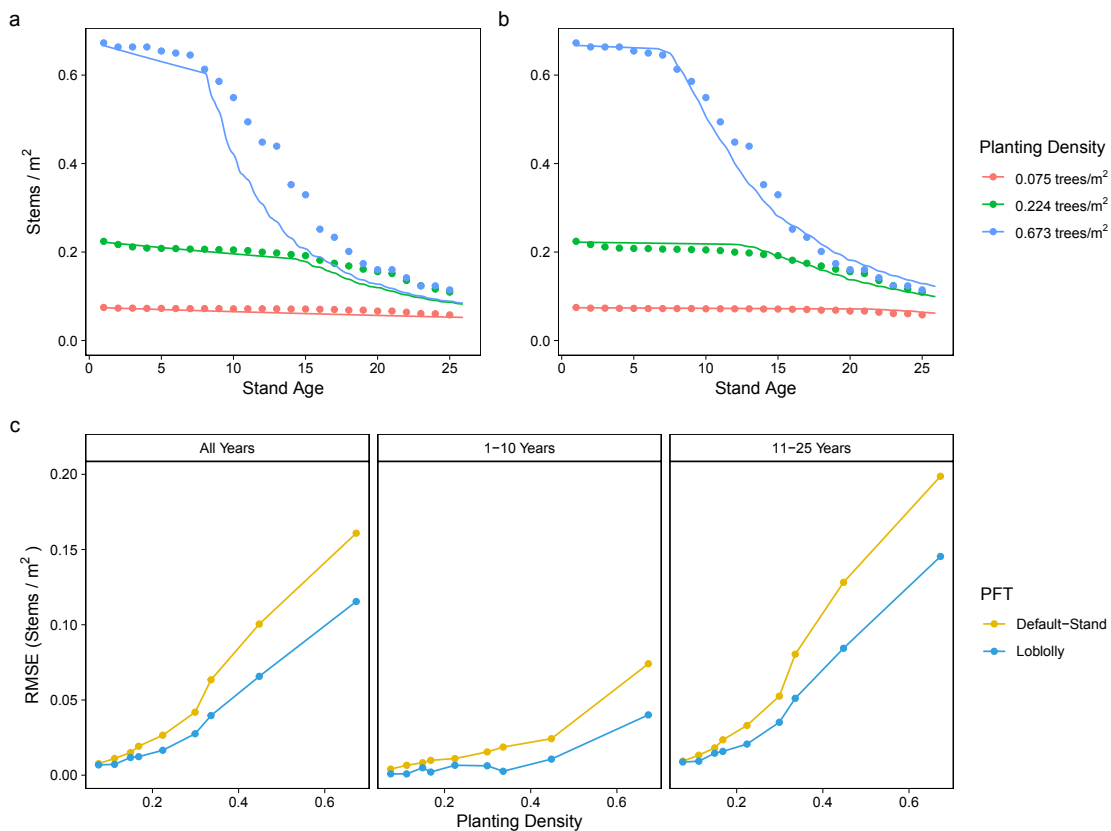


Figure 2.11: PFT Performance for Stem Density: Observed (dots) versus simulated (lines) stand stem density for (a) the default PFT and (b) our loblolly PFT. The high, middle, and low planting densities experiments are shown. (c) The RSMEs for all planting densities for all, early, and late years of the experiment.

The loblolly PFT's simulated DBH more closely match the observations for all plant-

ing densities compared to the default PFT (Figure 2.8a). However, the DBH for the different densities diverge more slowly from each other than the observations and do not capture the fast early growth of trees at low planting densities (Figure 2.8b). Simulate heights are quite accurate at young ages but become less accurate after age ten (Figure 2.9b). As a result, for densities of 0.224 trees/m<sup>2</sup> and greater the Loblolly PFT performs less well overall than the default PFT simulations, especially at later ages (Figure 2.9c). Aboveground biomass predictions are very similar up to year 10 (Figure 2.10c). After year 10 the loblolly PFT simulations show decreasing rates of growth that keep them closer to the observations (Figure 2.9b).

The loblolly PFT showed improvements in stand level properties such as stem density, basal area, and crown area. Stem density shows a small improvement in accuracy for the early years prior to canopy closure and the timing of canopy closure. The rate of self-thinning after canopy closure was lower and more accurate across planting densities (Figure 2.11b). Basal area became more accurate in the early years of stand development, with greater improvements at the higher planting densities. BA has more reasonable values after canopy closure and exhibits plateauing more similar to the results (Figure 2.12b). Crown area for the early years is not greatly different for the two PFTs, with the loblolly PFT doing slightly worse for the lower planting densities. The loblolly PFT shows a smooth transition to a lower rate of crown growth as stand closure occurs (Figure 2.13b). The crown area over ground area stabilizes on a value closer to 1, which is far lower than with the default PFT simulations.

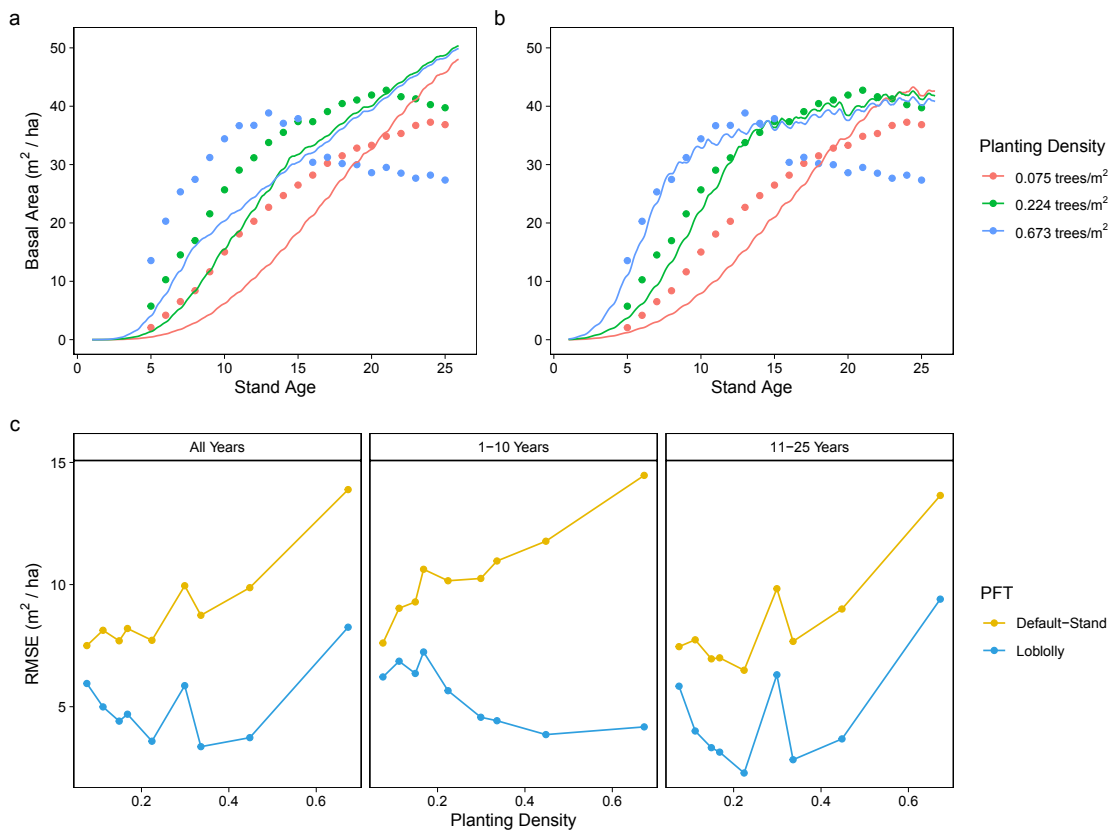


Figure 2.12: PFT Performance for Stand Basal Area: Observed (dots) versus simulated (lines) basal area for (a) the default PFT and (b) our loblolly PFT. The high, middle, and low planting densities experiments are shown. (c) The RSMEs for all planting densities for all, early, and late years of the experiment.

## 2.4.2 Thinning Experiment

Our simulations demonstrate the ability of the Vegetation Management Module to simulate mid-rotation stand thinning in FATES. The thinning simulations also showed that implementation of the thinning method influences the accuracy of post-thinning stand demography. However, post thinning stand recovery was largely

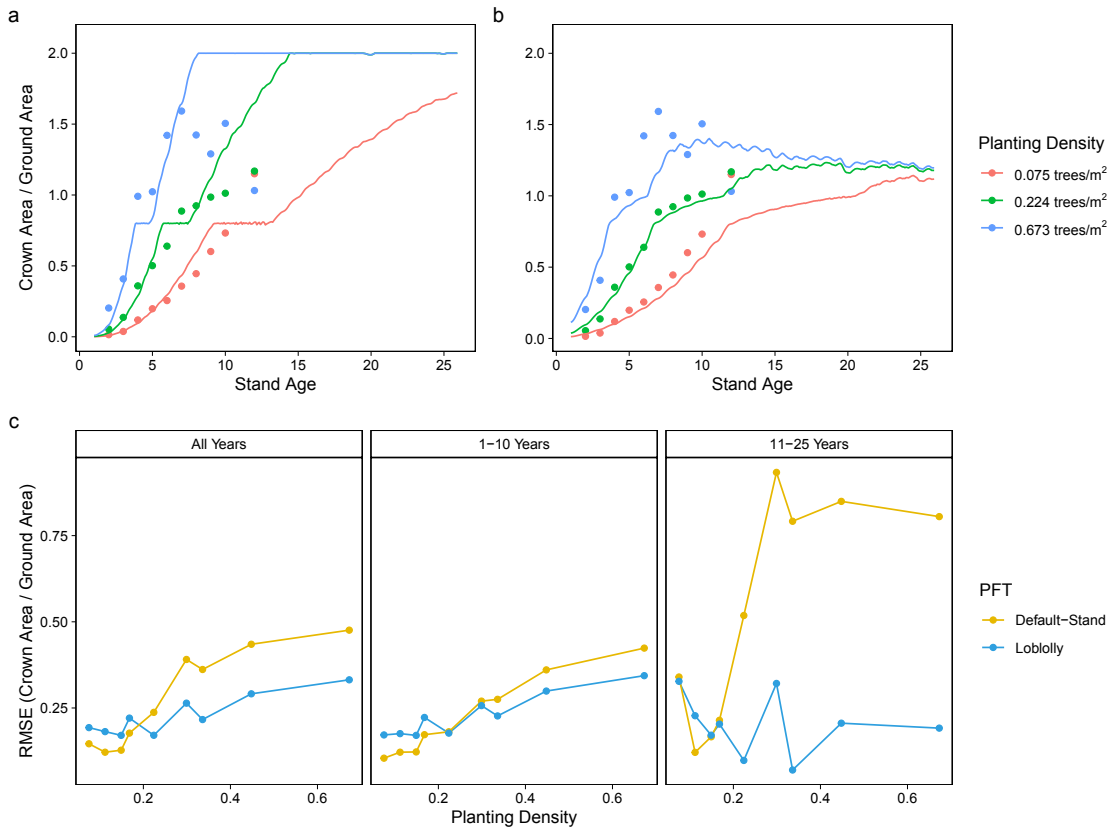


Figure 2.13: PFT Performance for Crown Area: Observed (dots) versus simulated (lines) crown area over ground area for (a) the default PFT and (b) our loblolly PFT. The high, middle, and low planting densities experiments are shown. (c) The RSMES for all planting densities for all, early, and late years of the experiment.

insensitive to the thinning method.

Figure 2.14 illustrates the ways our two thinning simulations types were performed. The top row shows simulations that were initialized from plot inventories at the first observation. The bottom row shows simulations that were initialized to inventory just prior to the thinning event.

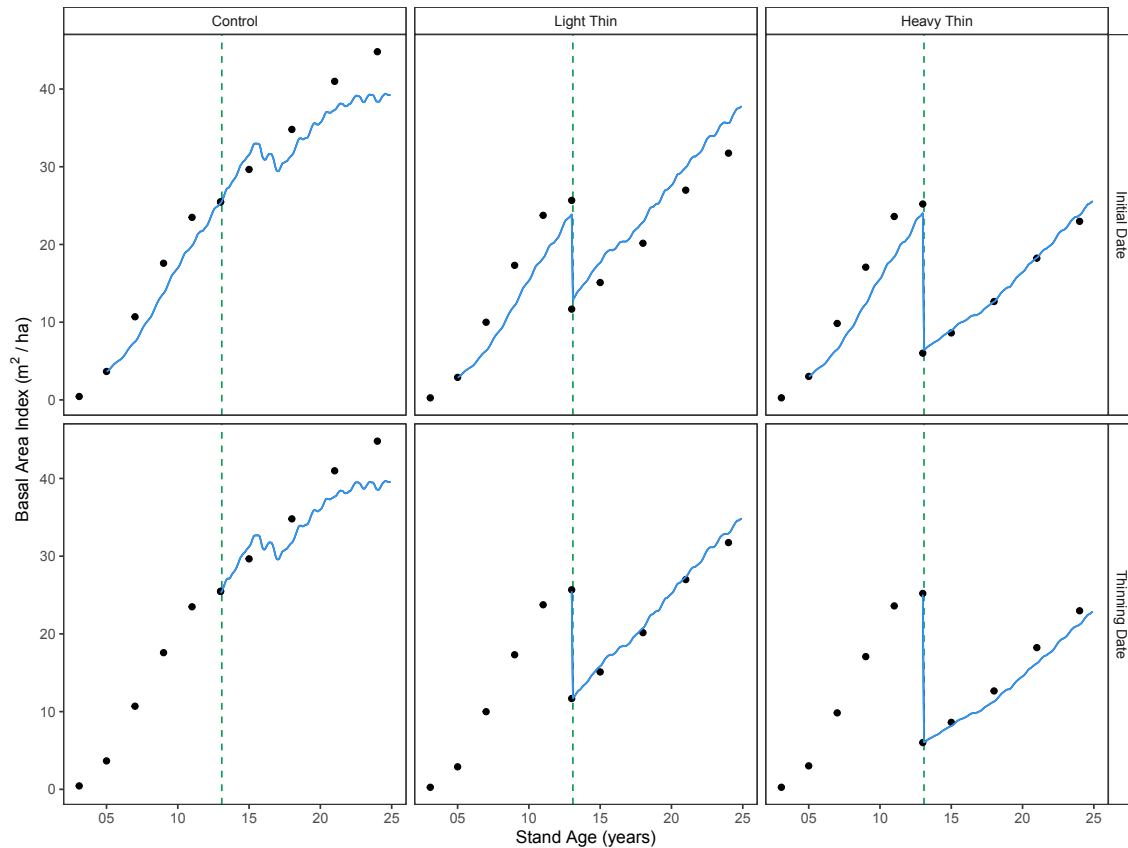


Figure 2.14: Simulated Thinning Validation: Shown are observations (dots) for three plots at one study location, one unthinned, and two thinned. The top row illustrates simulations (lines) initialized at the the first available observation. For the thinned plots in the center and left panels thinning occurs at the correct date, marked by a green dotted line. The lower row shows the same plots with simulations initialized just prior to thinning. Under these conditions the simulations can precisely reproduce the thinning effect.

The simulations initialized at the first observation date demonstrate the VM module's full thinning functionality. The effect of thinning can be seen as a marked decrease in basal area (Figure 2.14, center and right). The simulated date of thinning aligns with the thinning in the field plots, but is it difficult to visually validate that the

thinning had been performed accurately because of differences in the simulated and observe trajectories prior to thinning. Since the stands develops according to the models simulated vegetation dynamics following initialization the simulations do not align exactly with the observations at the time of thinning.

Our second set of thinning simulations were initialized to inventory just prior to thinning for more straightforward comparison (Figure 2.14, lower row). By initializing at the thinning date we can isolate the effect of the thinning event from modeled stand growth. For these simulations we specified the thinning events to remove trees to the observed BA after thinning. The plots show that simulated thinning results in the correct final BA under these conditions (Figure 2.16).

To examine the effect of our three thinning methods we simulated each of our thinned plots using each approach. The demography of thinning for the observed sites would be best described as imperfect low thinnings. All the smallest trees were removed, and some of the largest as well (Figure 2.15). The different simulated thinning methods had different effects on simulated demographics, consistent with their individual idealized thinning representations. Simulated proportional thinning overestimated the number of small trees remaining (Figure 2.15, second column). Simulated low-perfect thinning resulted in a high bias in the mean tree size and resulted in highly simplified demographics (1-3 cohorts) (Figure 2.15, third column). Simulated probabilistic-low thinning retained a few small trees not present in the observations but captured the overall distribution best, both visually and in terms of distribution statistics (Figure 2.15, fourth column). The proportional and perfect-low thinnings left cohorts that did not capture the mean or variance of the observed thinned stands

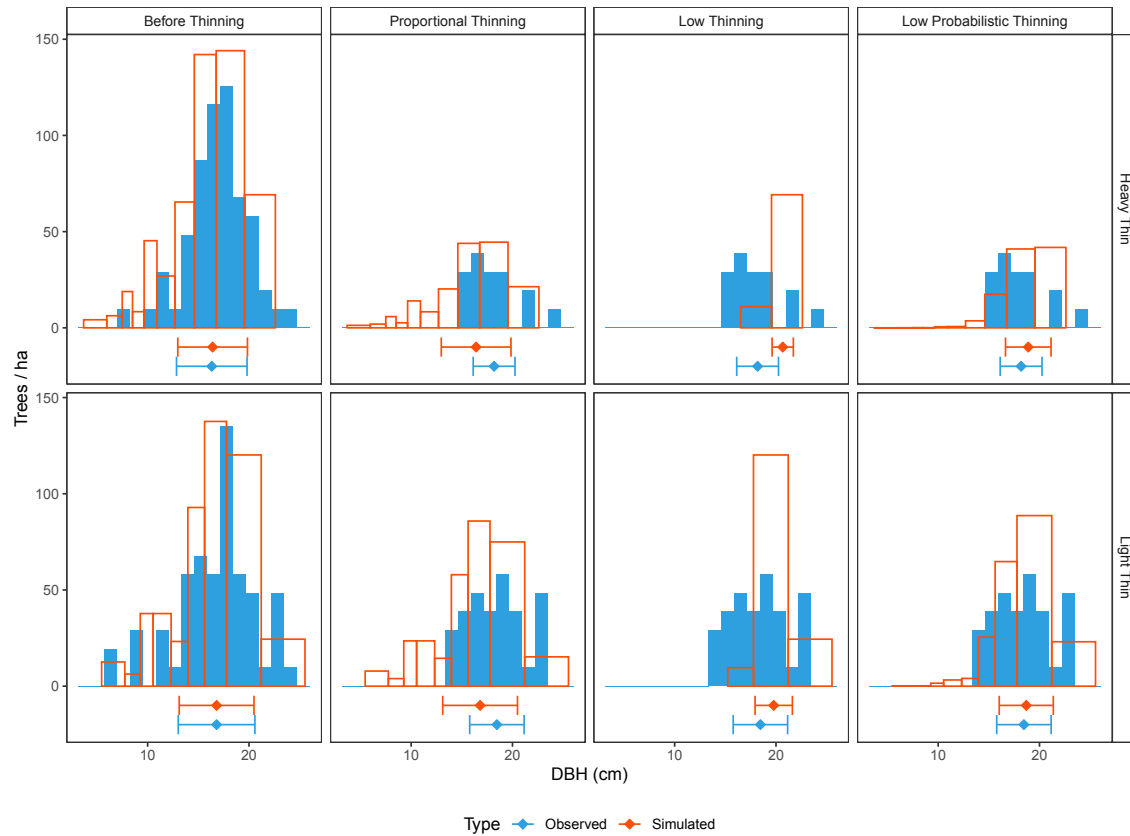


Figure 2.15: Simulated Thinning Demographics: Two experiments thinning plots (rows) are shown. The observed (blue) and simulated (red) stand diameter distributions are shown prior the thinning in the leftmost row. The diameter distributions following thinning are show for different simulated thinning methods in the three rows on the right. The dots below the histograms mark the mean DBH and the bars one standard deviation for the distributions.

as well.

Thinning was performed using a goal basal area for all three methods so basal area did not differ among the methods immediately after thinning (Figure 2.16). However, by virtue of the fact they remove different size trees to achieve the same basal area goal the do differ in their post thinning stem density. By capturing the thinning demog-

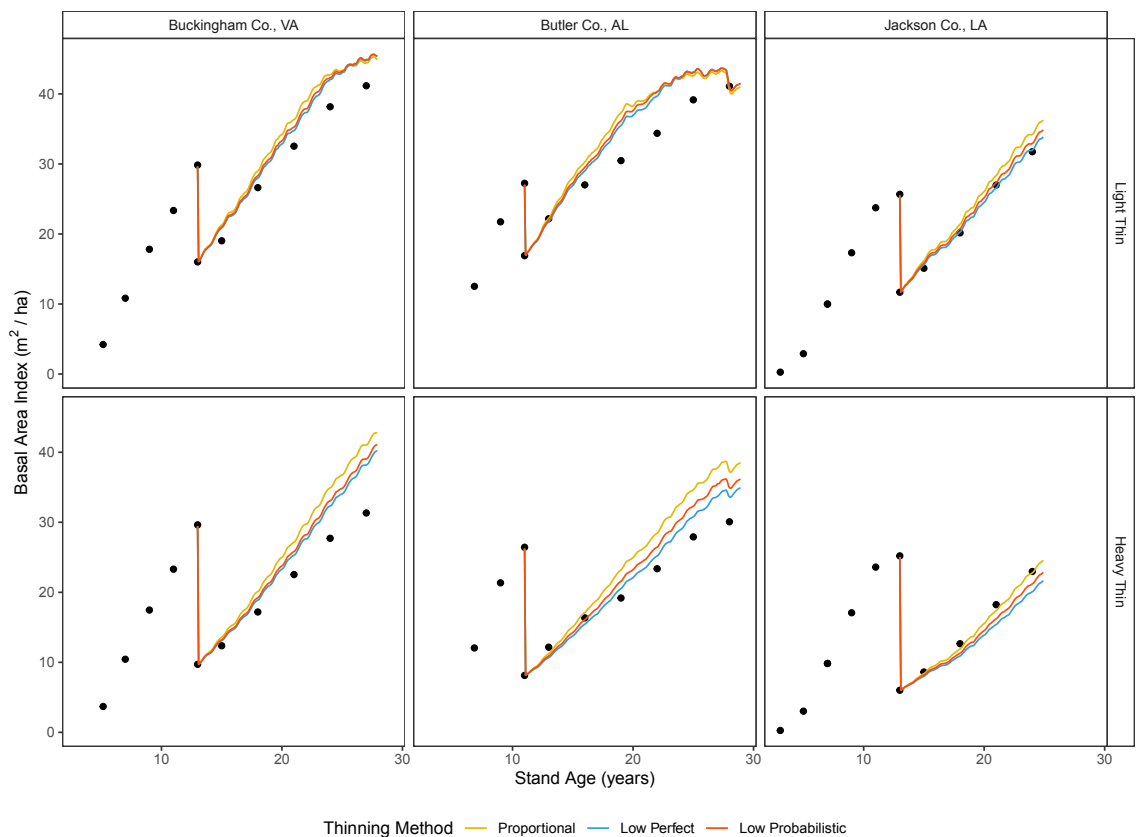


Figure 2.16: Response of Basal Area to Thinning: Observed (dots) and simulated (lines) basal area in response to thinning. For each of three location two thinned plots are shown. Three simulated thinning methods were performed for each plot.

raphy more accurately, the observed stem density also matched the probabilistic-low thinning method more closely (Figure 2.17). The low and proportional thinning methods were more biased than the probabilistic-low thinning for all thinning cases examined.

Despite the notable differences in demography among the three thinning methods, the thinning method had only a small effect on regrowth following thinning. Neither

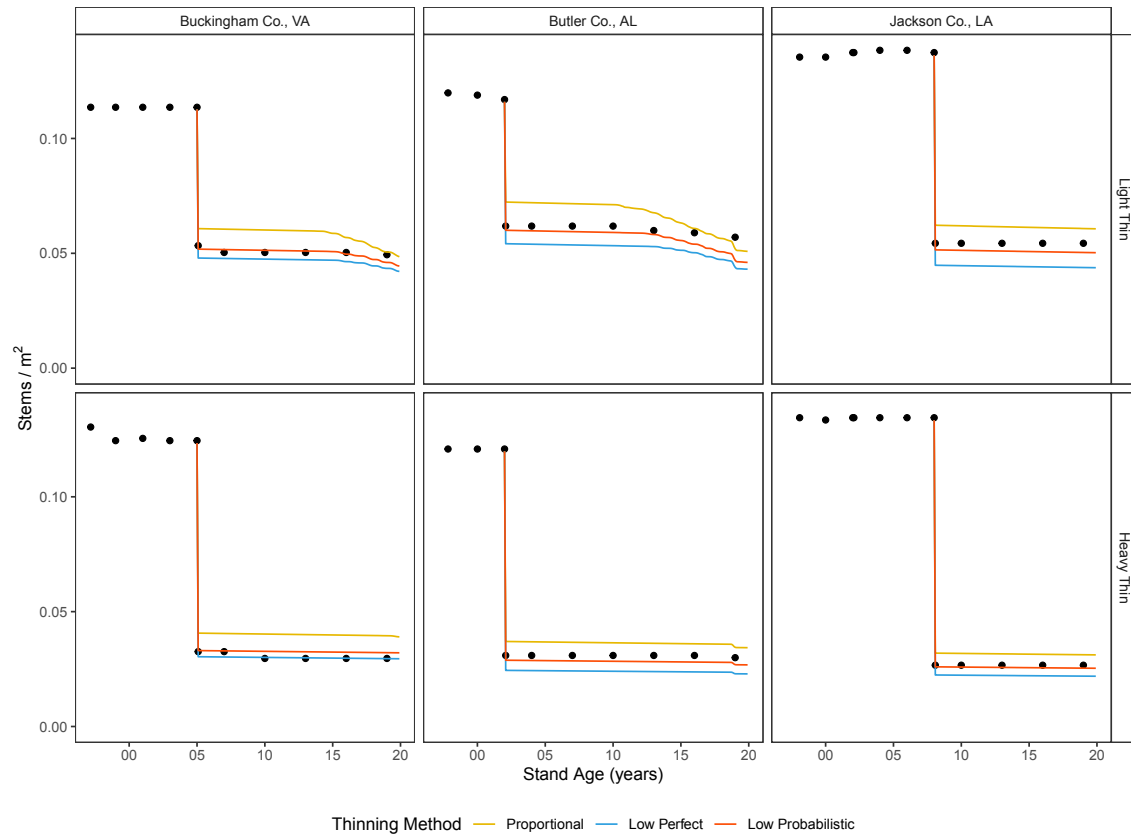


Figure 2.17: Response of Stem Density to Thinning: Observed (dots) and simulated (lines) stem density in response to thinning. For each of three location two thinned plots are shown. Three simulated thinning methods were performed for each plot.

basal area (Figure 2.16) nor AGB (Figure 2.18) diverged much in the years following thinning for the three methods. The dominant pattern for simulated recovery after thinning is an overgrowth bias. Although several simulations show recovery similar to or slightly less than the observations, most show a greater increase in basal area (Figure 2.16) and aboveground biomass (Figure 2.18). The bias is more pronounced for basal area (Figure 2.16) but in some simulations the simulated basal area returns closer to the observed values at later time points.

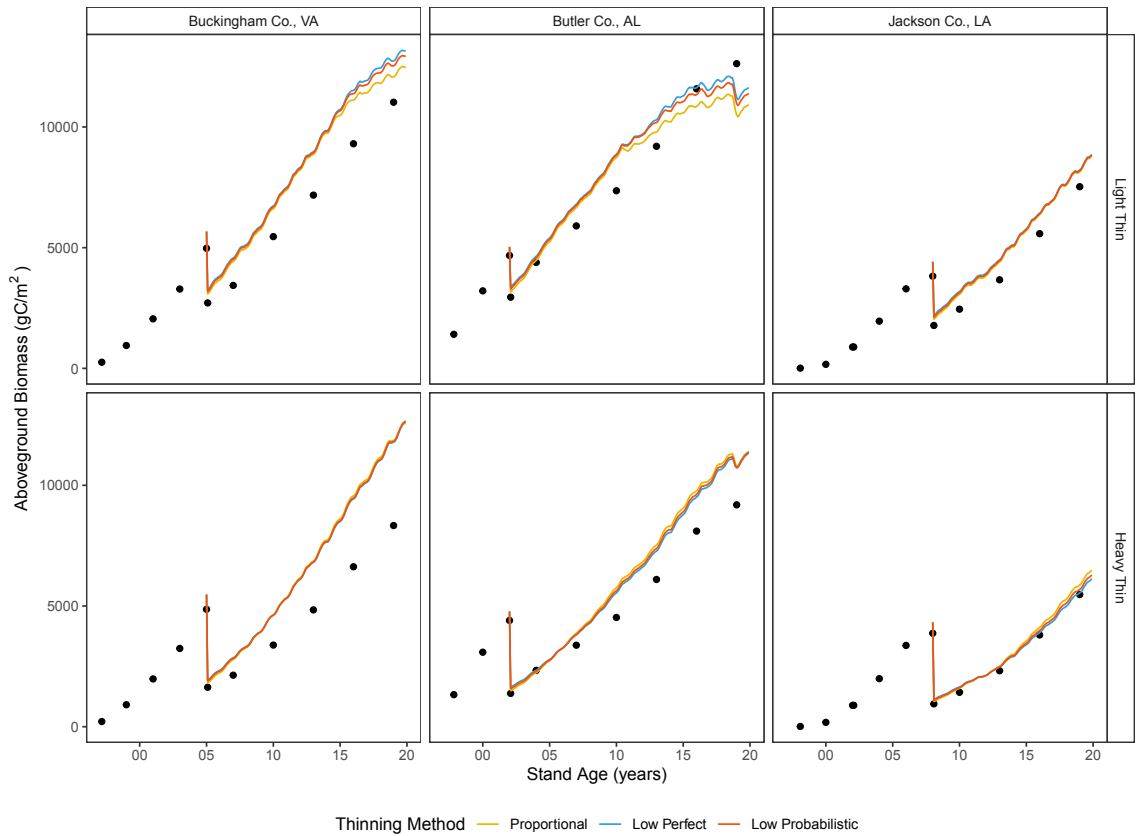


Figure 2.18: Response of Aboveground Biomass to Thinning: Observed (dots) and simulated (lines) aboveground biomass follow thinning. For each of three location two thinned plots are shown. Three simulated thinning methods were performed for each plot.

## 2.5 Discussion

### 2.5.1 Spacing Trial PFT Evaluation

We found that the default FATES NEET PFT that represents conifers does a reasonable job capturing the early stages of stand development in our spacing trial

simulations but becomes less accurate as the stand ages in terms of growth, mortality, and stand level properties. Our new loblolly PFT performs better both in terms of producing more realistic stand behaviors and increasing accuracy across multiple metrics, especially in the later years of stand development.

Different factors drive the accuracy at different phases of stand development. The early years of stand development represent a pre-competitive phase that precedes canopy closure, during which time trees grow with limited influence from their neighbors. In the simulations the stand level aboveground biomass growth is nearly identical for the two PFT up to year 10 (Figure 2.12). However, the default PFT simultaneously has diameters that are too small (Figure 2.8a) and heights that are too large (Figure 2.9a). This suggests that the default allometry does not accurately capture the relationship between DBH and height. The revised DBH-height allometry we used for the loblolly PFT improves the accuracy of both DBH and height at these early ages.

The stand level properties of stem density and basal area improve with the loblolly PFT in the pre-competitive phase. In this phase mortality occurs for reasons that are often hard to identify in the field. In FATES this mortality is modeled empirically as a constant background mortality rate. The spacing trial stem density data shows the pre-competitive phase as a period of slow, roughly linear mortality that precedes a negative exponential phase following canopy closes (Figure 2.11). Fitting the background mortality rate to observations improved the accuracy of the loblolly PFT by a small amount in the pre-competitive phase. The combination of improvements in matching tree size and numbers resulted in a improved accuracy for basal

area in the early years (Figure 2.12).

Despite a new crown area allometry with more realistic, narrower tree crowns, the loblolly PFT does not model crown area better than the default PFT up to year 10 (Figure 2.13c, middle panel). While the default PFT has wider crowns, its survival is lower. As a result the total crown area is roughly correct for the default PFT despite there being too few trees in the stand. Additionally the revised allometry has larger crowns when trees are very small leading to slightly reduced agreement with observations for the first few years of the experiment. The alteration we introduced in the way tree crowns contract upon interaction eliminates the ‘step’ effect seen in the default PFT (Figure 2.13 a vs. b). However, this qualitative improvement in realism is not reflected in a large numerical change in RMSE (Figure 2.13c).

During the competitive phase PFT properties related to the simulated forest canopy are important drivers of model accuracy. This phase begins as the canopies of neighboring trees get close enough to start competing for light, which happens earlier for higher planting densities. The default PFT becomes increasingly less accurate following canopy closure. In the observations total crown area peaks at the highest density before year ten and then begins to decline. This occurs because loblolly pine is a shade intolerant species. The default PFT behaves more like a shade tolerant tree. For the default PFT crown area over ground area rises until it reaches a value of two, a full double layer canopy, the maximum allowed by default in FATES. For the higher densities the onset of the competition induced mortality doesn’t occur until a full double layer canopy is formed ( $\sim 8$  yrs at  $0.673$  trees/m<sup>2</sup> and  $\sim 14$  years at  $0.224$  trees/m<sup>2</sup>). Competition induced mortality occurs faster for the default PFT than in

the observations (Figure 2.11a), which may be due to the high canopy density. The trees that survive are larger than those in the field (Figures 2.8a and 2.10a). Basal area, which was too low in early years, becomes too large as a result in later years for the default PFT (Figure 2.12a).

After year 10 the loblolly PFT crown area is far more accurate because it doesn't greatly overshoot the observed crown area like the default simulations. Observations stopped at year 12 after canopy closure occurred in all the plots. The loblolly PFT would likely score even better compared to the default PFT if data was collected beyond this point, as the canopy area was beginning to stabilize at values closer to one. The loblolly PFT crown area peaks and stabilizes at a value a little over one, indicating a shift to shade intolerance similar to loblolly pine. More accurate crown area improved simulated competition, which leads to a more accurate decrease in stem density after canopy closure (Figure 2.11b). Basal area is improved as well with values closer to observations and a realistic maximum basal area plateau (Figure 2.12b).

Our results show that our PFT does not capture the growth of all planting densities equally well. The highest densities in particular are difficult for the model to reproduce. However, based on our background research, the densest experimental stands are well above that which has been used historically. At the time the spacing trial began in 1983 the lowest experimental density used was well below that typically used in plantations. Changes in management practices over the past several decades have seen a shift to lower planting densities. The lowest experimental density now coincides with the low end of what is now actually used in practice (Figure 2.7). So

while our PFT is not equally good for all planting densities it performs well for the most common.

## 2.5.2 Thinning

Our thinning experiments demonstrate our ability to perform thinning within a CLM simulation using the VM Module. By performing dedicated simulations starting right before thinning events we showed that we can accurately reproduce the resulting stand level reductions in basal area and stem count. We also showed we could perform different types of stand thinnings that mimic different thinning practices, and that by selecting the right one we could reproduce the post-thinning demography of real-world thinnings in loblolly pine plantations.

Our simulations showed the manner in which thinning is implemented does not have a major impact on stand level regeneration following thinning. Basal area and above-ground biomass are quite similar between thinning methods (Figures 2.16, 2.18). This may be explained in part by the canopy development within the simulations. In our simulations thinning occurred before or shortly after canopy closure. Following thinning the canopy remains open, closing only in the last few years for some of the lightly thinned plots (Figure 2.17). Under open canopy conditions the simulated trees do not compete for light and there is less of a role for size differences between them. After canopy closure stand demographics may play a larger role as competition for light between different size cohorts resumes, but the experimental stands do not get old enough to confirm this.

For most locations we saw regrowth rates following thinning that were higher than those observed (Buckingham and Butler Co. plots in Figure 2.16), although others are quite realistic (Jackson Co. plots in Figure 2.16). There are several factors that may contribute to this mean high bias. First, understory competition was omitted from our simulations. The observed plots had competing vegetation in the understory but we did not simulate it because we lacked sufficiently detailed inventories and validated PFTs to represent the understory species. Understory competition can reduce overstory growth (Haywood et al., 1997; Miller et al., 2003; Sanchez and Eaton, 2010) so its presence could account for part of the difference between our simulations and observations.

Second, our examination of the canopy behavior following thinning also revealed a structural problem within the model that may bias release following disturbance. As discussed above FATES uses an approach that adjusts the crown area to approximate the crown plasticity seen in real canopies. When the canopy is very open the crowns of trees are allowed to maintain their maximum area dictated by allometry. As the canopy begins to close the tree crown area contracts to simulate the response to crown shading. Under conditions where stand level growth and mortality rates are gradual this process is also gradual. However, thinning results in a sudden change in stand structure, removing a large number of trees, and reopening the canopy. Following a canopy opening disturbance like thinning surviving trees will grow their branches into the resulting gaps to take advantage of the newly available light. The literature suggests that this process occurs on the order of six or more years for loblolly pine (Peterson et al., 1997; Yu et al., 2003). In our simulations we see a rapid adjustment

of the spread factor that regulates crown width resulting in crown area growing dramatically in a short period. In some of our simulations we see the canopy area double in the first few months after thinning. Within the model the existing foliage is rapidly redistributing over this larger area, without regard to physiological limits to branch growth and at no cost to the simulated trees. This is clearly not realistic and likely has the effect of artificially increasing light use efficiency and subsequently growth. The impact of this effect is not easy to quantify. It should unrealistically increase canopy area primarily for the period when crown expansion actually occurs in real trees. Even so any increased growth during this period will alter the simulated trajectory in a way that will not be reversed.

## 2.6 Conclusions

In this study we performed a novel validation of competitive behavior in the CLM-FATES model and developed a set of tools that will allow for new explorations into the role of forest management using this model. Using highly controlled forest manipulation experiments we showed that CLM-FATES can reproduce forest stand development over a range of competitive intensity with reasonable fidelity. We were able to improve the model's accuracy with species specific parameters and model improvements. This study expands the scope of testing of FATES in several important ways. Most testing of FATES has been done with unmanaged mature stands of mixed composition and age. This study tests FATES against monospecific stands from establishment through canopy closure and subsequent self-thinning mortality.

The ability of the model to robustly capture the behavior of a stand of relatively simple composition provides an important test of the model. Also, to date the development of FATES has been largely focused in the tropics ([Koven et al., 2020](#)). This represents one of the first examinations of FATES in the temperate zone. In the process we developed a new plant functional for loblolly pine, a species of great economic value that covers 13-15 million ha in the Southeastern United States ([Chen et al., 2017](#); [Schultz, 1997](#); [Zhang and Polyakov, 2010](#)). The development of the Vegetation Management Module allows full forest management cycles to be simulated in CLM-FATES. Together these advances open up new opportunities to explore the interplay of forest management and climate using CLM-FATES.

	Description	NEET Default	Loblolly PFT	Basis for Change
<b>Initial Conditions and Data Comparison</b>				
fates_history_height_bin_edges		Default	0.1m	Increase output to observation resolution
fates_history_sizeclass_bin_edges		Default	0.1in	Increase output to observation resolution
fates_recruit_hgt_min		1.3	0.35	Mean size at year 1 from data.
fates_recruit_initd		0.2	Variable	Match to initial planting densities
<b>Stand Conditions</b>				
fates_seed_alloc	Seed allocation parameter	0.1	0	Supress recruitment
fates_mort_disturb_frac	Disturbance mode	1	0	Prevent patch splitting
<b>Allometry</b>				
<i>DBH-Height Function</i>		Default	New	<a href="#">Pienaar and Turnbull (1973)</a> ; <a href="#">Richards (1959)</a>
fates_allom_hmode	Height allometry function index	1	6	
fates_allom_d2h1	DBH to height allometry parameter 1	0.64	0	Fit to data.
fates_allom_d2h2	DBH to height allometry parameter 2	0.37	0.02136	Fit to data.
fates_allom_d2h3	DBH to height allometry parameter 3	-999.9	1.0974	Fit to data.
fates_allom_dbh_maxheight	DBH where maximum height occurs	90	50	Estimated from data.
fates_allom_amode	AGB allometry function index	1	4	
fates_allom_agb1	AGB biomass parameter 1	0.06896	0.037403	<a href="#">Gonzalez-Benecke et al. (2014)</a>
fates_allom_agb2	AGB biomass parameter 2	0.572	2.676835	<a href="#">Gonzalez-Benecke et al. (2014)</a>
fates_allom_agb3	AGB biomass parameter 3	1.94	-999.9	Unused in Loblolly PFT.
fates_allom_agb4	AGB biomass parameter 4	0.931	-999.9	Unused in Loblolly PFT.
fates_allom_agb_frac	Fraction of woody biomass that is above ground	0.6	0.666	<a href="#">Albaugh et al. (2005)</a>
fates_allom_lmode	Leaf biomass allometry function index	1	6	
fates_allom_d2bl1	DBH to maximum leaf biomass parameter 1	0.07	0.0214	<a href="#">Zhao et al. (2015)</a>
fates_allom_d2bl2	DBH to maximum leaf biomass parameter 2	1.3	3.1169	<a href="#">Zhao et al. (2015)</a>
fates_allom_d2bl3	DBH to maximum leaf biomass parameter 3	0.55	-1.3647	<a href="#">Zhao et al. (2015)</a>
<i>Crown Area Function</i>		Default	New	<a href="#">Gering and May (1995)</a>
fates_allom_l2fr	Fine root to leaf carbon ratio	1	1.75	Optimized
<b>Leaf Properties and Photosynthesis</b>				
fates_leaf_jmaxha	Activation energy for Jmax	43540	38000	<a href="#">Ellsworth et al. (2012)</a>
fates_leaf_jmaxhd	Deactivation energy for Jmax	152040	2.00E+05	<a href="#">Ellsworth et al. (2012)</a> ; <a href="#">Medlyn et al. (2002)</a>
fates_leaf_vcmax25top	Maximum RuBisCO carboxylation rate at 25C, top of the canopy	65	73	<a href="#">Ellsworth et al. (2012)</a>
fates_leaf_vcmaxha	Activation energy for vcmax	65330	60900	
fates_leaf_vcmaxhd	Deactivation energy for vcmax	149250	2.00E+05	<a href="#">Ellsworth et al. (2012)</a> ; <a href="#">Medlyn et al. (2002)</a>
fates_leaf_long	Leaf longevity	4	2	<a href="#">Sampson et al. (2003)</a> ; <a href="#">Schoettle et al. (1994)</a>
fates_leaf_slaptop	SLA at the top of the canopy	0.01	0.00845	<a href="#">Baldwin et al. (1997)</a>
<b>Other</b>				
fates_root_long	Root longevity (years)	2	5	<a href="#">Matamala et al. (2003)</a>
fates_wood_density	Wood density	0.7	0.46	<a href="#">Jordan et al. (2008)</a>
fates_mort_bmort	Background mortality rate	0.014	0.002	Fit to data.

Table 2.5: PFT parameters and allometry functions for the default FATES Needleleaf Evergreen Extratropical Tree and the new Loblolly PFT.

## Chapter 3

# The Effects of Climate Change and Management on Loblolly Productivity and Yields in the 21st Century

### 3.1 Abstract

The managed pine forests of the Southeastern United States cover 13-15 million of hectares and make this one of the leading wood producing regions in the world. Climate change over the next century has the potential to change the way these forests grow with unknown consequences for future wood production. In this study we used the CLM-FATES earth system model with the Vegetation Management Module to predict the growth and wood production of loblolly pine (*Pinus taeda*) plantations in the Southeastern United States under potential future climates to 2100. We also examined how three forest management practices influence predicted wood yields. We simulated loblolly plantations across the species native range until the end of the 21st century under two bounding Coupled Model Intercomparison Project Phase 6 (CMIP6) climate scenarios (SSP1 RCP2.6 and SSP5 RCP8.5) with management scenarios examining the impact of planting practices, mid-rotation stand thinning, and the timing of harvest on wood yields. We found that loblolly pine is sensitive to climate change, with increases in yields of 70% from the start to the end of the century for the SSP5 RCP8.5 scenario. Increasing the planting density or increasing the management rotation length decreased total wood yields under both climate scenarios by 6.1-7.5% and 15.3-17.8% respectively. Mid-rotation stand thinning had the largest effect, increasing yields by 44.3-49.4% over the whole study period. When we allowed the model to control the timing of harvests based on modeled growth rates we found that rotation lengths varied realistically across the loblolly range and responded to climate change, decreasing in length by almost half under SSP5

RCP8.5. Our results show that forest management activities can have similar or greater effects than climate change on wood production from forest plantations. Our work is the first regional study of managed forests using the CLM-FATES model. The techniques developed in this work opens up new opportunities to examine the climate impacts of managed forests in the Southeastern U.S. and beyond.

## 3.2 Introduction

Forest plantations represent a small fraction of global forests (3% ([FAO, 2020](#))) but produce an disproportionate fraction of wood products. In the Southeastern United States (SEUS) plantations represent 18–28% of forests ([Fagan et al., 2018](#)), making this region a hotspot for plantation forestry and one of the leading wood producing regions in the world ([Fox et al., 2007](#)). These forests are economically valuable for the forest products they produce and may be a tool for helping mitigate climate change. Consequently, predictions of future productivity of these forests are critical for anticipating changes to wood supply and carbon storage.

Researchers use several different approaches to predict how forests will grow in the future. Scientists have long used empirical models to predict forest growth, including some efforts to used these model for simulating the influence of climate change and atmospheric CO<sub>2</sub> ([Burkhart et al., 2018](#)). However, empirical models have limitations when environmental conditions are novel and are not captured in the historical data used to construct the model ([Burkhart et al., 2018](#); [Johnsen et al., 2001](#)). Experimental approaches have been used to study how forests may experience climate change.

Forest manipulations experiments that subject trees to altered soil conditions and meteorology (e.g. PINEMAP's rainfall exclusion experiment ([Will et al., 2015](#))) or elevated CO<sub>2</sub> (Free-Air CO<sub>2</sub> Enrichment studies, or FACE) ([Norby and Zak, 2011](#)) have been performed, with others ongoing. While these studies have yielded important insights, these experiments are complex, expensive, and take years to give results. Mechanistic forest models integrate knowledge from field, lab, and statistics to extrapolate forest behavior beyond current conditions and can be used to explore more scenarios than is feasible with field experiments.

One type of mechanistic model, Earth System Models (ESMs), link forest ecosystem models with climate prediction models to enable the simulation of both the influence of climate on forests and the influence of forests on climate [Bonan and Doney \(2018\)](#). Forests are a major terrestrial driver of climate ([Bonan, 2008](#); [Jackson et al., 2008](#)) and are an important component in how an ESM simulates the carbon cycle. We also know that management has a large influence on climate and carbon stocks ([Erb et al., 2018](#); [Foley et al., 2005](#); [Luyssaert et al., 2014](#)). Unlike simpler models, ESMs track the full ecosystem carbon balance and can calculate climate feedbacks from vegetation on the atmosphere. Ultimately, predictions of how forests can be used as climate mitigation tools depend on the climate coupling and carbon accounting provided by ESMs.

The simulation of terrestrial ecosystems across the globe requires simplifications to how the ecosystems are represented in the models. It is important to understand how the simplifications potential influence the inference drawn from ESM simulations. For example, to date most ESMs have not specifically represented managed forests

and active management processes (Pongratz et al., 2018). Most ESM land models have represented forests as stocks of carbon, rather than individual plants. They are unable to simulate the details of forest management since they do not represent age and size structure in forests. Therefore, management of forest occurs in most current ESMs as changes in forest area and wood removals as dictated by socioeconomic scenarios, commonly the Coupled Model Intercomparison Project (CMIP) Shared Socioeconomic Pathways (SSPs).

Recent advances in some ESMs have added demographic forest representations (Fisher et al., 2018). The carbon stored in a simulated forest is now contained in trees of different size and ages, with trees competing for resources. By manipulating the simulated forest composition and resources it becomes possible to simulate more aspects of management in these models and evaluate what processes are important to include in climate change simulations. In fact, when demographic forest representations are added to an ESM it becomes necessary to represent some of the specifics of forest management because the model now has to specify how wood from trees of different size and ages is harvested. The choice is not whether to represent management but rather what level of detail to include. Ultimately, simulating managed forests in ESMs will help better characterize the role of actively managed forests in the coupled climate system and their influence on the trajectory of climate change.

Here we used an ESM (specifically CLM-FATES), and a new management extension, the Vegetation Management Model (see 2.3.3), to simulate how pine plantation forests in the SEUS respond to climate change over the 21st century, focusing both on the productivity and harvest yields. First, we asked how the productivity and wood

yields of loblolly pine plantations will change under two bounding climate scenarios: SSP1 RCP2.6 and SSP5 RCP8.5? Second, how do different aspects of forest management such as planting density, mid-rotation stand thinning, and rotation length change wood yields with climate change? Finally, we explore how the timing of the management cycle (harvest rotations) across the region responds to climate change.

### 3.3 Methods

To examine the impact of management in loblolly pine plantations under climate change we designed a series of simulation experiments that compared different aspects of the management cycle. Loblolly pine is typically managed in single age stands where all trees are removed in a clearcut harvest when the trees reach the desired marketable size. The management cycle, or rotation, then begins again with another round of planting. We chose to investigate the effect of three elements of the management cycle: the density at which trees were planted at the beginning of the cycle, whether or not stand thinning was performed in the middle of the rotation, and the length of the rotation, i.e. the time from planting to final harvest. This required us to research the planting densities used in practice, the timing of thinning, and typical rotation lengths in the field. We used this information about the variability in these practices to design idealized management scenarios with contrasting management properties that could be compared to each other. Future climate is uncertain, the extent of future climate change being highly dependant on human decisions over the next century. We used two bounding climate scenarios (with the lowest and high-

est radioactive forcings) developed by the scientific community in conjunction with our management scenarios to perform a set of simulations to predict the change in loblolly productivity and wood yields between 2015 and 2100 under different possible climate futures.

### 3.3.1 Model

#### CLM-FATES

For our experiments we employed CLM-FATES. The Community Land Model (CLM) is an instantiation of the Community Terrestrial Systems Model (CTSM) for use within the CESM earth system model. The Functionally Assembled Terrestrial Ecosystem Simulator (FATES) is an alternate vegetation model for CLM (and the ELM land model in the E3SM) with demographic representation of plants. We used a version of the CLM that we modified slightly to include parameters needed for the Vegetation Management Module ([doi:10.5281/zenodo.7335275](https://doi.org/10.5281/zenodo.7335275)). Within FATES, we used the Vegetation Management Module from Chapter 2 to simulate management activities. In brief, the VM Module allows forest management events such as planting, competition control, stand thinning, and harvest to be prescribed using an input file.

Version 1.1 of the Vegetation Management Module ([doi:10.5281/zenodo.7335612](https://doi.org/10.5281/zenodo.7335612)) adds the ability to specify specific regions in which events will occur, recurring events, and a set of conditional management events. Conditional events use criteria that a

vegetation patch must match in order for the event to execute, such as size, basal area, age, etc. Conditional events details (timing, location demographic details) are recorded to a log when they occur so that the simulated management history for any location can be examined after the fact. These new features allow for simulation of management activities that vary over space, change over time, and respond to growth and development of simulated vegetation.

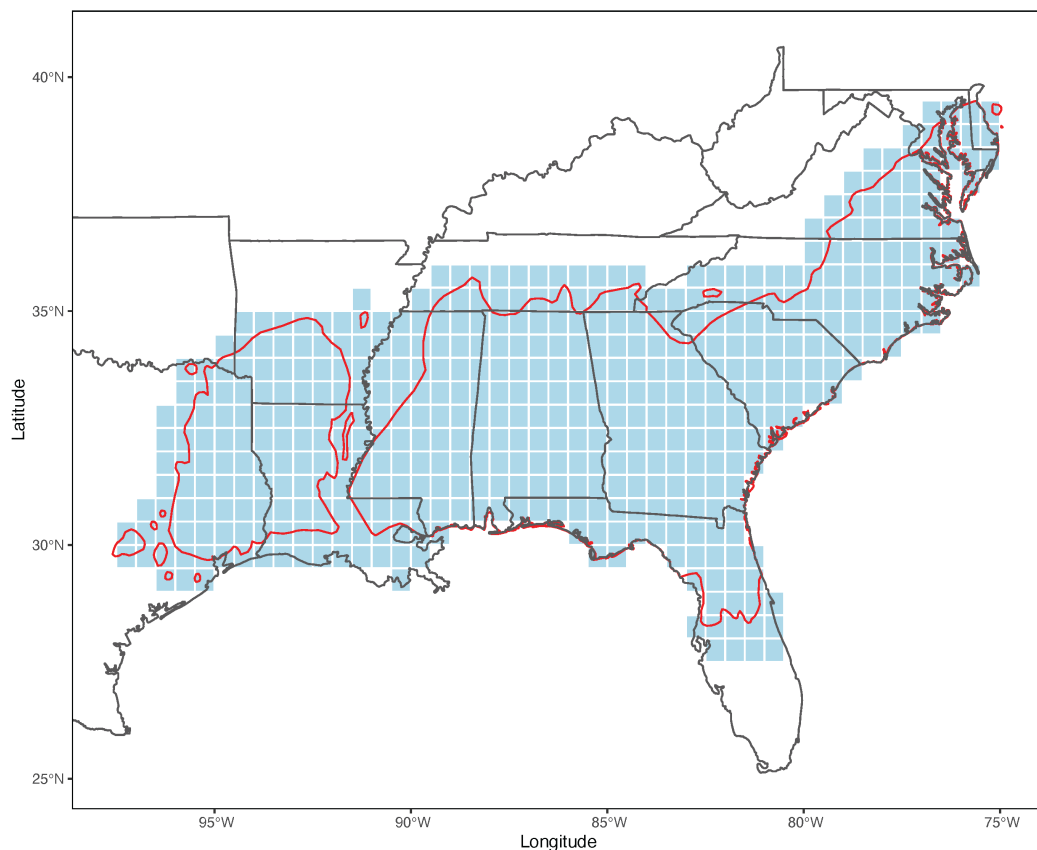


Figure 3.1: Study Region: The region of the Southeastern United States simulated in this study. The historical species range for loblolly pine is outlined in red (Little, 1971; Prasad and Iverson, 2003). The grid cells simulated are shown in blue.

### 3.3.2 Study System

#### Region

Our study focused on the loblolly plantation system of the Southeastern United States. We included grid cells that fell within or just outside the historic growth range of loblolly pine from the work of Little ([Little, 1971](#); [Prasad and Iverson, 2003](#)) ([Figure 3.1](#)). Loblolly pine is cultivated outside its native range but this should represent most of its North American extent in cultivation today.

#### Loblolly Plantation Management Practices

While loblolly pine is heavily studied, the scientific literature provides little information about the specifics of operational loblolly silvicultural practices. To obtain information about loblolly management as practiced today we reviewed literature targeting foresters and landowners and interviewed academic experts on loblolly silviculture. We obtained current publications on loblolly management from state forestry agencies and university agricultural extension services from across the Southeast U.S. ([Table 3.1](#)). We reviewed these sources and compiled the criteria they listed for determining when and how to thin loblolly stands. The sources vary in the exact thinning criteria and values that they recommended. We developed a consensus management prescription that used values shared across sources and used stand characteristics calculable in FATES. We consulted with experts in the Forest Resources and Environmental Conservation department at Virginia Tech to refine our

prescription based on their estimation of typical management for the region.

Source	State
<a href="#">Cunningham (2021)</a>	Arkansas
<a href="#">Megalos (2019)</a>	North Carolina
<a href="#">Demers et al. (2019)</a>	Florida
<a href="#">Dickens et al. (2004)</a>	Georgia
<a href="#">Traugott and Dicke (2006)</a>	Mississippi
<a href="#">Nebeker et al. (2015)</a>	Mississippi
<a href="#">Billings (2008)</a>	Texas

Table 3.1: Sources of Management Criteria

Experts and sources generally give estimates of rotation lengths in the range of 25 to 40 years. Shorter rotation lengths in the lower 20s and longer lengths up to 50 years can occur in the most and least productive parts of the range. Longer rotation lengths can also be associated with less intensive management practices. We chose the extremes of the core range for our experiments. Experts state that the more typical value is around 25 years so we chose that as our default value with 40 years as our alternate practice.

We used the review of planting density in the region that we previously performed (Chapter 2, section 2.3.7) to inform the planting densities for this study. We used 1250 trees per hectare as our default value as it reflects a typical value for current day practice. Planting densities of 2000 trees per hectare were used as recently as the 1960s and it is also the default value used by FATES when establishing stands from bare ground so we chose this value as our alternate practice.

Mid-rotation thinning typically occurs between 12 and 18 years. We chose an age of 15 years for our fixed prescription, which was judged a typical age for a rotation

length of 25 years. Simulated stands were thinned to a basal area of 16 m<sup>2</sup>/ha. For our dynamic simulations we used a basal area of 28 m<sup>2</sup>/ha as the triggering criteria for thinning. We also added a minimum age limit of 6 years to ensure thinning could not occur at improbably young ages and an upper stand mean diameter at breast height (DBH) of 24 cm to prevent thinning occurring when trees were approaching a harvestable size.

Our sources and experts gave us an estimate of 30 cm DBH as the cutoff for commercial sawlogs used in the production of boards and lumber. For our dynamic simulations we set the triggering criteria for the final clearcut harvest to be a stand mean diameter of 32 cm. We chose this value to ensure the majority of stems in the simulated stand would meet our sawlog criteria.

### 3.3.3 Future Climate Scenarios

To test the sensitivity of forest management under differing climates we chose the two bounding CMIP6 shared socioeconomic pathways, SSP1 RCP2.6 (SSP1) and SSP5 RCP8.5 (SSP5), for our simulations. SSP1 RCP2.6 represents a possible future where society makes strong efforts to reduce emission. Under this scenario atmospheric CO<sub>2</sub> peaks around mid-century and then declines along with radiative forcing. The SSP5 RCP8.5 scenario has high CO<sub>2</sub> emissions that climb through the end of the century producing high radiative forcing that reaches 8.5 Wm<sup>2</sup> (O'Neill et al., 2016). We chose these scenarios because they represent the extremes of SSP tier 1 with forcing output available from CESM fully coupled runs.

### 3.3.4 Model Settings and Driving Data

#### Model Forcing

We performed our simulations in an “offline mode” where the land component is driven with prescribed meteorological, aerosol, and CO<sub>2</sub> forcing. In this mode the land surface and vegetation respond to the forcing but the resulting changes in surface energy balance and CO<sub>2</sub> absorbed from or emitted to the atmosphere do not feedback onto the atmosphere or adjacent grid cells, i.e. the land is uncoupled with the atmosphere.

For our SSP simulations we used CLM5’s anomaly forcing dataset as forcing inputs. The anomaly forcing method uses the calculated monthly climate anomaly, compared to recent climate, predicted by the fully coupled CESM CMIP6 simulations. To provide sub-monthly variability in metrology the monthly anomalies are applied on top of a looping reference period of historical reanalysis meteorological forcing. We used the standard years for CMIP6 anomaly forcing, 2000-2014. CO<sub>2</sub> and aerosols are prescribed explicitly for each scenario.

#### General CLM-FATES Settings

Simulations were performed for the Southeastern U.S. region with a 0.5 degree grid. As previously described (Chapter 2, section 2.3.8) we altered the land surface input files such that for each simulated land grid cell only the natural vegetation component was simulated. We enabled FATES “Pure PPA” mode with parameter settings such

that mortality does not result in patch splitting. Together this allowed us to simulate a homogeneous forest at each grid location. No land-use change was specified. Simulation output variables were recorded monthly.

### **Model Initialization**

When the CLM-FATES model is first initialized no vegetation is present and ecosystem carbon stocks are empty. Therefore, it is necessary to bring the model to a state with vegetation cover and soil carbon suitable to simulate current day conditions.

The model's soil carbon stocks require an extended period of simulation to reach a state of near equilibrium between soil carbon inputs and decay. In the CLM this is accomplished through a special set of simulations called a spin-up that build up the soil carbon stock. We spun-up CLM-FATES's soil carbon stocks from bare ground using the default Plant Functional Types (PFTs) for the temperate zone with accelerated decomposition and simulated preindustrial climate for 4000 years. Accelerated decomposition was then turned off and the model was run for an additional 400 years. At this point soil carbon stocks were changing slowly.

We then transitioned to historical climate starting in 1850. In 1901 we altered the vegetation cover by switching to experimental parameters, cutting all vegetation using the VM Module, and replanting with our loblolly PFT at 2000 tph. The experimental parameter set includes the stand and loblolly PFT parameters previously described (Chapter 2, section 2.3.4). Additionally we turned seed germination off for all PFTs and changed the parameter controlling the leaf area profile from 1 to 1.02

to address a model bug related to the canopy demotion process when trees become large <sup>1</sup>. The grid cells were clearcut again in 1935, 1965, and 1990. In 1991 the stands were replanted at 1250 tph.

### Simulation of Management Events

Management events were scheduled using the VM Module event driver file. In all simulations planting events were scheduled on the first of March, thinning events on the first of February, and clearcuts on the first of January. For the fixed rotation simulations the date at which each event would occur was prescribed across the whole region. In the dynamic simulations repeating conditional events were used such that the model checked once a year to see if criteria triggering planting, thinning, or clearcut harvest should occur. As FATES only has limited capacity to simulate very small trees, we perform planting in the year following harvest with trees 0.35m in height, the approximate size of a loblolly seedling at one year of age.

We simulated harvest rotations as either having a fixed duration or a dynamic duration. For the fixed simulations clearcuts were scheduled at either 25 or 40 year of age. In the dynamic simulations a mean stand DBH of 32 cm was used as the criteria to trigger a harvest. We chose a mean DBH of 32 cm to help ensure that all cohorts would be above our sawlog timber cutoff of 30 cm. For the fixed rotation simulations thinning was scheduled to occur at age 15. In the dynamically timed simulations criteria were used so that thinning would occur after 6 years of age when the basal

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<sup>1</sup>[FATES GitHub Issue #714](#)

area reached 28 m<sup>2</sup>/ha. More than one thinning could occur if the criteria was met again. To prevent thinning occurring when the trees were approaching harvestable age thinning was prevented if the mean DBH exceeded 24 cm.

For thinning and final harvest (clearcut) events the below-ground, branch, and foliage biomass for trees experiencing harvest mortality were left on site to enter the appropriate litter pools, while the trunk (bole) biomass carbon was moved to the wood harvest pool. The default FATES harvest efficiency setting of 0.8 was used such that 20% of wood harvest was left on site to represent harvest inefficiencies. For clearcut harvests all trees were killed. For thinning events the VM Modules probabilistic low thinning algorithm was used (described in Chapter 2, section 2.3.3) to remove trees starting with the smaller diameters until the patch reached a basal area of 16 m<sup>2</sup>/ha.

### 3.3.5 Climate Decomposition Simulations

To isolate how climate and atmospheric CO<sub>2</sub> contributed to changes in vegetation behavior in the model we conducted a series of simulations that decompose the forcing into parts. We conducted a “constant climate” control simulation that used a loop of repeating meteorological forcing from 2000-2014, the same years used to provide variance in the anomaly forcing simulations. Aerosols were set to 2010 values and the CO<sub>2</sub> fixed at the 2015 value of 399.65 part per million, obtained from NOAA-ESRL (Dlugokencky and Tans, 2022). For each scenario we also conducted simulations that combined either the SSP climate and aerosols with the fixed CO<sub>2</sub> and “constant”

climate and aerosols with SSP transient CO<sub>2</sub> (Table 3.5). For each of these forcing sets we ran our baseline management 25yr rotation scenario.

### 3.3.6 Management Simulations

We conducted two classes of simulations with fixed or dynamic rotation lengths. We used fixed timing management experiments to examine the impact of specific aspects of forest management in a highly controlled design. Our dynamic simulations were used to see how real world management timing might change across the region and over time in response to contemporary and future climate.

We performed a baseline management scenario simulation to which we could compare each of our alternate management scenarios (treatments). The baseline simulation conditions were 1250 trees per hectare (tph), a 25 year rotation length, without thinning. The simulation period from 1990-2015 was used as a control for this management scenario under recent climate. The baseline management scenario was performed under both SSP scenarios.

Each of our alternate management simulations varied one management aspect from the baseline scenario. For the planting density and thinning experiments the 25 year rotation timing was retained. We were able to complete three full management cycles for the standard 25 year rotation and two cycles for the alternate 40 year rotation length simulations. The differing rotation lengths meant that simulations did not cover identical periods. The difference of five years is fairly small but should be considered when interpreting the results. Yields were normalized to mean annual

values across experiments for comparison across all treatments (see below).

Our simulation treatments were begun in 2015 (Table 3.5), except for the dynamic rotation length simulations, coincident with the transition from historical reanalysis forcing to projected future forcing. These treatment simulations shared the same initial conditions from the end of the main 1990-2015 simulation. All simulations were run until the end of the available forcing in 2100.

For the dynamic rotation length simulations we started the treatments in 1990. Starting the simulations in 1990 allowed us to get an estimate of the management variability under recent climate. It also gave more time for the dynamic behavior to evolve in these simulations. We ran fixed rotation simulations starting in 1990 to compare to the dynamic simulations. We refer to the simulations that start in 1990 as *extended* treatment experiments. Since our 2015 baseline simulation is preceded by the same management in the preceding 1990 simulation it acts as its own extended simulation.

### 3.3.7 Data Analysis

We examined the primary effect of how climate and atmospheric carbon dioxide concentrations changed net primary productivity (NPP) over the 21st century and the secondary effect that changes in NPP had on wood harvest yields. NPP is constrained by limits on the stand level photosynthetic machinery (i.e. leaf area index), climatic, and atmospheric factors. NPP is relatively stable for mature forests under stable climate and there are also many sources of NPP estimates that we can

compare to.

We chose to focus on NPP values for closed canopy forest conditions. As a young forest develops primary productivity rises quickly until around canopy closure when it begins to stabilize as the photosynthetic machinery at the stand level reaches its maximum. In this analysis we were interested in how climatic factors and carbon dioxide changes primary productivity itself and not how this in turn changes rates of early stand development. Therefore we chose to only compare NPP for ages after canopy closure. We found that across our decomposition simulations canopy closure occurred before age 16. Accordingly, we used annual NPP for stand ages 16-25 for each rotation of our simulations.

Annual NPP was calculated by adjusting reported monthly NPP by the number of days in a month before performing the average. Values were calculated for each grid cell before averaging to obtain the mean annual NPP for the region for each year.

The mean NPP effect was calculated as the percent difference between the mean annual NPP across all grid cells and dates from the final rotation (2080-2089) of the decomposition simulations (SSP climate only, CO<sub>2</sub> only, and SSP/CO<sub>2</sub>) to the “constant climate”/fixed CO<sub>2</sub> control. The mean annual NPP was calculated for all grid cells in each year for Figure 3.2a.

To compare management practices it made sense to focus on how changes in primary production affects relevant management metrics. We therefore used wood harvest yields to compare our management scenarios. Wood yields are closely related to productivity and economic returns and are therefore relevant to multiple constituen-

cies: ecological, forestry, economic, and ESM. Wood removals are also an aspect of forest management that are currently represented in a number of ESMs, making it a relevant variable for future management intercomparison. As with other ESMs the model currency of CLM-FATES is carbon so we report harvest amounts as such, rather than volumes or board feet as might be common in the forestry literature. Dynamic wood harvest yields over time are a product of the pattern of management timing (rotation length) and the amount of wood removed at each harvest event (yield per rotation), so we examined these factors as well.

CLM-FATES outputs the wood harvested as an accumulating wood product carbon stock at the grid cell level. We calculated the wood harvested for a single event as the change in the wood product pool from the month prior to the event to the month of the event. The cumulative yield for a period was calculated as the wood stock following the simulation's final clearcut harvest less the stock following the prior harvest at the start of the simulation. To make yields comparable across all simulations regardless of the simulation or management period length we computed the mean annual wood harvest yield as the cumulative yield divided by the number of years between the preceding and final clearcut harvest events (Equation 3.1).

$$Y(Mgmt, Clim) = \frac{(WoodC_{end}(Mgmt, Clim) - WoodC_{start}(Mgmt, Clim))}{(Year_{end} - Year_{start})} \quad (3.1)$$

Where  $Y$  is the mean annual wood yield for a given set of management and climate scenarios and  $WoodC$  is the wood product carbon stock. The yield by harvest type,

i.e. thinning vs. final clearcut harvest, was calculated as the sum of harvest for the events of each harvest type over the experimental period.

The relative effect of a management treatment within a climate scenario (SSP = SSP1 or SSP5) was calculated as the percent change in mean annual yield from the baseline management scenario (25 year fixed rotation, 1250 tph, unthinned) to the management treatment scenarios (either 2000 tph planting density, with thinning, or 40yr rotation length) (Equation 3.2).

$$\Delta Y_{Tx}(Treatment, SSP) = \frac{Y(Treatment, SSP) - Y(Baseline, SSP)}{Y(Baseline, SSP)} \times 100 \quad (3.2)$$

We calculated the relative climate change effect on yields as the percent increase in mean annual yield from SSP1 to SSP5 for a given management scenario (Equation 3.3).

$$\Delta Y_{SSP1 \rightarrow SSP5}(Mgmt) = \frac{Y(Mgmt, SSP5) - Y(Mgmt, SSP1)}{Y(Mgmt, SSP1)} \times 100 \quad (3.3)$$

The change in relative climate effect for a given management activity is then the difference in between the management treatment scenarios and the baseline management scenario (Equation 3.4).

$$\Delta Y_{SSP1 \rightarrow SSP5}(Treatment) - \Delta Y_{SSP1 \rightarrow SSP5}(Baseline) \quad (3.4)$$

For all analyses CLM-FATES simulation output was analyzed in R ([R Core Team, 2022](#)).

## 3.4 Results

### 3.4.1 Regional-scale Climate Drivers of Loblolly Productivity

Our regional simulations predict an increased net primary productivity across the loblolly range over the 21st century for both SSP scenarios examined. The effect was much smaller in SSP1 than in SSP5, 13.7% vs. 83.8% mean regional increase in NPP between the 2000s and 2080s.

Our simulations that decomposed this increase in NPP by controlling for meteorological and CO<sub>2</sub> forcing revealed that the increase in NPP was strongly driven by increasing atmospheric carbon dioxide. Simulations that only differ by their CO<sub>2</sub> (holding climate constant at 2000-2014 values) showed that productivity under CO<sub>2</sub> was 15.4% higher for SSP1 and was 100.5% higher for SSP5 at the end of the century compared to when CO<sub>2</sub> was held constant at 400 ppm. In SSP1, the response to CO<sub>2</sub> was larger mid-century than at the end due to declining atmospheric CO<sub>2</sub> levels. The effect under SSP5 increased continuously over the 21st century as atmospheric CO<sub>2</sub> continued to rise in this scenario.

In contrast to the simulations that controlled for changes in atmospheric CO<sub>2</sub>, the

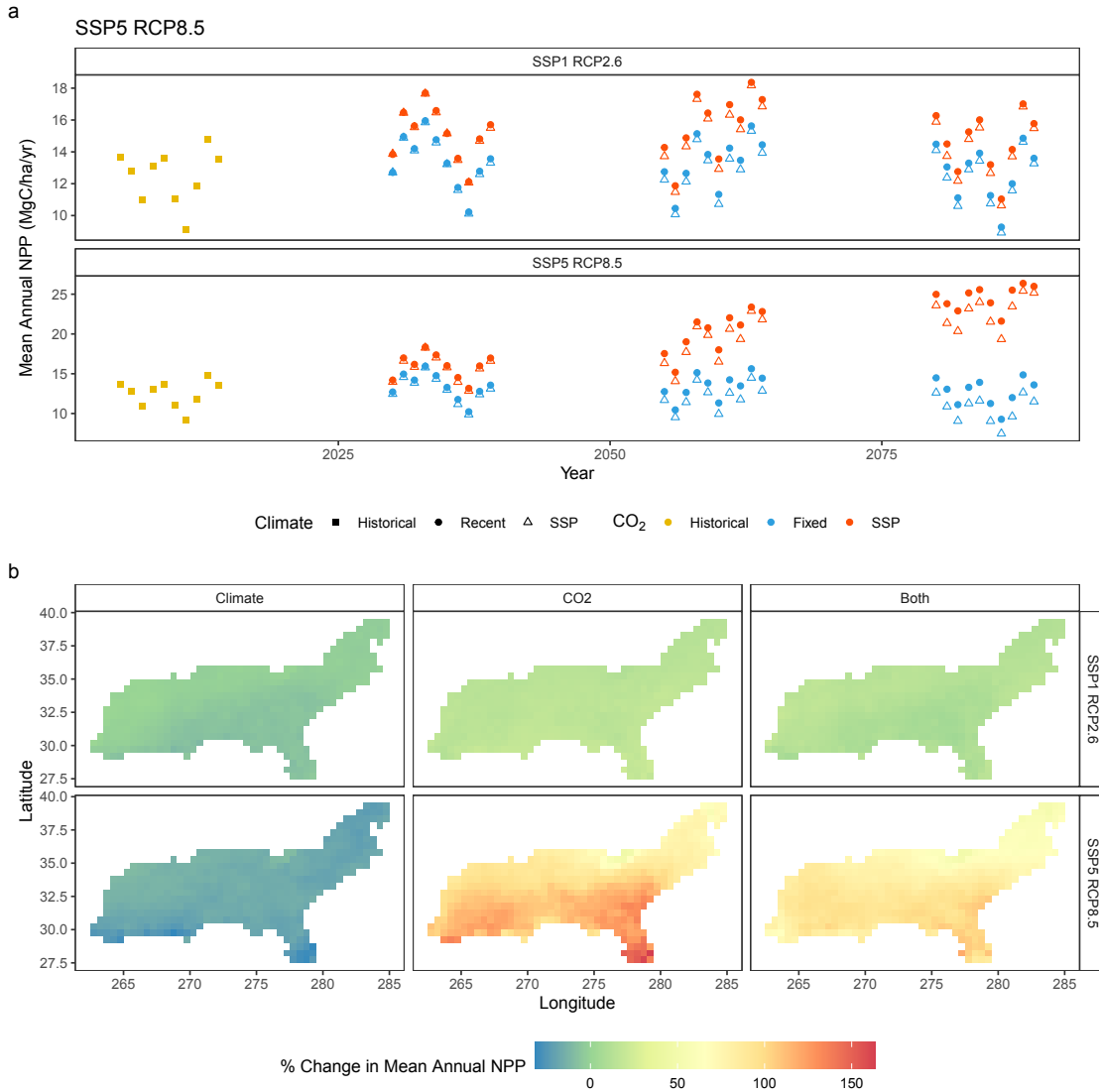


Figure 3.2: Drivers of Changes in Net Primary Productivity: (a) The effect of climate and CO<sub>2</sub> on NPP over time. Each point represents the mean simulated SEUS regional NPP for a given year and set of forcings. Historic NPP (2005-2014) is shown in yellow. NPP for future simulations with constant 400 ppm CO<sub>2</sub> are shown in blue and transient SSP CO<sub>2</sub> in red. Solid circles indicate simulations with repeating recent climate and empty triangles transient SSP climate. (b) Regional patterns of change in NPP over the 21st century. The percent change in the mean NPP from the start of the century (2005-2014) versus the end of the century (2080-2089) is shown. Forcings are decomposed by CO<sub>2</sub> and climate as in panel (a).

simulations that isolate the influence of climate change predict NPP to decrease over the 21st century for both SSP scenarios. Relative to repeating meteorological forcing from 2000-2014, productivity decreased by 3.5% when using SSP1 climate forcing and 17.1% when using SSP5 climate forcing (Figure 3.2a).

The percent decrease in NPP driven by SSP1 climate and the percent increase in NPP driven by SSP1 CO<sub>2</sub> are fairly consistent across the region as was their combined effect (Figure 3.2b, top row). For SSP5, the southern edges of the range (Figure 3.2b, bottom left) showed a slightly larger decrease in response to climate alone. In SSP5, the CO<sub>2</sub>-only response showed a strong latitudinal gradient with greater percent increases in NPP in the south (Figure 3.2b, bottom center). The similar spatial patterns and opposite sign of the climate and CO<sub>2</sub> components largely cancel each other out when combined, producing a more even regional pattern in the full SSP forcing (Figure 3.2b, bottom right).

The changes in productivity resulted in changes in wood harvest per rotation of a similar pattern to NPP. From 2015 to 2090 harvests increased by 18.1% with SSP1 forcing and 70.1% with SSP5 forcing (Figure 3.3).

### 3.4.2 Management Practices Within a Rotation

Silvicultural management practices influenced the wood harvest from simulated loblolly plantations. We found that these practices vary in their impacts from moderate to large.

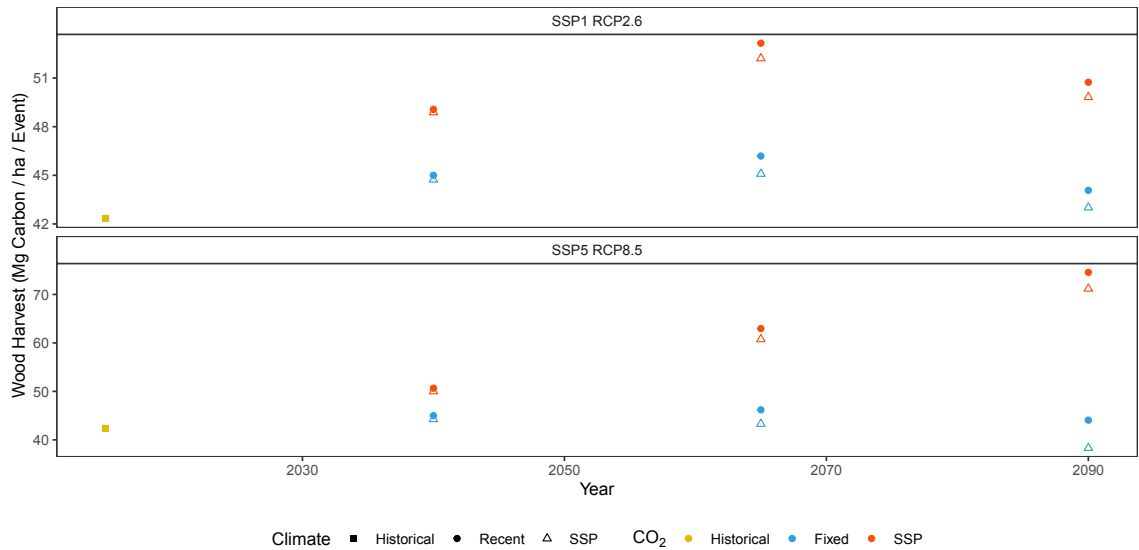


Figure 3.3: Drivers of Changes in Wood Yield: The effect of climate and CO<sub>2</sub> on wood harvest per rotation over the 21st century are shown. Each point represents the mean simulated SEUS regional wood yield per rotation for a given year and set of forcings. The mean wood yield for a harvest occurring in 2015 is shown in yellow. Wood yields for future simulations with constant 400 ppm CO<sub>2</sub> are shown in blue and transient SSP CO<sub>2</sub> in red. Solid circles indicate simulations with repeating recent climate and empty triangles transient SSP climate.

Changing the planting density from a typical present day value (1250 tph) to a density common in the early half of the last century (2000 tph) resulted in a decrease in mean annual wood yields of 7.5% under SSP1 and of 6.1% in the SSP5 scenario (Figure 3.4a). Within the Southeastern U.S. the greatest relative influence of planting density was in the western and the southeastern parts of the region with the least impact along the gulf and central Atlantic coasts (Figure 3.4b) for both SSP scenarios. The regional variation in the relative influence was lower in the SSP5 scenario (Figure 3.4c).

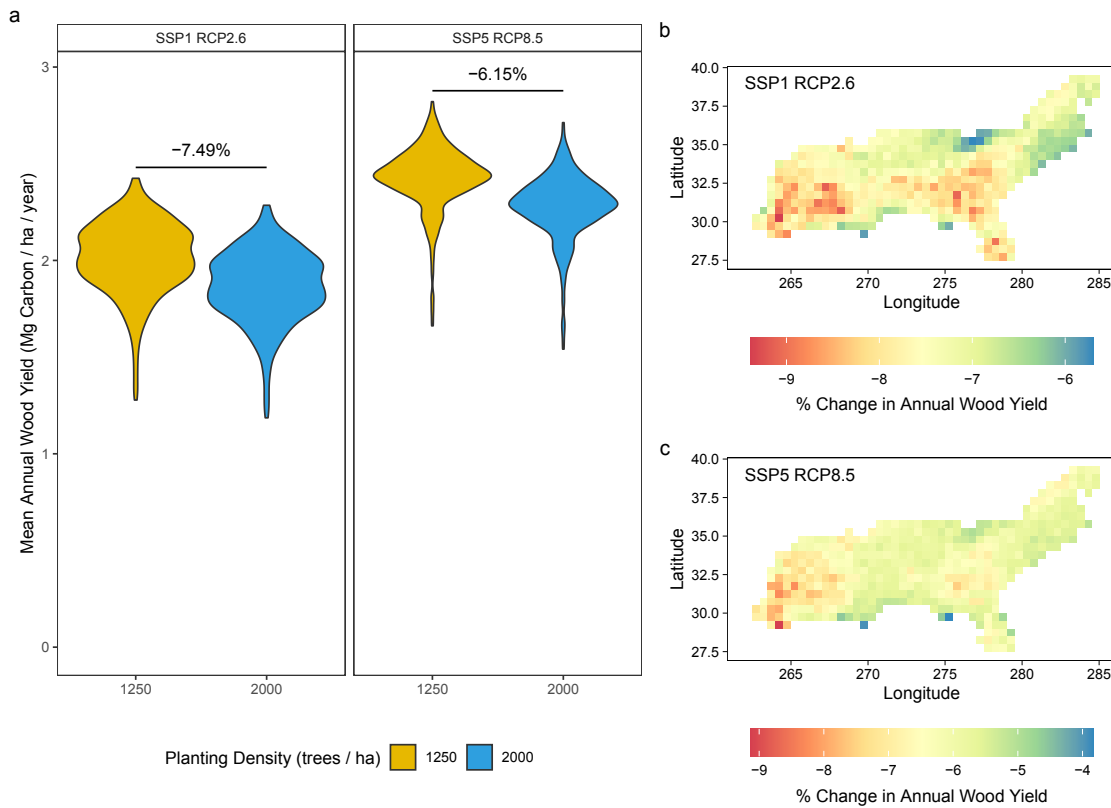


Figure 3.4: The Effect of Planting Density on Wood Yields: (a) The mean annual wood yield for all grid cells over the period 2015-2090 with two different planting densities for SSP1 and SSP5. The mean decrease in yield is shown for each climate scenario. (b,c) The regional pattern of change in mean annual wood yield with a change of planting density from 1250 tph to 2000 tph for (b) SSP1 and (c) SSP5.

The addition of mid-rotation stand thinning to the simulated management cycle increased mean annual wood yields substantially across the region under both SSP climate scenarios (Figure 3.5a). Yields increased by 44.3% under SSP1 and by 49.4% in SSP5 (Figure 3.5a). While all locations showed an increase in yield with thinning, the magnitude of the effect varied across the region, with smaller increases in the

western extent of the range and greater effects along parts of the gulf coast, Florida, and the southern Atlantic states in the east (Figure 3.5c-d).

The increase in yield with thinning was due to a combination of two factors. First, the addition of thinning increased the frequency of harvest events. Wood removed during the thinning itself accounted for the majority of the increase in total yield (Figure 3.5b, yellow bar). Second, the harvest from the final cut (clearcut) also shows an increase in yield with thinning (6.9% under SSP1, 9.1% under SSP5) (Figure 3.5b, blue bar above dotted line). Many of the trees that were removed with thinning would have experienced mortality after canopy closure and have been converted to coarse woody debris if they were not harvested. As a result the harvest gained from mid-rotation thinning does not decrease the magnitude of the final harvest.

The two within-rotation management activities had different interactions with climate change and increasing CO<sub>2</sub>. For the baseline management scenario (unthinned, low planting density) the mean annual yield increased by 20.9% from the low warming SSP1 scenario to the high warming and CO<sub>2</sub> SSP5 scenario. When we used the higher planting density (2000 tph) the change in mean annual yield from SSP1 to SSP5 was 22.7%, an increase of 1.8 percentage points (Table 3.3). The areas experiencing the largest relative climate increase with planting density were southern grid cells, mostly around the gulf of Mexico (Figure 3.7a). When thinning was added the change in mean annual yield from SSP1 to SSP5 was 25.4%, 4.5 percentage points higher than the baseline scenario (Table 3.3). Adding thinning increased the effect of climate on yields in the western part of region where productivity is generally lower (Figure 3.7c).

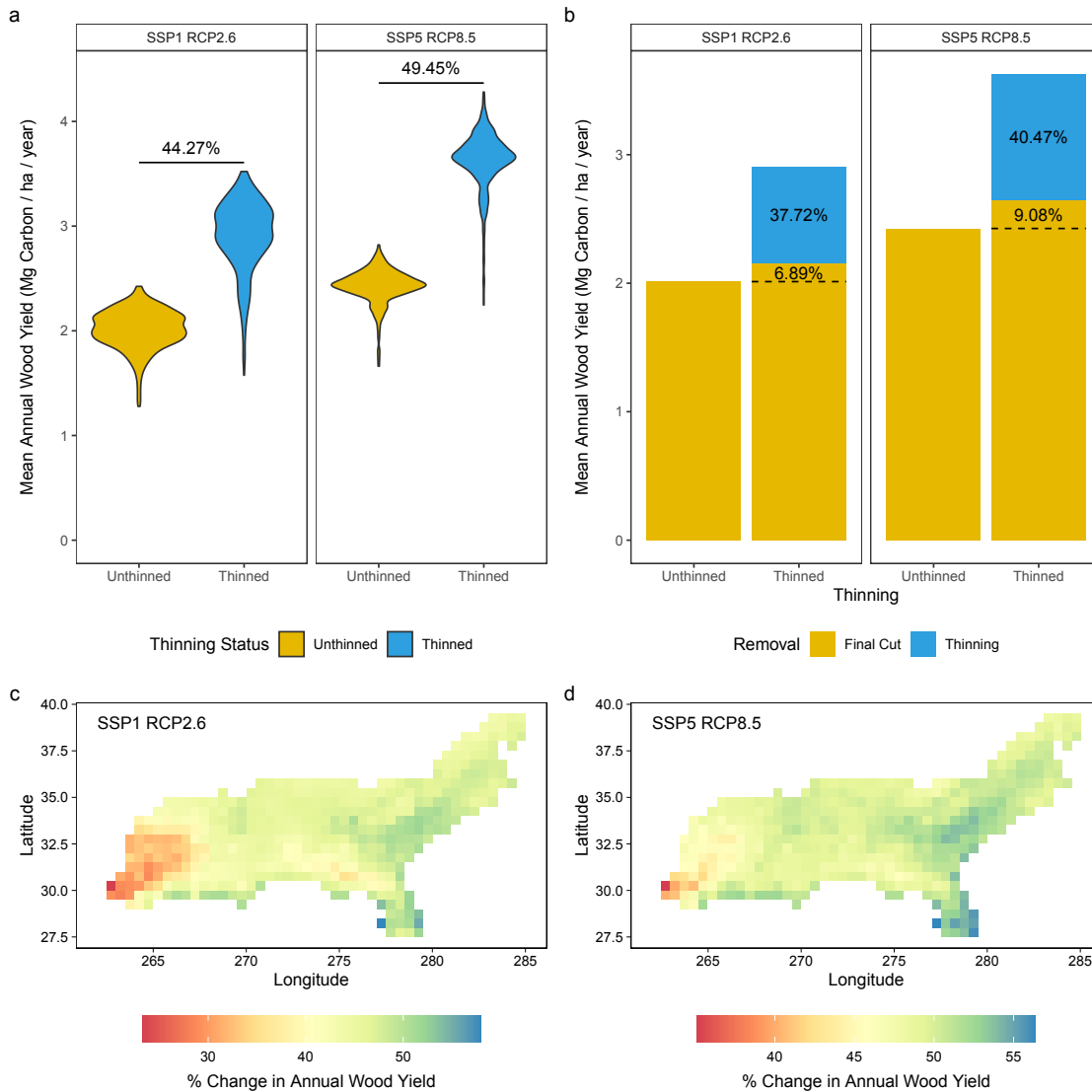


Figure 3.5: The Effect of Mid-rotation Stand Thinning on Wood Yields: (a) The mean annual wood yield for all grid cells over the period 2015-2090 without or with mid-rotation thinning for SSP1 and SSP5. The mean decrease in yield is shown for each climate scenario. (b) The breakdown in wood yield by harvest type. For the simulations with thinning the wood harvested from thinning (blue) and the increase in wood at the final harvest (yellow above the dashed line) are shown along with their contributions to the percent increase in yields. (c,d) The regional pattern of change in mean annual wood yield with the addition of thinning for (c) SSP1 and (d) SSP5.

### 3.4.3 Altering Rotation Timing

Our simulations show that the additional stand growth that is associated with an increase in rotation length from 25 to 40 years did not compensate for the fact that the 40 year simulations completed one less rotation than the 25 year simulations. The yield per rotation must be 60% greater for a 40-year rotation to have the same annual yield over time as the 25-year rotation. In our simulations the 40 year rotation yields only increase by 31.6% for SSP1 and 35.5% for SSP5. As a result the mean annual yields decreased by 17.8% and 15.3% in the SSP1 and SSP5 scenarios respectively (Figure 3.6a) when rotations were lengthened.

Under SSP1 the largest decreases in yields occurred in the middle Atlantic interior, Florida, and a small area of the western part of the region (Figure 3.6b). Under SSP5 the eastern interior and part of the coast as well as pockets of the west show the greatest decrease in annual yields with a longer rotation length (Figure 3.6c).

There was a small interaction between rotation length and climate change. When we increased the rotation length to 40 years the change in mean annual yield from SSP1 to SSP5 was 24.6%, 3.6 percentage points greater than the baseline scenario with a 25 year rotation. The locations showing the greatest change in climate response with increased rotation length are found in the southern part of the range while the least responsive are mostly in the north and western parts of the range (Figure 3.7b).

In the simulations where management timing was determined dynamically in the model, the mean age of harvest declined in response to climate change. Over the 21st century, the yields from the dynamic rotation length simulations were similar to the

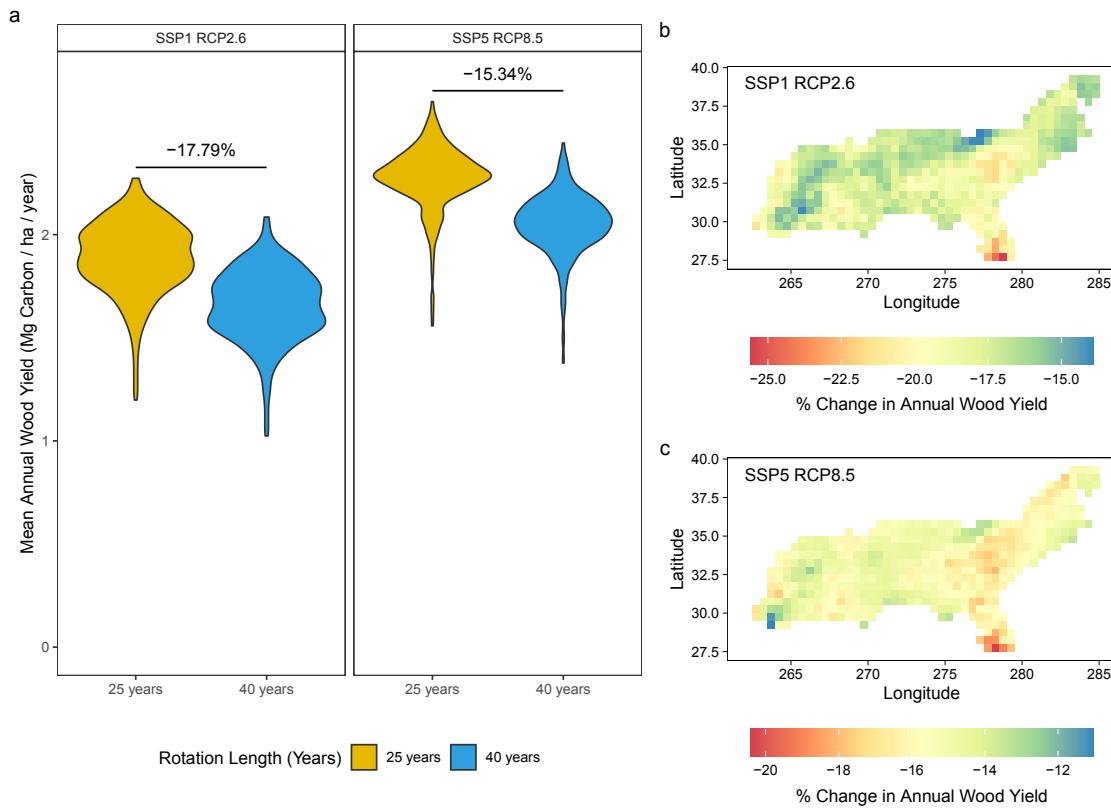


Figure 3.6: The Effect of Rotation Length on Wood Yields: (a) The mean annual wood yield for all grid cells for two management rotation lengths (25yr: 2015-2090, 40yr: 2015-2095). The mean increase in yield is shown for each climate scenario. (b,c). The regional pattern of change in mean annual wood yield with an increase in rotation length from 25 to 40 years for (c) SSP1 and (d) SSP5.

yields from the fixed rotations, although the timing of accumulation is more gradual (Figure 3.8a-d). Without thinning the mean first rotations length for the region was 40 years (31-51) years for both climate scenarios (Figure 3.9c). On a regional basis rotation lengths begin to decrease around mid-century in all scenarios (Figure 3.9a), but decrease faster with larger changes in climate. In the SSP1 simulations

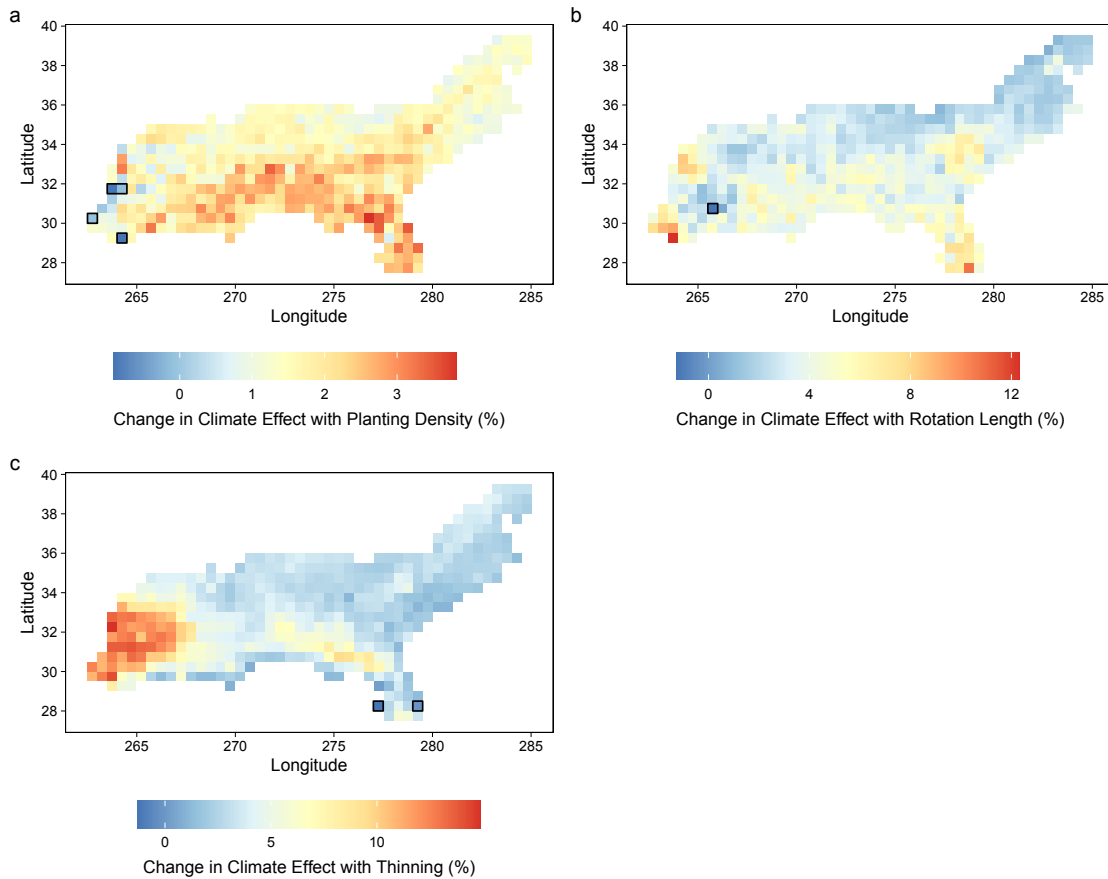


Figure 3.7: The Interaction Between Management and Climate: The change in relative climate effect from SSP1 to SSP5 climate with (a) an increase in planting density, (b) an increase in rotation length, or (c) the addition of mid-rotation stand thinning. Warm colors indicate locations where the management treatment amplifies the effect of increasing  $\text{CO}_2$  and warming climate. Grid cells that have a negative change, i.e. show a decrease in the climate effect with management treatment, are outlined in black. The change in relative climate effect was calculated using Equation 3.4.

without thinning, rotation lengths become fairly stable in the later part of the century (yellow & red curves) reaching a mean value of 32 (26-40) years in 2100. In the SSP5 simulations the rotation lengths decrease continually, reaching a mean length of 20

(15-27) years in 2100 (blue & green curves) without thinning.

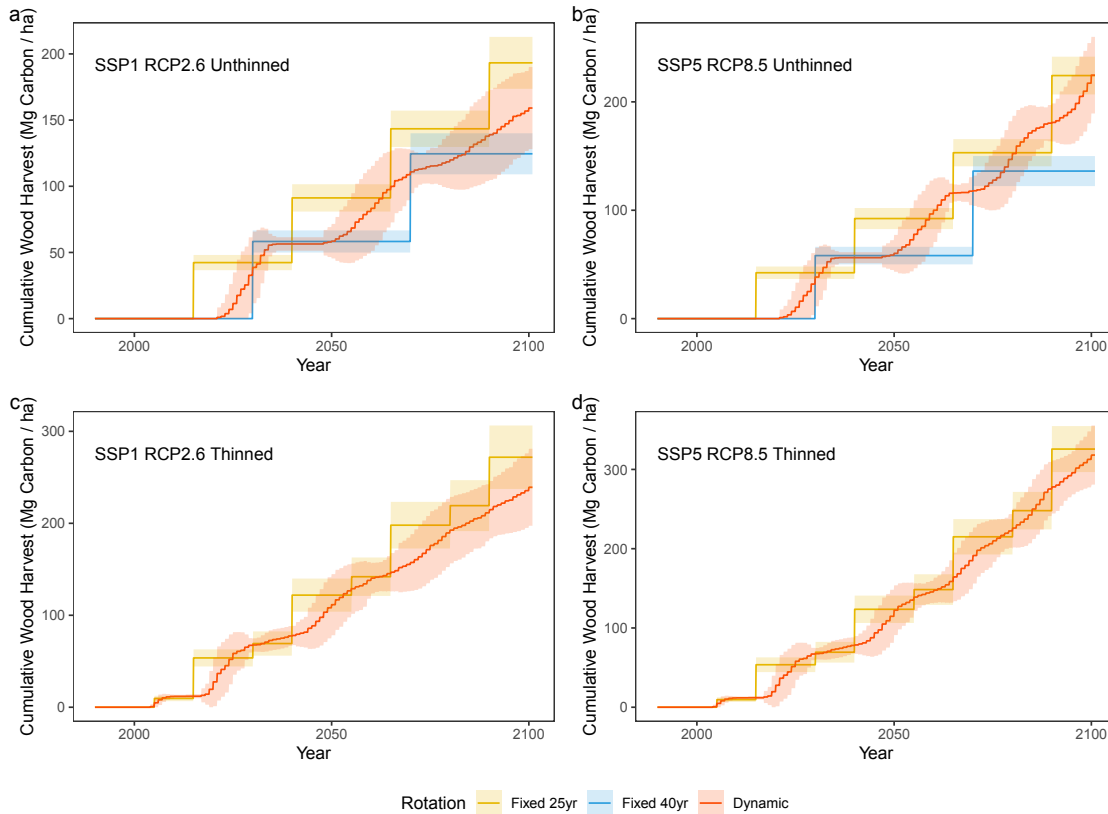


Figure 3.8: Wood Harvest Over Time with Dynamic vs. Fixed Rotation Timing: Lines represent mean grid cell accumulation of wood for each scenario. Shading represents +/- one standard deviation of the mean of all grid cells. The dynamic simulations are shown red. Fixed length rotation simulations are shown in yellow and blue for comparison purposes.

The length of the management cycle was further decreased with thinning (Figure 3.9a). When thinning was added the length of the first rotation decreased to a mean of 33 (27-41 years) for the first rotation (Figure 3.9c, Table 3.4), a decrease of 6 years for both SSPs. Over the rest of the century the rotation length of the thinned

simulations declined with a similar pattern to the unthinned. By 2100 the rotation length with thinning declined to 27 (22-32) years with SSP1 and to 17 (13-20) years with SSP5 (Table 3.4).

The spatial pattern of rotation length (Figure 3.9b) follows the regional patterns of productivity (Figure 3.6b,c), with longer rotations in the less productive central western portion of the range and the southeastern interior (Figure 3.9b). Under SSP1 the yield per rotation increases very slightly over time (Figure 3.10a, red & yellow). Under SSP5 the greater contraction in rotation length (Figure 3.9a) is accompanied by an increase in yield per rotation until the end of the century (Figure 3.9a, green & blue). This increase in the mean yield is driven by increased tree numbers at harvest, specifically in the areas of the region that have low yields at the start of the simulations (Figure 3.10b-c). In contrast, areas of high productivity show relatively less increase in mean yields. There is less variation across the region in the final rotation yields compared to the first rotation under SSP5 (Figure 3.10d-e).

## 3.5 Discussion

### 3.5.1 How does Climate Change Alter Loblolly Productivity and Yields?

Loblolly productivity and wood yields increased in both of our climate scenarios. The increase for SSP1 was small and partially transitory, while the increase with

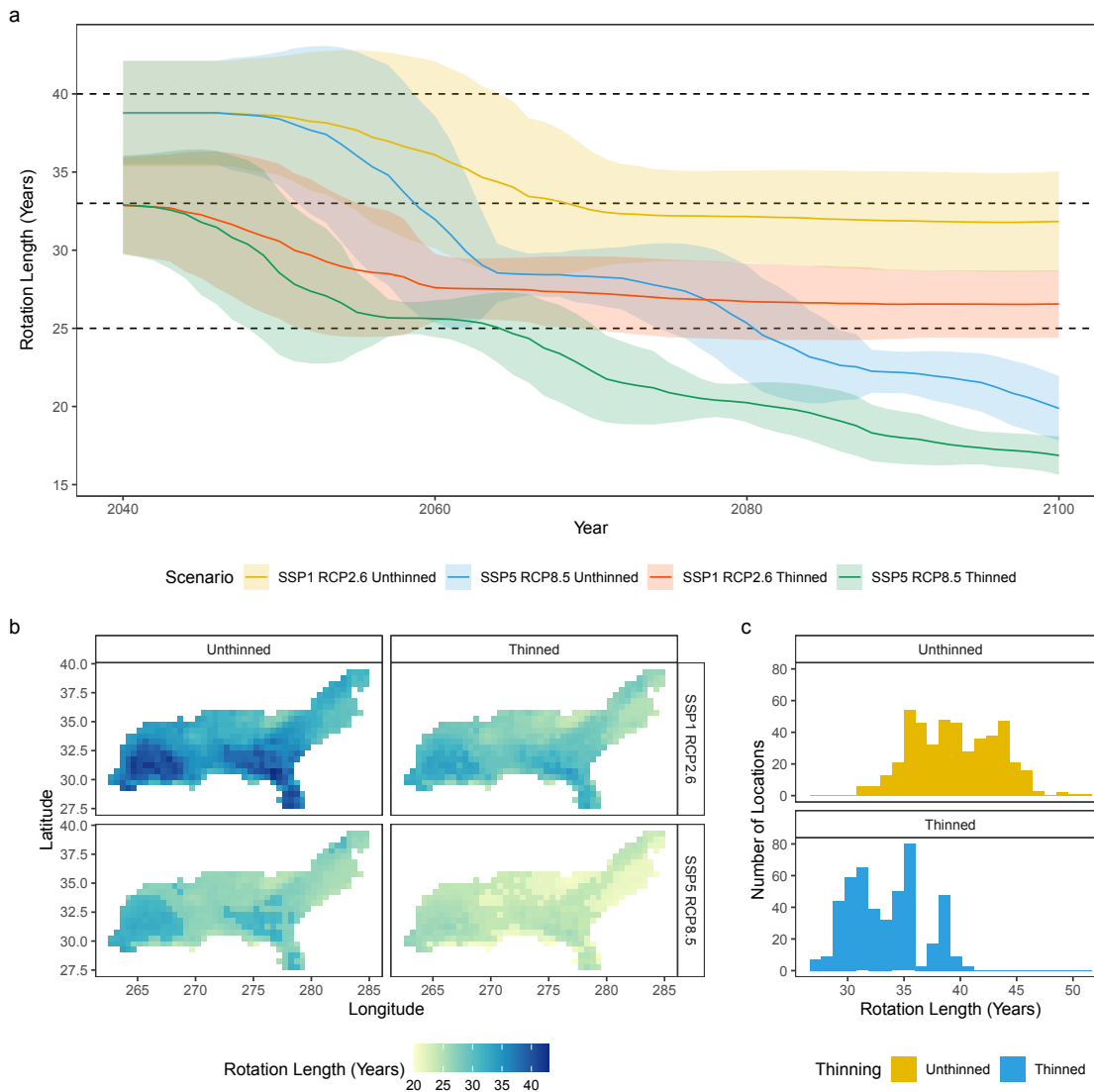


Figure 3.9: Changes in Dynamic Rotation Length: (a) The change over time in the mean rotation length for simulations with dynamic timing of management events. Lines represent mean rotation length across the study region for each year. Shading represents  $\pm$  one standard deviation of the mean. Black dotted lines show the extremes and center value of our central estimate of contemporary rotation length for the region. (b) The regional pattern of rotation length (mean of 2015-2100) for each climate / management scenario. (c) The distribution of the lengths for the first rotation across the region under constant climate, without and with thinning.

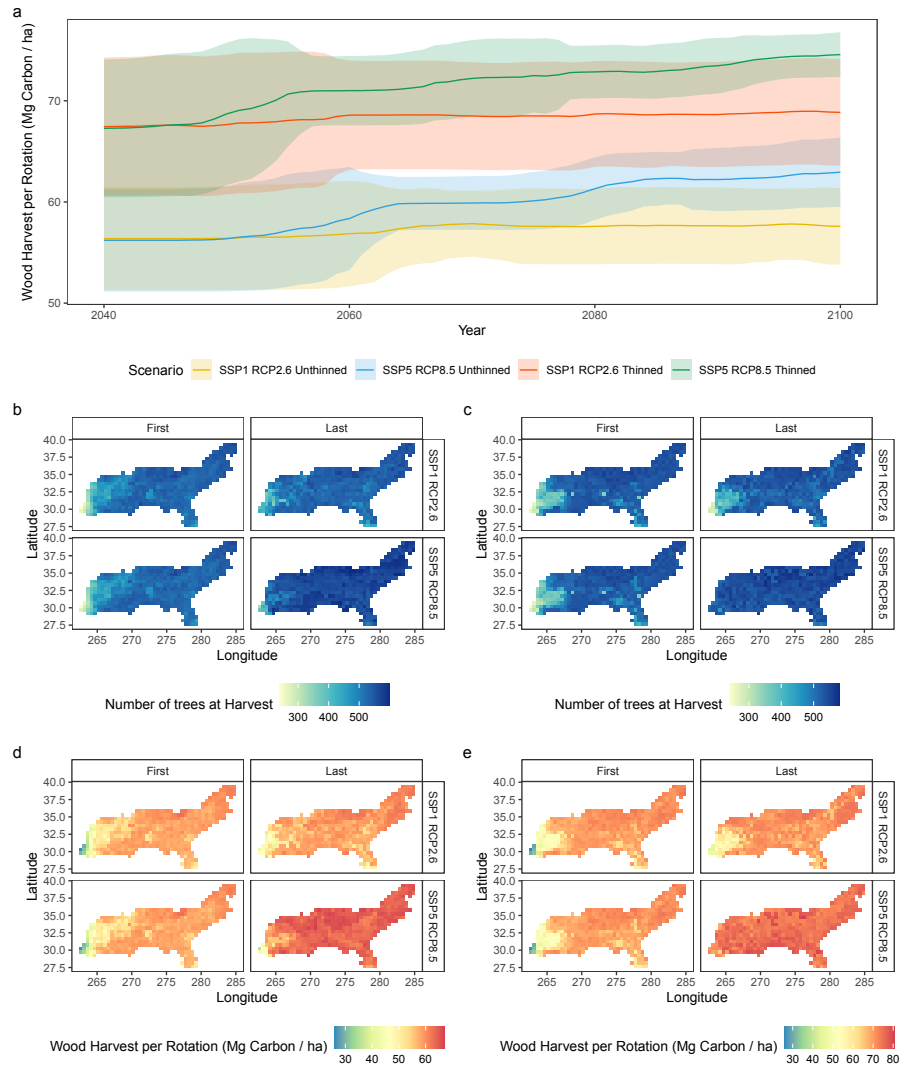


Figure 3.10: Changes in Dynamic Wood Harvest: (a) The change over time in the mean harvest per rotation for simulations with dynamic timing of management events. Lines represent mean rotation length across the study region for each year. Shading represents  $\pm$  one standard deviation of the mean. (b,c) Regional patterns of the number of trees per hectare at the time of harvest for the first and last rotations (b) without thinning and (c) with thinning. (d,e) Regional patterns of the wood harvest per rotation for the first and last rotations (d) without thinning and (e) with thinning.

SSP5 was large and sustained. Our climate decomposition experiments revealed that the main forcing that drives the increases in primary productivity and wood harvest yields is the increase of atmospheric CO<sub>2</sub>. Changes in meteorological forcing had a negative effect on productivity for our two climate scenarios. The effects of climate and CO<sub>2</sub> alone are roughly additive, the sum of the two effects being very similar to the effect of the full SSP forcings. Since the negative impact of the climatic forcing is much smaller than the positive CO<sub>2</sub> effect, the net effect is an increase in productivity and wood yields.

Our predictions of increased loblolly productivity for the middle of the 21st century are similar to other published region-wide estimates. Our mean regional increase in stem biomass from 2015 to 2055 was 35.3% with CMIP6 RCP forcing. [Burkhart et al. \(2018\)](#) used an empirical modeling system to estimate the productivity across the loblolly range until mid-century under climate change. They predicted a mean change in stem biomass for the region from 2005 to mid-century (2040-2059) of 30.9% with CMIP5 RCP 8.5 forcing. Another study, [Thomas et al. \(2018\)](#) used the DAPPER data assimilation system with the 3-PG ecosystem process model to predict productivity changes for loblolly pine. Their mean regional increase in total biomass from 2010 to 2055 with CMIP5 RCP 8.5 was 30.4%. Both estimates were for 25 year rotations without thinning, similar to our baseline scenario.

### 3.5.2 How do Management Practices Change Wood Yields?

We saw varying effects of the specific management practice we explored on yields (Table 3.2). Practices changed wood yields from  $\sim 7\%$ , for planting density, to  $\sim 50\%$ , for thinning. Mid-rotation stand thinning had the largest impact on yields of our three management practices. The effect of introducing thinning caused a greater increase in yields (44.6-49.5%) than changing the SSP scenario (20.5-24.7%). Thinning has a large impact on real forests and is a common practice in the United States, with 61% of forest harvest being practiced by partial harvest methods, including thinning (Masek et al., 2011). The large increase in yields in our results is due to how we modeled commercial thinning, where the thinned wood counted towards our total removals. It is important to note that trees removed during the thinning are not equivalent in their potential uses to the larger trees that are removed at the end of the rotation, even though in terms of carbon accounting there is no distinction. Following thinning, changes to the canopy allows the remaining trees to capture more light and grow larger and faster than they would without thinning (Peterson et al., 1997; Sword Sayer et al., 2004; Yu et al., 2003). The increase in yield attributable to this effect on the final clearcut harvest is a smaller part of the total increase in yield with thinning.

The increase in planting densities had a negative effect on yields because it increased competition related mortality. The growth of trees that died before harvest were not available to contribute to the yield. The planting density that simulated higher yields was similar to that recommended today (Chapter 2 section 2.3.7. The decreases in

yields we saw with increased planting density (6.2-7.5%) were on the same order as the increases in the final clearcut harvest with thinning (6.9-9.1%), which is mediated by an opposite effect on competition in the stand.

The influence of changes to the rotation length had a greater effect than planting density and a lesser effect than thinning (15.3-17.7%). The decrease in yields with rotation length was driven by the dynamics of simulated stand development. After canopy closure, competitive mortality among trees increases, which counteracts part of the biomass accumulation among the surviving trees. Therefore, increasing rotation length in a single-aged loblolly stand will in general show a decreasing marginal return on harvestable biomass beyond a certain point. In our simulations increasing the rotation length did increase the carbon removed at harvest but by less than the amount that would be required to maintain the same average rate of yield. Decreasing rotation length increases yields but also changes the age and size of trees at harvest. This has implications for the product classes that are harvested. Larger trees can be made into boards and poles while smaller trees are limited to pulp and engineered wood products. These different wood products have very different potential lifespans, affecting how long they will sequester the carbon they contain. Therefore higher yields should not be considered inherently 'better' for climate. More analysis is needed to understand the full climate implications of rotation lengths.

The effects of climate and the aspects of management examined here appear to be largely but not completely independent. The interactions between management and climate were fairly small and the causes are not clear in all cases. The largest interaction effect we observed was for thinning (4.5%), the management operation

Treatment	SSP	Change in Annual Wood Yield (Mg Carbon / ha / year)			% Change
		Mean	Min	Max	(Mean)
<b>Planting Density</b> 1250 → 2000 tph	SSP1 RCP2.6	-0.1499	-0.1707	-0.0850	-7.49
	SSP5 RCP8.5	-0.1483	-0.1808	-0.1084	-6.15
<b>Rotation Length</b> 25 → 40 years	SSP1 RCP2.6	-0.3568	-0.4514	-0.2401	-17.79
	SSP5 RCP8.5	-0.3719	-0.4701	-0.2003	-15.34
<b>Thinning</b> → Thin at 15 years	SSP1 RCP2.6	0.8975	0.2980	1.1938	44.27
	SSP5 RCP8.5	1.2018	0.5842	1.4980	49.45

Table 3.2: Effect of Management Changes on Wood Yields: The change in annual wood yields compared to the control management scenario (25 year fixed rotation, 1250 tph, unthinned).

with the largest overall influence on yields. For thinning, the interaction is greatest in the west of the region (Figure 3.7c) where productivity is lowest. Under SSP1 the stands in this area have a lower peak basal area than the rest of the region and recovery following thinning is slow. Under SSP5 recovery following thinning increased and biomass achieved higher values by harvest time for the later rotations. This resulted in a greater benefit to total yields from thinning for these western grid cells. The interaction effects for planting density and rotation length also have a regional pattern, with the larger interactions in the south of the region (Figure 3.7a,b). The south has lower productivity than locations to the north at the start of the century but with SSP5 productivity becomes similar to points further north by the end of the century. We were not able to determine why longer rotations or higher planting densities would amplify this difference.

Treatment	Planting Density (tph)	Rotation Length (years)	Thinning	Change in Mean Annual Wood Yield	
				Mg Carbon/ha/year	%
Control	1250	25	Unthinned	0.4135	20.9
Planting Density	2000	25	Unthinned	0.4150	22.7
Rotation Length	1250	40	Unthinned	0.3983	24.6
Thinning	1250	25	Thinned	0.7177	25.4

Table 3.3: Management Climate Interactions: The absolute and percent change in mean annual wood yields when changing from SSP1 RCP2.6 to SSP5 RCP8.5 forcing.

### 3.5.3 How does the Timing of Management Change with Climate?

Our dynamic simulations responded to differences in regional productivity with variable rotation timing. Since thinning had the largest impact in our fixed rotation experiments we included scenarios without and with thinning. The addition of thinning to the management cycle greatly shortened the time from planting to final harvest and increased the associated wood yield consistent with our fixed rotation results.

These simulations add more realistic behavior that is missing from our simulations with fixed timing, as management cycles are a product of management goals, silvicultural practices, and environmental factors. Forest growth is influenced by local climate, soil properties, pests, disease, and the risk of severe weather. Best practice guidelines generally include ranges for their recommendations to allow adjustment for local conditions. Foresters use best practices to guide their decisions of when to

plant, thin, and harvest but also respond to the specific conditions in the stands they are managing. When trees grow slower or more quickly than expected managers will respond accordingly, adjusting the timing of interventions. With productivity of sites differing greatly there is a good deal of variability in the length of the management cycle across the Southeastern U.S. It also seems certain that foresters will respond to changes in plantation development driven by climate change in the future. A realistic model will therefore show variation over space and time in the management cycle. While we aren't able to fully verify the variability produced by our dynamic simulations the data we do have suggests it is not unrealistic.

Our dynamic simulations with thinning produced rotations early in the century that very closely matched our literature estimate of the rotation lengths across the region today. Our research provided us with a range for rotation length but limited information about the length distribution within that range. Since thinning is pervasive we think our estimate reflects primarily thinned stands. Our simulated early rotations range from 27-41 years similar to our central estimate of 25-40 years for the region (Figure 3.9c, bottom). Given the uncertainty in our estimate this seems quite reasonable. These values might also have been slightly lower if we had used a lower mean DBH cutoff for harvest. We used a value of 32 cm for the mean threshold to ensure smaller trees would be above the 30 cm, our cutoff for commercial timber wood. However, this buffer was not really necessary as we saw narrow ranges in simulated tree sizes (not shown). Our simulations were also performed on a coarse grid resolution that may bias our results towards lower variability than that observed in the real world. We think is a promising result that real world management crite-

Climate	Thinning	First Rotation			Last Rotation			Change	
		Mean	Min	Max	Mean	Min	Max	Years	%
Constant	Unthinned	40	31	51	38	29	49	-2	-4.6
SSP1 RCP2.6	Unthinned	39	31	46	32	26	40	-7	-17.8
SSP5 RCP8.5	Unthinned	39	31	46	20	15	27	-19	-48.8
Constant	Thinned	33	27	41	32	26	40	-2	-4.9
SSP1 RCP2.6	Thinned	33	27	40	27	22	32	-6	-19.2
SSP5 RCP8.5	Thinned	33	27	40	17	13	20	-16	-48.8

Table 3.4: Rotation Lengths for Dynamically Timed Simulations: Shown are the range of rotation lengths (in years) across the region for the first and last rotations of 21st century along with the change in mean rotation length between them.

ria applied to a simulated loblolly stand produces management cycles with realistic lengths.

The dynamic simulations provide an opportunity to predict how management practice may change in the future with climate change. While we cannot fully predict how all aspects of management will change in the future it seems clear that with changing growth rates the timing of the management will change in the future for a given set of forest products. Our simulations show such a response. SSP1 is an optimistic low climate change scenario that reflects an aggressive commitment to decarbonization. Even under this minimal climate change scenario we saw decreases in the mean regional rotation length of 6-7 years by the end of the century.

Under the SSP5 high climate change scenario we saw rotation length greatly decrease and yields increase by the end of the century. Mean rotation lengths fell to 20 years and 17 years with thinning. Are such dramatic changes even physiologically possible? Some insight can be drawn from the cultivation of loblolly pine in exotic locations. Loblolly pine has been used in growth trials in Hawaii, South Africa, and Australia,

and is a major commercial species in southern Brazil (Burns and Hu, 1983). In these locations loblolly can achieve prodigious growth rates. In Brazil rotation lengths below 20 years are common (IBA, 2019). This suggests that these growth rates may not be impossible for the species, but it is still reasonable to be skeptical that rates of growth found in the tropics will be seen in North America by the end of the century. We must consider that RCP 8.5 climate forcing is considered by some to be less likely than scenarios with some reductions in CO<sub>2</sub> emissions (Hausfather and Peters, 2020). We chose this scenario because our main intention was to test sensitivity in the model. It may be less useful when we are looking to predict the *most likely* future of managed forests.

### 3.5.4 Limitations and Future Work

This work is a step forward towards understanding how managed forests of the South-eastern United States might respond to changes in climate over the next century using an ESM, but refinements will be needed to improve the confidence in our results. Our modeling of loblolly plantations in FATES does not address some important ecological factors that will regulate forest growth along with climate change like the effects of nutrient limitations, competing vegetation, disturbance, and physiological climate acclimation. We also made assumptions about management in the future that require further examination and work remains to contextualize how changes in managed forest productivity might impact regional wood yields in the future.

The simulations presented here were not subject to nutrient limitation. FATES has

an infrastructure for soil nutrient availability that is under development but is not available yet for use with the CLM host land model. This is important as it has been well demonstrated that pine plantations are sensitive to nutrient limitation ([Bracho et al., 2018](#); [Haywood et al., 1997](#); [Jokela et al., 2004](#)). As a result it is considered best practice to test plantation soils and fertilize to amend any deficits in nutrients. We expect this practice will continue in the future. In this light our results can be viewed as predictions of productivity under best management with optimal soil conditions or fertilization. In the real world we expect that optimal fertilization may not always occur, even under intensive management. Higher growth rates driven by climate change may also require greater or more frequent fertilization, which may be more difficult to sustain in the future. Therefore, even if current practices continue into the future nutrient limitation may reduce the yields we predict here.

In our simulations we do not model competing understory vegetation. Competing understory vegetation can have a significant negative influence on loblolly growth through competition for light, water, and nutrients, especially in the early years of the rotation ([Haywood et al., 1997](#); [Miller et al., 2003](#); [Sanchez and Eaton, 2010](#)). We expect that including competing vegetation would lower the productivity of our stands. Since competition control is currently a best practice in loblolly silviculture the extent of this bias may be reduced. Also, our loblolly PFT was developed from observations that were not completely devoid of competing vegetation, so some reduction in growth due to competition may be built into our PFT parameters. Still the effect of competing vegetation is likely underrepresented in our experiments. Again, our simulated stands represent a silvicultural best case likely to produce somewhat

optimistic results for the region as a whole. Work remains to be done to represent understory competition accurately in the model. There are challenges associated with both finding observational data to constrain understory demography and determining parameters for realistically behaving temperate understory PFTs, such as herbs and hardwoods. In future work, we can explore the influence of understory vegetation on yields as the Vegetation Management module allows for the selected removal of vegetation by plant type.

Our simulations also do not take into account the effects of all forms of disturbance on yields. While CLM-FATES can simulate disturbance in the form of mortality-inducing temperature extremes, fire, and drought it does not currently simulate large-scale disturbance (e.g. storm damage) or disease and insect outbreaks. Disturbances of these types could change with climate change. In particular, we performed our simulations with fire turned off. Fire suppression in managed forest would need to be considered to accurately represent fire accurately in this system. Failing to account for losses from disturbance may be another source of a bias that would overestimate our growth estimates.

In our simulations we see sustained gains in productivity as climate change increases, which may not be realistic. We know that some plants show transient changes in growth with changing environmental conditions that do not persist over the long term. There is some evidence that the photosynthesis of loblolly pine will become lower after extended exposure to elevated temperatures ([Teskey and Will, 1999](#)) or carbon dioxide ([Rogers and Ellsworth, 2002](#)). On the other hand, respiration may be lower than expected in trees following extended exposure to elevated temperatures

(Reich et al., 2016; Teskey and Will, 1999). FATES does not yet represent these acclimation effects for vegetation. Since acclimation effects can have opposite effects on NPP so the net effect on growth are uncertain.

In our simulations we assumed that current pine forestry practices in the Southeastern United States will persist into the future. Current forest management practices in the region are the product decades of experimentation and research (Fox et al., 2007). It seems likely that forestry practices will remain rather similar in the near term but we must expect some changes over the next century. Timber markets can change rapidly, shifting the value of pulp vs. timber for example. We chose to focus on management for timber as the primary objective. Timber products will always occupy part of the product mix and timber is associated with longer lifespan products. A comprehensive treatment of management within a SSP would address changes in demand for different product types over time but that was beyond the scope of this project. Our focus was on the interaction between changing climate and specific management practices so constancy over time was important for comparability. In our dynamic rotation simulations we relaxed the fixed assumption of rotation timing as this seemed something that would logically need to change with changes in stand growth rates. How other practices, such as planting density, might change in the future are harder to predict.

We also assumed that properties of trees being planted will remain the same in the future. Genetic improvement programs have led to substantial improvements in yield, tree form, and disease resistance in loblolly pine and other managed tree species (Fox et al., 2007; McKeand et al., 2003). We can expect that this work may increase

growth rates further in the future or provide accelerated adaptation to changing climate conditions. How ESMS might move from static PFTs to representations that allow tree properties to change over time is an interesting problem for future research.

In this work we simulated productivity for representative loblolly stands in locations across the Southeastern United States but the results could be scaled to the region. Translating our estimates of plantation productivity to regional timber production requires scaling by the plantation area for each grid cell and conversion to timber units such as board feet or wood volume. Estimates of loblolly plantation area are available for present day (Chen et al., 2017; Fagan et al., 2018) but there is more uncertainty about how plantation area may change into the future (Wear and Greis, 2012; Zhang and Polyakov, 2010).

### 3.5.5 Comparison to Work in Other ESMS

Representing many aspects of management in ESMS has historically been limited by the representation of forests in these models. ESMS have modeled forests as one or more plant functional types, with all individuals within a PFT represented by grid cell level stocks. Introduction of vegetation demography makes it possible to represent management processes that were not possible before. To date more detailed management has only been further examined in the vegetation model of two other ESMS.

The ORCHIDEE model with the Forest Management Module (ORCHIDEE-FM) can simulate some aspects of management through a process that converts the model's

big-leaf PFT based stocks into an equivalent distribution of individual trees, which can be used to calculate management related mortality from events like thinning and harvest (Bellassen et al., 2010, 2011). This “demography after the fact” improves the models predictions of forest properties compared to inventories in Europe but only at large spatial scales (Bellassen et al., 2011). They performed idealized simulations that showed a large impact when thinning was added, increasing stand NEP by 40% over the course of a rotation (Bellassen et al., 2010). A forest management module was recently added to the LPJ-GUESS dynamic vegetation model (Lindeskog et al., 2021). This module allows the simulation of automated thinning and manually specified harvest in single-age and uneven-age management systems. In their experiments model estimates of stand properties for Europe were more similar to observations with the addition of thinning. Thinning also increased the carbon sink (NEE) by 46% on managed lands, bringing their values much closer to estimates for the region (Lindeskog et al., 2021). Neither of these studies explored aspects of management as completely as our study because these studies assumed rotation length and planting properties were fixed. Overall, the importance of thinning found in these two models is in line with our results and highlights this an important management process to represent in ESMs.

## 3.6 Conclusions

While it is known that human management of ecosystems has a large impact on their climate properties (Erb et al., 2018; Luysaert et al., 2014) most ESMs represent few

forest management practices. More research needs to be done to understand how forest management will interact with climate change to effect the future provisioning of forest products and climate services. We have previously demonstrated the ability of the Vegetation Management Module for CLM-FATES to reproduce past observations of loblolly stands. Here for the first time we use this module to simulate pine plantations across the Southeastern United States and over multiple management cycles in an ESM. Our work predicts increased growth in loblolly pine plantations with climate change similar to other predictions in the literature. We demonstrate that management activities at different stages of the management cycle can have significant impacts on the yield of wood products. Rotation length and stand thinning have impacts on wood yield similar or greater than the difference between alternate future climate extremes. We also demonstrate simulation approaches that can improve realism in terms of spatial variability, adaptation to changing climate, and provide the means to specify management using alternate data sources. The fact that we were able to reproduce realistic responses to management is a further validation of the FATES model. ESMs require more data and computing power to run than conventional forestry models but may serve a useful role in complementing other management tools in a rapidly changing world.

	1990-2014			2015-2100						
	Planting Density (tph)	Thinning	Rotation	Planting Density (tph)	Thinning	Rotation	Climate	CO <sub>2</sub>	Aerosols	
<b>Climate Decomposition</b>	<i>1250</i>	<i>None</i>	<i>25yr Fixed</i>	<i>1250</i>	<i>None</i>	<i>25yr Fixed</i>	2000-14	400 ppm	2010	
							RCP 2.6	400 ppm	RCP 2.6	
							2000-14	RCP 2.6	2010	
							RCP 8.5	400 ppm	RCP 8.5	
							2000-14	RCP 8.5	2010	
<b>Fixed Management Timing</b>	<i>1250</i>	<i>None</i>	<i>25yr Fixed</i>	<i>1250</i>	<i>None</i>	<i>25yr Fixed</i>	RCP 2.6			
							RCP 8.5			
								RCP 2.6		
								RCP 8.5		
		15yr fixed						RCP 2.6		
								RCP 8.5		
		None			2000	None		RCP 2.6		
	RCP 8.5									
	2000							RCP 2.6		
								RCP 8.5		
	1250	None			1250		40yr Fixed	RCP 2.6		
								RCP 8.5		
				40yr Fixed				RCP 2.6		
							RCP 8.5			
<b>Dynamic Management Timing</b>	1250	None	Auto	1250	None	Auto	2000-14	400 ppm	2010	
							RCP 2.6			
								RCP 8.5		
		Auto				Auto		2000-14	400 ppm	2010
	RCP 2.6									
								RCP 8.5		

Table 3.5: Simulation List: The CLM-FATES simulations used for the analysis in in this chapter. Management settings for the 1990-2014 historical simulations (left) and management settings and climate forcing conditions for the 2015-2100 future climate simulations (right) are shown. The baseline management conditions are are indicated in italics.

## Chapter 4

### Climate Change and Forest

### Management Influence the Forest

### Area Required to Meet Harvest

### Demand over the 21st Century

## 4.1 Abstract

Decades of advancements in pine plantation management practices have turned the Southeastern United States into one of leading wood producing regions in the world. Over the coming decades the effects of climate change are expected to increase the productivity of these forest even further. Increases in the efficiency of wood production from plantation forests have the potential to change the area of forest needed to supply the wood products demanded by society. Here we estimated the loblolly pine (*Pinus taeda*) forest plantation area that will be needed to meet the potential demand for wood from the Southeastern U.S. over the 21st century. We used regional wood demand predicted by the LUH2 database for two Coupled Model Intercomparison Project Phase 6 (CMIP6) socioeconomic scenarios and used the CLM-FATES model with the Vegetation Management Module to predict forest wood yields. We show that changing wood demand drives a decrease in required forest area of 40.5-41.5% from 2015 to 2099 under limited climate change with SSP1 RCP2.6. Increases in forest productivity with extreme climate change under SSP5 RCP8.5 drives similar decreases (38.6-39.9%) in required forest area. The addition of a common forest management practice, mid-rotation stand thinning, also decreased the area needed to support the regional SSP projected wood demand by 27.6-28.5%. This work highlights the importance of considering the effect of climate and forest management along with socioeconomic factors when predicting how forests of the future will meet societal demand for forest products. Understanding how forest plantation area could change in the future is necessary to predict the future climate role of managed forests

globally.

## 4.2 Introduction

The dynamics of forest ecosystems are a central component of climate change projections over the 21st century (Bonan, 2008; Jackson et al., 2008). Projections of climate change depend on scenarios of forest cover change, wood harvest, and land use that influence the emissions and uptake of carbon (C) by forests. Emissions occur through increases in harvesting for wood products or land-conversion and uptake occurs through forest expansion or reduction in harvesting rates. These harvesting and land-use processes are a prescribed input to climate change projections and are defined by assumptions about future policy, energy demands, and population size (Eyring et al., 2016; O'Neill et al., 2016). Earth System Models (ESMs) represent the C cycle of forest ecosystems across the globe and calculate the impact of these harvest and land-use inputs on forests to simulate the net influence on atmospheric CO<sub>2</sub>. Changes in the area of forest required for harvesting changes distribution of land-cover and land-use types used in models, each with different carbon cycle dynamics, thus altering the net influence of terrestrial ecosystems on atmospheric CO<sub>2</sub>. As a result, it is important to understand how the representation of forest C cycling in an earth system model influences the required amount of forest area necessary to meet the prescribed harvest demand.

ESMs differ in how they represent forests that are harvested (Pongratz et al., 2018). Recent developments in some ESMs support the simulation of different forest types

that change in area over time within a model grid cell<sup>1</sup> (Fisher et al., 2018). These developments allow forests with active management to be simulated separately from unmanaged or less intensively managed forests, with potential implications for the net carbon cycle of all the forest types in a grid cell. Consequently, we are now able to examine how the details of forest management in the harvested component of the grid cell influences the forest area required to meet wood harvest demand for that grid cell.

The establishment of forest plantations is a common management practice that can now be represented in an ESM. They are an efficient way to grow wood but they can store less carbon than unmanaged natural forests (Erb et al., 2018; Liao et al., 2010). Numerous management actions can be applied to plantation forests over a rotation (i.e, the managed cycle of planting, tree growth, and harvesting) to increase productivity and wood yields, including controlling planting density, mid-rotation tree removal (thinning), and fertilization. Some researchers have hypothesized that because plantation forests can provide more wood from a smaller area that managed forests may allow more room on the landscape for unharvested natural forest. In doing so they may increase landscape level carbon storage, similar to carbon storage within an entire ESM grid cell (Paquette and Messier, 2010). This hypothesis, that intensively managed forests can spare natural forests, recently termed the *plantation conservation benefit*, has been around for over two decades (Pirard et al., 2016; Sedjo and Botkin, 1997), yet to our knowledge it has not been examine using an ESM.

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<sup>1</sup>Earth System Models represent the earth's surface as a grid of locations called grid cells. There is no spatial information below this level, but the cell may be divided into fractions of different land cover types, e.g. urban, agricultural, forest, etc.

Here we evaluate how the estimated forest area that is required to meet prescribed harvest demands is sensitive to the representation of plantation forest management in an ESM (CLM-FATES). First, focusing on the Southeastern United States as a region with widespread use of plantation forests, we simulate the productivity of pine plantation forests over the 21st century and quantify the area of plantation forest that is required to meet the prescribed harvest demand. Second, we compare the change in required forest area over the 21st century (2015-2099) between simulations that use thinning and do not use thinning as a management practice. Finally, we evaluate how the required forest area is sensitive to model predictions of how forests respond to change in climate and elevated atmospheric CO<sub>2</sub> over the 21st century. By determining the area of a grid cell that is required to meet harvest demand, our simulations are able to define the area of a grid cell that is available for other land uses that include potential forest preservation for carbon storage.

### 4.3 Methods

We conducted an analysis to estimate the amount of forest area in the Southeastern United States (SEUS) that is required to meet the demand for forest products through the end of the century under two different Shared Socioeconomic Pathway (SSP) scenarios. The demand for products was defined by the harvest rates in the SSP scenarios. For each scenario, we first simulated the ecosystem dynamics of loblolly pine plantations using an earth system model (ESM) to estimate how much wood these forests can produce per area across the SEUS. We then compared

the simulations of wood production with projections of future wood demand for the SEUS and calculated the forest area needed to produce that amount of wood.

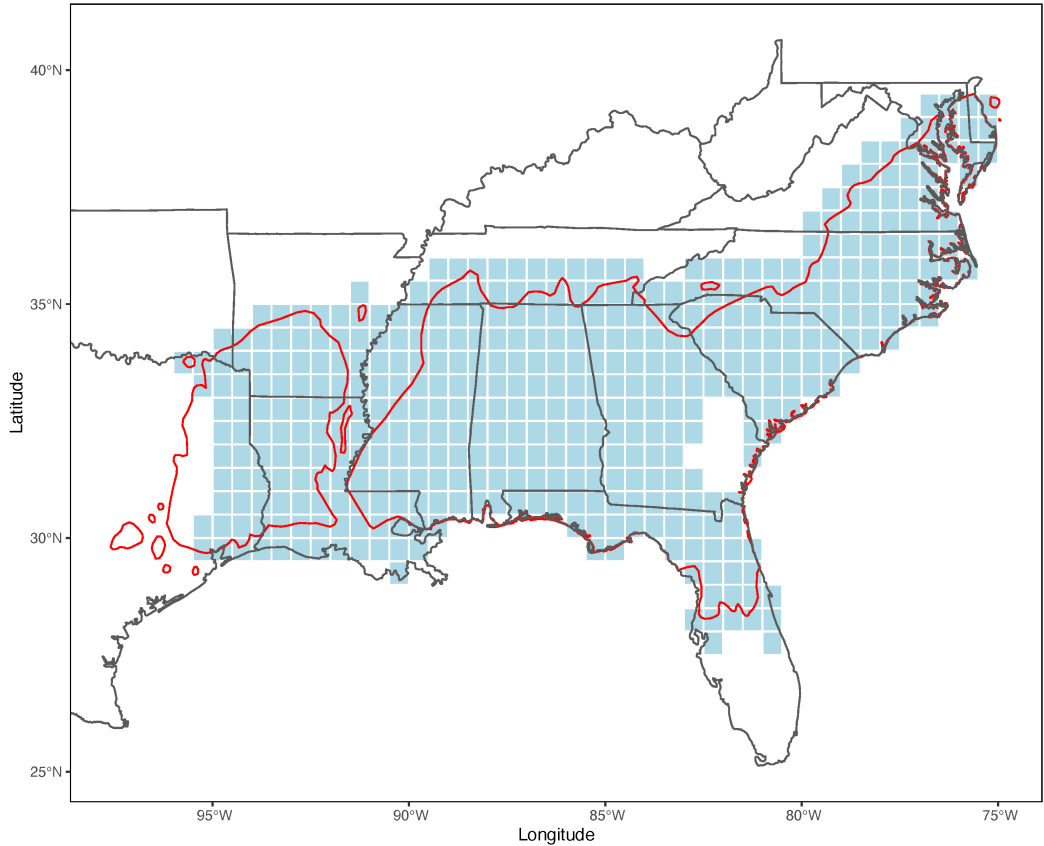


Figure 4.1: Southeastern U.S. Study Region: Analysis locations (grid cells) are marked in blue. The borders of the historical loblolly pine range are marked in red (Little, 1971; Prasad and Iverson, 2003). The study region differs slightly from that in Chapter 3 because parts of the range in East Texas and East Georgia have zero harvest demand in the LUH2 land-use data set. Grid cells for these areas were not included in the analysis.

### 4.3.1 CLM-FATES Model

ESM simulations were performed with the Community Land Model (CLM) version 5 with the Functionally Assembled Terrestrial Ecosystem Simulator (FATES) and the FATES Vegetation Management Module version 1.1 (CLM DOI: 10.5281/zenodo.7335275, FATES DOI: 10.5281/zenodo.7335612), hereafter CLM-FATES. FATES is a vegetation model for CLM that adds plant demography and competition. The Vegetation Management (VM) Module is an extension to the FATES model that allows the simulation of a broad range of management practices.

### 4.3.2 Future Climate Scenarios

We chose two of the Shared Socioeconomic Pathways (SSPs) from Coupled Model Intercomparison Project Phase 6 (CMIP6) that represent two extremes of possible future climate and human consumption. SSP1 RCP 2.6 (SSP1) represents a scenario where the societies of the world make a concerted effort towards decreasing the extent of climate change, decreasing fossil fuel consumption, and expanding forest area. With these behaviors, atmospheric CO<sub>2</sub> and radiative forcing both peak around mid-century before declining in SSP1 (O'Neill *et al.*, 2016). Our previous work shows a small increase in loblolly productivity under this scenario (Chapter 3, section 3.4.1). SSP5 RCP 8.5 (SSP5) represents a future where the world continues forward with contemporary practices of unconstrained fossil fuel consumption leading to ever increasing levels of atmospheric CO<sub>2</sub>, and as a result significant climate warming. In previous work we have shown that managed forests experience greatly increased

growth and wood product yields under this scenario (Chapter 3, section 3.4.1).

### 4.3.3 Simulations

#### General CLM-FATES Settings

Simulations were performed for the SEUS region using a 0.5 degree grid that encompassed the historical loblolly species range, with the exception of locations with no wood harvest in the LUH2 dataset (Figure 4.1). The land surface input files were modified so that only the vegetation component was represented in each grid cell. FATES uses patches to represent areas of vegetation within a grid cell that have different age and composition. These patches can split into smaller, younger aged patches following mortality of individual trees. To model even-aged plantation development where tree mortality does not alter the age and number of the patch, we used FATES’s “Pure PPA” mode to prevent patch splitting. As our analysis only required simulations of loblolly pine plantation dynamics, we did not simulate any other land-cover types in each grid cell.

#### Model Initialization

Our simulations that started in 2015 required initial conditions for model states. To generate these initial conditions, we ran CLM-FATES from bare ground with simulated pre-industrial climate using the default Plant Functional Types (PFTs) for the temperate zone for several thousand years to spin-up model soil carbon stocks.

Historic climate forcing from the use GSWP3 reanalysis projection was used to simulate from 1850-2015. For the preindustrial period prior to 1901 a loop of historical forcing from 1901-1920 according to standard practice. In 1901 we transitioned the default vegetation distribution to 100% loblolly plant functional type using the VM Module by harvesting the existing plant functional types (PFTs) and replanting with our loblolly PFT. Our loblolly PFT has parameters and code modifications that have been evaluated to more accurately capture the growth and allometry of loblolly pine. We also turned seed germination off for all PFTs so that VM planting events solely controlled the recruitment process and made a change to the leaf area profile that addresses a model bug when trees become large. During the 1850-2015 simulation, all locations were harvested and replanted in 1935, 1965, and 1990 to approximately represent historical harvests.

### **Dynamic Management Simulations**

In 1991 simulated loblolly stands were planted at 1250 trees per hectare (tph) in all grid cells. From 1991 to 2100 the model was run with the model controlling the timing of management using the VM module. Two management scenarios were performed. Both allowed trees to grow until the mean diameter of all trees in the stand exceeded a commercial timber size cutoff of 32 cm diameter at breast height (DBH). Following a clearcut harvest trees were then replanted at 1250 tph to start a new management cycle (i.e. rotation). The first scenario did not include mid-rotation thinning. The second scenario included mid-rotation thinning, which would occur once the trees were at least 6 years old and the stand had reached the basal area

exceeding 28 m<sup>2</sup>/ha. A probabilistic low thinning algorithm in the VM was used to thin the stand to a final basal area of 16 m<sup>2</sup>/ha. This thinning method removes trees according to a probability that decreases with size. This removes most of the smaller trees and fewer of the larger trees to approximate the demographics of real-world thinnings. Additional thinnings were possible at least 6 years apart as long as the mean tree diameter was still below 24 cm DBH.

The simulations shared the same historical climate from 1990-2015. From 2015 to 2100 the management scenarios were run under three different climate scenarios: SSP1 forcing, SSP5 forcing, or constant climate and CO<sub>2</sub> forcing, for a total of 6 experimental conditions. Beginning the simulations prior to the start of SSP anomaly forcing was necessary to estimate harvest and rotation length throughout the 21st century. For dates beyond 2015 we used CLM's anomaly forcing method for climate forcing. This technique provides future climate forcing by applying monthly climate anomalies calculated from fully coupled CESM CMIP 6 simulations on top of a loop of recent climate.

#### 4.3.4 LUH2 Wood Harvest Data

Projections of future wood harvest under CMIP6 future climate scenarios SS1 and SSP5 were obtained from the Land-Use Harmonization project (LUH2) ([Hurtt et al., 2020](#)). These data sets provide gridded annual estimates of wood harvest amounts for several classes of forest from 2015-2099. The wood harvest data was re-gridded from its native 0.25 degree resolution to 0.5 degrees using the raster package (version

3.5.15) (Hijmans, 2022) in R (R Core Team, 2022) to match the available forcing resolution in CLM-FATES. We used the secondary “mature” forest wood harvest field in the LUH2 data which includes all harvest from managed (thus secondary) forests. LUH2 did not include any harvest in the secondary “young” wood harvest variable for the study region, and thus was not used.

We focused our analysis on the grid cells that were contained in the loblolly native range. Within this region of the LUH2 data there are some grid cells that have no wood removals. These locations include the western edge of the region and a cluster of grid cells in the east (Figure 4.1). In the final year, 2099, the harvest amounts diverged dramatically from previous years for many grid cells. We suspect that this is an artifact of the harmonization process and we excluded 2099 from the following analysis.

### 4.3.5 Calculation of Forest Area Required to Meet Harvest Demand

To determine the forest area that would be needed to support the annual wood demand required by the LUH2 data set we used the predictions of wood harvest yields we obtained from our CLM-FATES simulations. Our dynamic forest management simulations completed between 2 and 5 complete rotations between 2015 and 2099, depending on the climate scenario and grid cell. For each location we compiled the length and dates of each rotation and the total amount of wood harvested (Mg wood carbon / ha). We used this data to estimate the harvest properties for a management

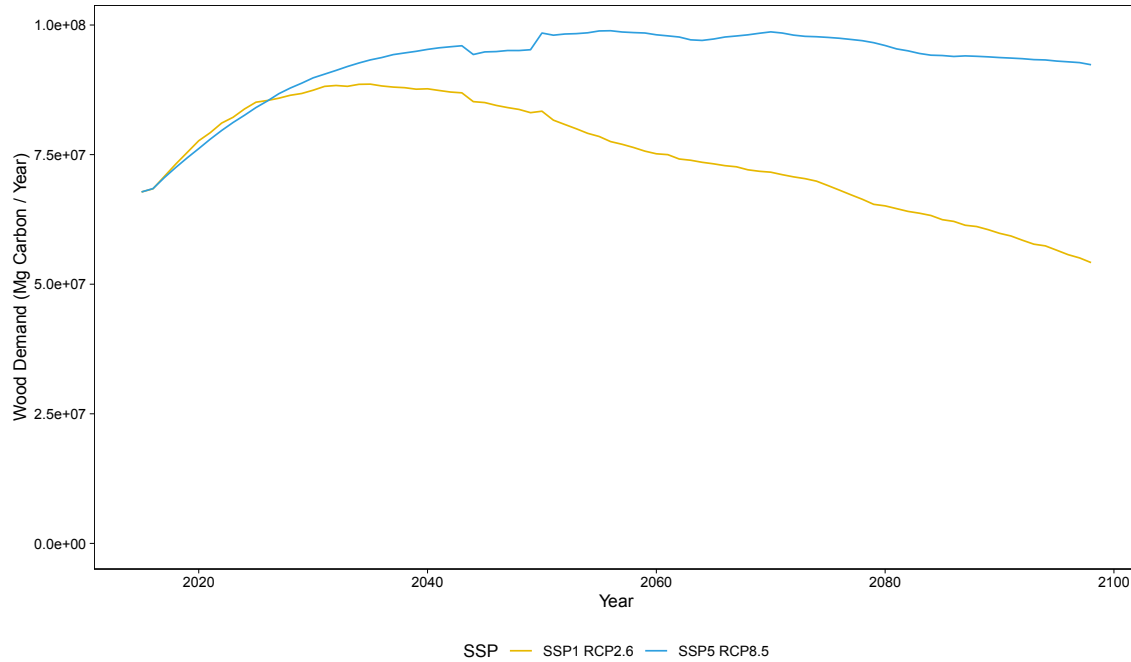


Figure 4.2: LUH2 Harvest Demand: The total study region wide wood demand predicted for each year for the SSP1 (yellow) and SSP5 (blue) socioeconomic scenarios in the LUH2 land-use data set.

cycle ending in each year and each location from 2015-2099. Since grid cells were not harvested every year, we used linear interpolation to estimate rotation lengths and total harvest amounts (Mg wood carbon / ha / rotation) for years between the end of the first and last rotations for each grid cell. For years prior to the completion of the first rotation, which ranged from 2017-2036, we used harvest and rotation length estimates from the first rotation for that location. For years following the end of the last complete rotation we used harvest and rotation length estimates from that last rotation completed. For the simulations with thinning we made the simplifying assumption that all the wood harvested during thinning was added to

the wood harvested at the end of the rotation to determine the total harvest amount. In reality wood from mid-rotation thinning would be available to partially meet the harvest demand in the year of the thinning.

To calculate the land area required to meet the LUH2 harvest demand we divided the wood yield per hectare (ha) by the specific wood demand for each location in each year. While this provides the number of hectares that must be harvested in a given year to meet the demand, it does not fully quantify the total area required over time. Specifically, a forest stand harvested in a given year must be planted several decades earlier, therefore the total area of forest that must exist on the landscape in a given year will include that area of multiple stands of different ages that will be harvested over the years to come. To calculate the total area we use the estimated rotation length at each year of harvest and projected the required area back in time for that number of years. This calculation was performed for each year and the total area is the sum of all rotations that overlap a given year. We performed this process for one rotation length beyond the 2098 end-point to get the full estimate of the area for dates late in the century.

The required area was calculated for each of our management scenarios under SSP1 and SSP5. For simulations driven with SSP forcing the LUH2 data from the matching SSP was used. For comparison purposes we also calculated the required area for both LUH2 SSP harvest demands using the yield estimates from our constant climate simulations. The unthinned and thinned scenarios were compared against each SSP. The total forest area across all grid cells of the study region were used to compare the different scenarios (Figure 4.1).

The analysis was performed in the R computing language ([R Core Team, 2022](#)).

## 4.4 Results

The initial LUH2 regional wood demand for the SEUS was the same for the two SSP scenarios in 2015 and remained similar until around 2030 when they began to diverge (Figure 4.2). Demand under SSP1 peaked in the mid 2030s and then declined for the rest of the century. In SSP5 the wood demand reached a relative plateau around 2050 before beginning a slow decline in the 2080s and 2090s.

Despite the difference in wood harvest demand between the two SSP scenarios, the area of managed forest necessary to supply this demand was similar between the two scenarios without thinning (Figure 4.3). All management and climate scenarios show a steady decline in the forest area required to meet the wood harvest demand over the course of the century. Without thinning, managed forest area declines by around 40% (SSP1: 21.1 million hectares / 40.5%, SSP5: 20.0 million hectares / 39.9%) between 2015 and 2098.

Forest management that included mid-rotation thinning reduced the forest area required to meet the harvest demand. Thinning reduced the initial area required in 2015 to meet harvest demand (Figure 4.3) because mid-rotation thinning increased the wood yield per hectare. The required forest area remained lower when thinning was added through the end of the 21st century. However, in the thinning simulation, the decline in required forest area over the 21st century (SSP1: 15.4 million hectares,

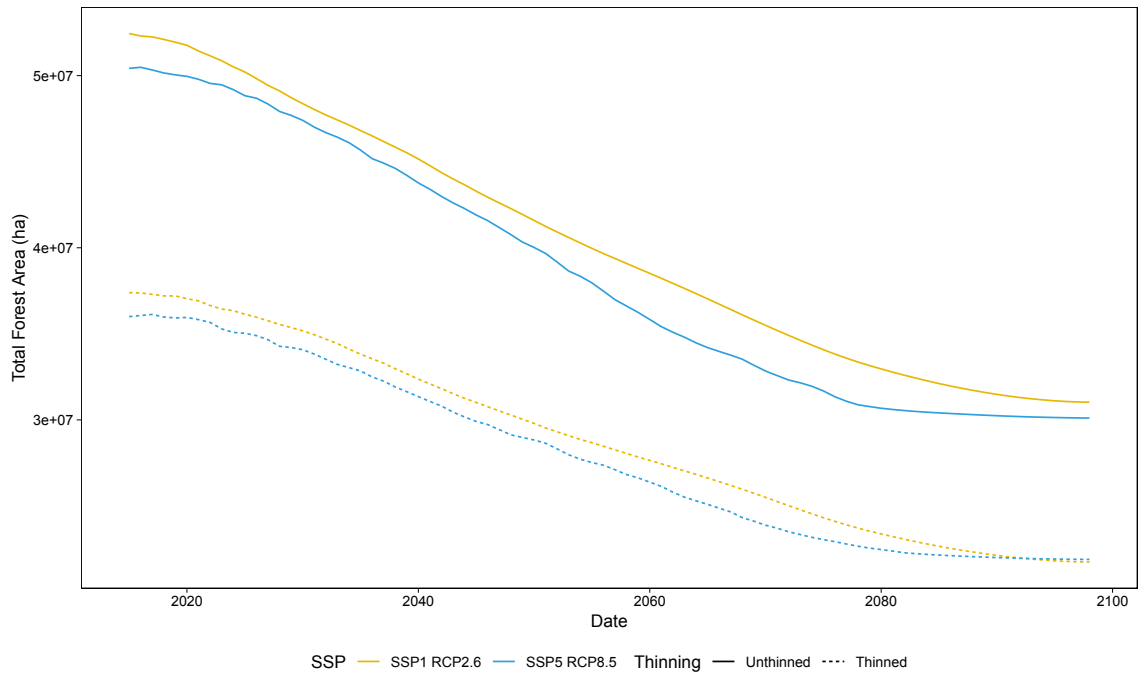


Figure 4.3: Required Forest Area Under Changing climate: The total predicted loblolly forest plantation area (hectares) that would be required to meet the wood demand under the SSP1 RCP2.6 (yellow) and SSP5 RCP8.5 (blue) socioeconomic and climate scenarios for the Southeastern United States. Management scenarios without or with thinning are indicated by solid and dashed lines respectively.

SSP5: 13.8 million hectares) was not as large as the decline without thinning (20-21 million hectares). As with the unthinned simulations the area required with thinning was similar between the two climate scenarios.

The declining harvest area in the SSP5 simulations strongly depended on the influence of climate change and CO<sub>2</sub> on forest productivity and harvest yields. When we removed the influence of climate change on yields by using a constant climate and CO<sub>2</sub> simulation, the area needed to meet the harvest demand increases under SSP5 (Figure 4.4). In SSP5, the higher wood demand drives an increase in the required

forest area that peaks mid-century. After the mid-century peak, forest areas remain higher than the start of the century with and without thinning.

Under SSP1 the decline in harvest area did not depend on climate, but rather the decreasing harvest demand later in the century under this scenario. The decline in area we observed with the SSP scenarios (Figure 4.3) remained when we switched to constant climate and CO<sub>2</sub> (Figure 4.4).

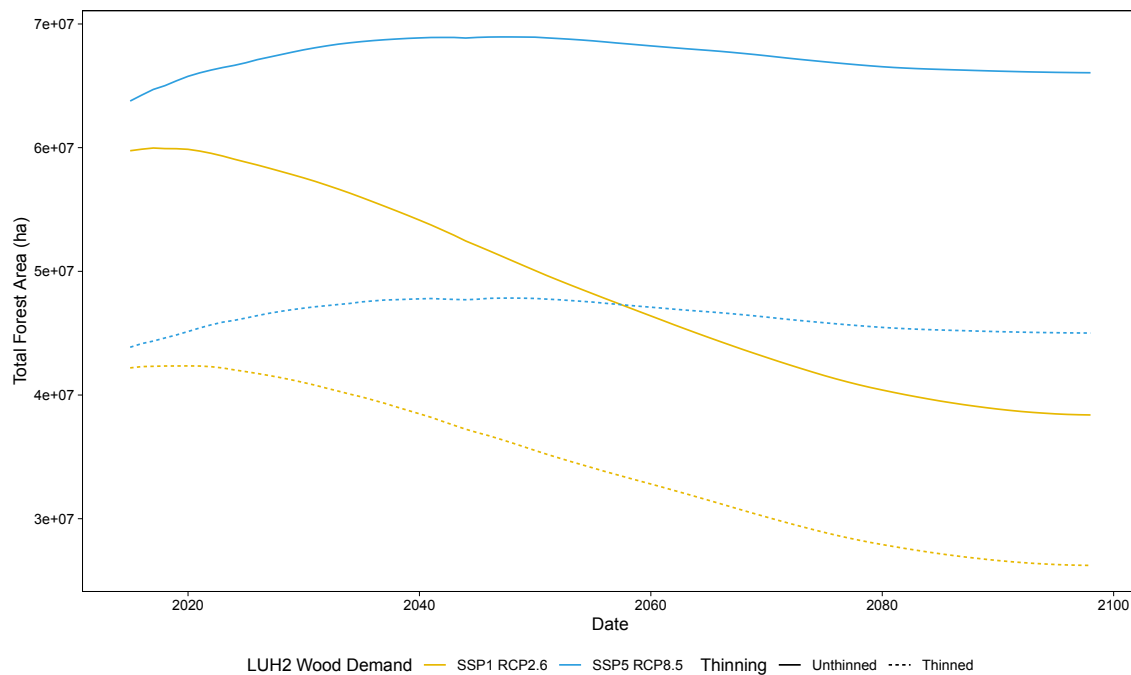


Figure 4.4: Required Forest Area Under Constant Climate: The total predicted loblolly forest plantation area that would be required to meet the wood demand of SSP1 (yellow) and SSP5 (blue) if forests did not experience the effects of climate change from 2015 to 2099. Management scenarios without or with thinning are indicated by solid and dashed lines respectively.

## 4.5 Discussion

Our work predicts that the area of plantation forest required to satisfy demands for wood products in the SEUS decreases as climate change and atmospheric CO<sub>2</sub> increases. This effect can be large enough to counteracted potential increases in demand for wood over the 21st century. In our simulations increases in forest growth rates are driven primarily by increasing atmospheric CO<sub>2</sub> (Chapter 3, section 3.4.1). Increasing productivity allows trees to reach commercial size more quickly, which raises wood yields on an annual basis. As a result the amount of forest land required to meet a fixed demand for wood decreases. The gain in yields are larger than the increase in projected wood demand under SSP5, resulting in a predicted net decrease in forest area, assuming all demand was met by loblolly plantation. Under SSP1 CO<sub>2</sub> increases less so productivity does not rise as much as under SSP5. This scenario shows a decrease in forest area that is driven by decreasing wood demand.

We also examined how the practice of mid-rotation stand thinning influenced the expectations of harvested forest area. We found that the addition of mid-rotation thinning also decreased the area required to meet future wood demand. Our previous work showed that thinning increases total wood yields by capturing wood from trees that would be otherwise be lost to competition driven mortality, while maintaining the amount of wood harvested at the end of the rotation (Chapter 3, section 3.4.2). The influence of thinning on forest area was equal in magnitude to the influence of climate change (under the SSP5 scenario), highlighting that the details of how forest management is simulated can be as important as how the impact of climate change

is simulated for determining the required forest area.

When we ignore the model's predicted change in plantation productivity due to climate change the area required to meet the harvest demand increases for the rest of the century for all wood demand and management scenarios. This appears to be a straightforward result. Decreasing productivity per unit land area must increase the area of forest needed to meet a fixed wood demand. A less obvious aspect of the result is that predictions of the near future are highly sensitive to the estimates of future productivity. At the beginning of the simulations in 2015 wood demand and climate has yet to diverge significantly between the scenarios. However the required plantation area at 2015 increased by as much as 10 million hectares when we switched to the constant climate scenario. The reason is that while the area needed to meet the wood demand for 2015 is nearly identical between climate scenarios, there is also additional land planted in forest to supply future demand. Since the harvest cycle is on the order of decades this area is subject to change based on differences in climate well into the future. This implies that while uncertainty about climate in the near term may be low, increasing uncertainty about climate further in the future increases uncertainty in our predictions of forest area today.

Thinning's impact on plantation area remains strong even when we ignore the effect of climate on productivity. The effects of thinning and climate on loblolly yields are largely independent (Chapter 3, section 3.4.2). Thinning increases productivity and decreases forest area by similar fractions regardless of what the model predicts the effect of climate change to be.

Reducing the area of forest that is needed to meet wood demands could allow for changes in land use, including preservation and expansion of natural forest. It has been proposed that limiting extraction of wood to managed forest plantations can reduce pressure on natural forests and thereby increase carbon storage at the landscape scale (Paquette and Messier, 2010; Sedjo and Botkin, 1997). Natural forests, which are generally older and more diverse, store more carbon than intensively managed forests that are typified by young fast-growing trees, often in monocultures (Erb et al., 2018; Liao et al., 2010). The literature gives some evidence that forest plantations do reduce pressures on nearby natural forests, although there also can be risks to natural forest as income from them is lost (Pirard et al., 2016). Uncertainty remains about how best to manage our forests for maximum climate benefits, balancing carbon sequestration and storage with changing climate (Bellassen and Luysaert, 2014; Paquette and Messier, 2010). Exploring the role of forest sparing and different types of forest use and management has not been previously possible in most ESMs. Future work can use the techniques we have developed to represent forest plantations in simulations with dynamic mixed land use to more fully explore these questions.

It is important to recognize that increasing plantation yields will not necessarily by itself result in beneficial changes in land cover. Changing forest yields could have effects that are hard to predict due to different potential socioeconomic feedbacks. Increasing profitability of forest plantations could devalue natural forest incentivizing their conversion to plantation or increase the risk of loss to urbanization. Planners need to consider these perverse incentives when looking at how to influence the mix

of forest on the landscape for climate mitigation purposes. Other groups have made predictions of how SEUS plantation area will change in the future ([Wear and Greis, 2012](#); [Zhang and Polyakov, 2010](#)). These predictions use different approaches than ours that integrate region-specific social and economic factors. They forecast increasing pine plantation area and decreased in natural forest area in the future. Our study used two demand scenarios based on certain global socioeconomic assumptions. These do not represent the only possible future demand pathways, and a more regional specific demand analyses would be an useful next step for this work. We do not claim that our results represent a complete picture of the future. Rather we show the high sensitivity of predictions in forest area with changes in yields due to differences in climate and management. This high sensitivity should encourage researchers and planners to consider employing models that represent mechanistic growth and management processes when making predictions of future forest use and forest cover.

Recent developments in the FATES model within the CLM were critical for this study. CLM's default "big-leaf" vegetation model is unable to fully simulate the processes that govern the dynamics of a plantation forest. Big-leaf vegetation models represent forests as a single growing carbon pools. They don't represent forest age and size heterogeneity, which make management activities like planting a specific number of trees, or thinning out smaller trees, difficult to represent. In contrast, by representing different sizes, ages, and patches of trees it is possible to simulate more management processes in a demographic vegetation model like FATES. The Vegetation Management Module takes advantage of these demographic features of

FATES and provides a means to execute management activities such as planting, competition control, thinning, and wood harvest in a simple way.

We made the simplifying assumption in our analysis that wood demand was only met with loblolly plantation, which is unrealistic. As a result of our idealized simulations the estimate of loblolly plantation area at the beginning of the century is well in excess of estimates of current loblolly forest cover for the region. Our values start at ~40-50 million ha vs. an estimated contemporary value around 13 million ha (11.7-13.4) (Baker and Langdon, 1990; Chen et al., 2017; Schultz, 1997). While pines are the dominant plantation type in the SEUS (Chen et al., 2017), wood products in the SEUS are harvested from a mix of upland and lowland hardwood and coniferous forests. Several other species of pine are used in plantations of the region, in addition to loblolly. Our loblolly PFT likely represents some of these species well, but this has yet to be tested. To get a more complete and accurate estimate of how harvested forest area will change in the future we will need to be able to simulate the other forest types of the region, managed and natural. Currently we lack well validated PFTs for temperate hardwoods, broadleaved evergreen trees, and shrubs.

Our approach for simulating loblolly plantations may also overestimate their productivity. First, we do not explicitly represent the competitive understory that is often present in loblolly stands and is known to reduce loblolly growth (Haywood et al., 1997; Miller et al., 2003; Sanchez and Eaton, 2010), due to a lack of validated understory PFTs. Second, the version of FATES that we used also does not incorporate nutrient limitation. Pine plantation productivity is sensitive to nutrient limitation (Bracho et al., 2018; Haywood et al., 1997; Jokela et al., 2004), and nutrient limitation may

become more pronounced as CO<sub>2</sub> fertilization in the future increase nutrient demand. Third, the model does not currently represent the insects and pathogens that can increase mortality and negatively impact loblolly yields ([Baker and Langdon, 1990](#)). Without these growth limiting factors we expect that our loblolly simulations probably best mimic loblolly pine under optimal conditions, i.e. stands with fertilization and competition control treatments implemented according to best practices. However, management of pine plantations varies and growth limitation may remain even when intensive management is used. Neglecting these factors will on average contribute to a high growth bias. Correcting this bias would increase the forest area needed to meet the harvest demand, especially under high climate change scenarios like SSP5 RCP8.5.

The efficiency of harvest in the model is likely too low, which has the effect of lowering predicted wood yields. We ran our simulations with the default FATES setting for harvest export efficiency. This assumes that only 80% of the wood harvested is transferred off the harvest site. This value was developed in a tropical forestry context. We do not have a well constrained estimate of harvest efficiency for the SEUS but we think it is likely well higher than 80%. Raising the harvest efficiency would increase our estimate of wood yield per hectare, and thereby would decrease our estimate of the area required to meet the SEUS harvest demand. Due to the linear nature of our calculations the a change in the value of the harvest efficiency will change all scenarios equally, so the patterns presented here would be preserved even though the hectare values would be reduced.

Finally, our results could be sensitive to the assumption that all harvested wood can

be used to meet harvest demand. This assumes that the smaller trees removed during mid-rotation harvest are equivalent to the larger trees removed at the end of rotation. In reality, the two harvests have different fates, as thinned trees are often used for pulp production while larger trees are used for saw timber. This assumption was necessary given the wood harvest input data. Here we used the total wood harvest demand in the LUH2 data that is specified as wood carbon mass representing an unspecified mix of wood products including pulp, wood chips, timber, and poles. By using a dynamic vegetation model that represents individual tree sizes, our analysis could be extended to represent different size-based wood product classes once the LUH2 data includes different product categories.

## 4.6 Conclusions

Currently, wood harvest, land cover, and land-use transitions are provided to ESMs as prescribed inputs from the LUH2 data set. As a result, projections of terrestrial carbon storage depend on how these drivers are simulated in ESMs. Here we show that the land area required to meet the prescribed wood harvest removals in an ESM is sensitive to how the model simulates changes in growth and forest management. For the particular ESM and scenario for future wood harvest, our simulations showed that the required forest area declined in the future, an outcome that has implications for the distribution of other land uses and carbon storage in the Southeastern U.S. Current generations of ESMs used in CMIP6 and IPCC reports do not internally simulate the reallocation of land-area as harvest demands are met. Therefore,

quantifying the implications of these dynamics on projections of atmospheric CO<sub>2</sub> and climate change are critical for understanding the role of managed forests in the trajectory of Earth's climate.

# Chapter 5

## Conclusions

In this dissertation I set out to improve the representation of forest management in the Community Land Model in order to better understand the role that forest management plays in the climate system. This work was motivated by earlier work by others in our lab (Thomas et al., 2018) and department (Burkhart et al., 2018) that came out of the PINEMAP project (Will et al., 2015). The work of this dissertation presents answers to the question of how changing climate may effect pine plantations of the Southeastern United States (SEUS) and how management interplays with those changes.

Chapter 2 was devoted to method development and validation, specifically Plant Functional Type (PFT) parameter selection, model software changes to add new allometric relationships, revised behavior for canopy closure, and model management activities with the Vegetation Management Module. These developments were necessary to answer questions about forest management in later chapters. The validation process also tested the FATES model in several new ways that will be of interest to other FATES users. FATES uses tree trait parameters that can, in principle, be obtained from field measurements and the literature. I successfully used this approach to develop a new loblolly pine (*Pinus taeda*) PFT that outperformed the default PFT that represents conifers in the temperate and boreal zones. The number of parameters was large and as a result this was an involved process. In this process I developed a good deal of data about the sensitivity and role of these parameters in simulating forest stands. With some additional work these results could be used as the basis of a paper that explores how variation in FATES parameters influence the simulation of managed forests. However, I found that PFT parameters changes

alone were not sufficient to accurately capture the allometric relationships of loblolly pine. Therefore, I also introduced several new general allometric equation forms to the model code that improved the size relationships of loblolly pines and can be used by others in future work.

Competition is a central feature of FATES and is fundamental to its potential to improve vegetation realism in the ESMs that use it. The spacing trial experiments I performed allowed me to look at competition as a nearly continuous variable and I showed the FATES does a reasonable job modeling competition over a range of competitive intensities. The process of canopy closure drives competition for light in the developing stand. Improving this behavior in the model required me to modify the model code that controls this important transition. Together with my modifications to tree crown related parameters, this change improved model realism and accuracy in simulated stands as they aged.

I developed the Vegetation Management Module to enable simulation of the management cycle from planting to harvest and validated it in detail for mid-rotation stand thinning. The design of the VM module is flexible and generic in a way that will allow others to use it in other forest management contexts. I collaborated with Kathryn Murenbeeld, a graduate student at Boise State University, to help her use the VM module for simulations of management in ponderosa pine (*Pinus ponderosa*) forests in the Western U.S. which she used in her Ph.D. dissertation ([Murenbeeld, 2022](#)). I also identified several model bugs during development, contributing fixes to the FATES community.

In chapter 3 I employed the tools I developed in chapter 2 to run simulations of loblolly forest plantations for the entire species range in the SEUS from the end of the 20th century through the end of the 21st century. I used the bounding members of tier 1 CMIP6 SSP scenarios to predict growth under mild to extreme levels of climate change and increasing atmospheric CO<sub>2</sub>. These simulations showed loblolly pine simulated with CLM-FATES to be very sensitive to climate change and management practices. Increases in growth and wood yields were related primarily to the extent of increases in atmospheric carbon dioxide CO<sub>2</sub>. Changes in climate in the scenarios examined had a smaller negative impacts on growth. The SSP1 RCP2.6 scenario avoids the worst effects of climate change and therefore simulated changes in loblolly productivity were small for this scenario. At mid-century the increases in productivity I simulated with SSP5 RCP8.5 were a couple of percent higher than those previously estimated by other teams using different techniques as part of the PINEMAP project (Burkhart et al., 2018; Thomas et al., 2018). As in my work Burkhart et al. (2018) also show that the CO<sub>2</sub> effect was the dominant driver of increased productivity but differed in showing climate factors as driving a small increase as well. My study extended further, to the end of the century, with very large productivity increases under RCP 8.5. I identified several unmodeled factors and limitations that would reduce yields on average if represented in CLM-FATES, so these estimates should be considered an upper limit on future productivity increases. The growth of loblolly pine in exotic locations outside its natural range confirm that loblolly is capable of growth rates well higher than what is seen in the SEUS today (Burns and Hu, 1983; Jokela et al., 2004; Schultz, 1999). However, the factors driving

growth increases in exotic locations are thought to be largely climatic (Burns and Hu, 1983; Samuelson et al., 2010), while in our simulations changes in atmospheric CO<sub>2</sub> were responsible. Confirming the realism of our CO<sub>2</sub> response is challenging beyond mid-century. The DUKE FACE experiment exposed loblolly pine to elevated CO<sub>2</sub> at 550 ppm, which is still well lower than in our simulations at the end of the century with SSP5 RCP8.5 (~1146 ppm). SSP5 RCP8.5 represents the most extreme pathway in CMIP6, with higher CO<sub>2</sub> and radiative forcing than other scenarios, and is considered fairly unlikely (Hausfather and Peters, 2020). I propose that the priorities in the near term should be simulations with nutrient limitation, which should be possible in the CLM-FATES model in the near future, and further analyses under the other SSPs that are considered more likely future scenarios.

Chapter 4 presents an analysis of the implications the changes in loblolly productivity predicted in chapter 3 would have on the plantation area needed to meet wood demand set forth in the LUH2 dataset. Under SSP1 RCP2.6 forest productivity increases by a small amount but the area of forest contracts significantly over the century due to decreases in demand for wood. Under SSP5 RCP8.5 demand for wood products for the region increases and remains high but the plantation area needed to meet this demand still decreases through the century due to increases in forest productivity. Other groups have predicted increases in the area of pine plantation in the SEUS into the early to mid-century (Wear and Greis, 2013; Zhang and Polyakov, 2010) using very different models. My analysis was idealized in that it treated loblolly plantation as the only source of wood products for the region, which makes hard to directly compare to these other studies. It would be interesting to

examine the predictions of these other studies more closely to see how altering their assumption of pine plantation productivity would change their results. If increasing productivity in forest plantations is able to decrease the area of forest needed to meet society's demand for wood this could allow more forest to remain in a natural state, with potential ecological and climate benefits. However, increasing forest productivity may not result in the sparing of natural forests without accompanying policy to counteract socioeconomic factors that favor other types of land cover transitions. The uncertainties associated with our predictions of future forest productivity discussed above propagate to our analysis of future forest area. Further reduction of these uncertainties is necessary before using the results presented here in a planning context.

Through the work in this dissertation I developed a set of extensions and tools for the CLM-FATES model to allow the simulation of loblolly pine forestry and validated them under recent climate. I then used the loblolly PFT and VM module that I developed to simulate loblolly growth for the SEUS until the end of the century and examined the implications of these changes on the area of plantation in the region needed to support the demand for wood from this region. This work sets the stage to answer additional questions about the role of forest management in the climate system. Future work should endeavor to improve the methods developed here and expand research to other regions with intensively managed forest systems. Future work should also focus on quantifying how management influences forest carbon storage, the exchange of energy between forest and the atmosphere, the storage of carbon in wood products, and how to manage these for climate change mitigation.

These priorities will help planners and policy makers understand the full implications of managing forests in a changing climate.

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