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Dendroclimatic Analysis and Site Index Modeling of Central Appalachian Red Spruce

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Dendroclimatic Analysis and Site Index Modeling of Central Appalachian Red Spruce

Eric Yetter

Thesis submitted
to the Davis College of Agriculture, Natural Resources, and Design
at West Virginia University

in partial fulfillment of the requirements for the degree of

Masters of Science in
Forest Resources Management

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Division of Forestry and Natural Resources

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2020

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ABSTRACT

Dendroclimatic Analysis and Site Index Modeling of Central Appalachian Red Spruce

Eric Yetter

Red spruce (*Picea rubens*) was historically an important and dominant timber species in the central Appalachian mountain range. The tree species is now found in a small fraction of its original home range. Threatened and endangered organisms such as the Cheat Mountain Salamander (*Plethodon nettingi*) rely on red spruce associated forests for survival. Recent concerns including air pollution and climate change may threaten the health of remaining red spruce populations.

I used dendrochronology data to conduct historic dendroclimatic analyses and construct future growth projections for red spruce throughout the central Appalachians. My research involves the use of tree core data collected from over 83 randomly selected trees across red spruce's range throughout the Monongahela National Forest. Major results of this research show red spruce is sensitive to extreme warming temperature conditions. Temperature extremes in the summer growing season can potentially lead to increased tree respiration which causes temperature induced drought stress. Increasing minimum temperatures in the fall have positive effects on spruce growth. This is a result of an extended growing season that allows red spruce to store more carbohydrate reserves which are necessary for next year's growth. Growth projection results under a future climate change scenario show that future expected increases in maximum monthly temperatures will have negative effects on future spruce growth. These negative future growth effects may be mitigated by an extended nontraditional growing season, which allows the tree to accumulate more growth reserves for next year's growing season. Dendroclimatic results and future growth projections should be considered when identifying locations that are most suitable for future red spruce restoration activities.

Anamorphic site index curves were created for central Appalachian red spruce using age-height data combinations. My anamorphic site index curves offer forest managers a potentially better model for determining red spruce site index values for central Appalachian red spruce. My site index models could be better suited for use in the central Appalachians as opposed to historic red spruce site index models created with data from northern or southern red spruce populations. I also developed linear models that use associated species, climatic, and geographic variables to predict red spruce site index where red spruce is absent from the overstory. These linear models are a useful tool that forest managers can use to determine red spruce productivity in terms of site index. Linear models that use associated species to estimate central Appalachian red spruce are important because red spruce is absent on much of its original home range. Being able to determine red spruce site index where the species is currently absent will serve as a useful decision-making tool at selecting locations for restoration activities.

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Table of Contents

ABSTRACT.....	II
Acknowledgements.....	iii
List of Tables.....	VI
List of Figures.....	VII
Chapter 1: General Introduction and Literature Review.....	1
1.1 Restoration Importance.....	1
1.2 Importance of Red Spruce.....	1
1.3 Red Spruce Silvicultural Characteristics.....	2
1.4 History of Management	4
1.5 Issues Effecting Red Spruce Management and Restoration	7
1.5.1 Red Spruce and a Changing Climate	7
1.5.2 Red Spruce and Pollution.....	10
1.6 Site Index and Red Spruce.....	11
1.7 Red Spruce Restoration Research and Findings	12
1.8 Thesis Structure	14
1.9 Conclusion	15
1.9.1 Works Cited	16
Chapter 2: Dendroclimatic Analysis of Central Appalachian Red Spruce	20
2.1 Introduction.....	20
2.2 Methods.....	23
2.2.1 Field Sampling Design.....	23
2.2.2 Sample Processing and Dendrochronological Analysis	25
2.2.3 Dendroclimatic Analysis.....	28
2.2.4 Future Growth Projections	29
2.3 Results.....	31
2.3.1 Historic Growth-Climate Results.....	31
2.3.2 Future Climate Projection Results	33
2.4 Discussion	36
2.4.1 Historic Growth-Climate Analysis.....	36
2.4.2 Future Climate Projection Discussion.....	39
2.5 Conclusion	41
2.6 Tables and Figures	42
2.7 Works Cited.....	57

Chapter 3:Site Index Modeling of Red Spruce.....	60
3.1 Introduction.....	62
3.2 Methods.....	64
3.2.1 Field Sampling Methods	64
3.2.2 Laboratory Methods	65
3.2.3 Height Modeling	67
3.2.4 Predicting Red Spruce Site Index with Associated Species.....	68
3.3 Results.....	70
3.3.1 Central Appalachian Red Spruce Height Model and Figure Results	70
3.3.2 Predicting Red Spruce Site Index Using Associated Species, Climatic, and Geographic Variables	72
3.3.2.1 Linear Models Developed for Carmean et al. (1989) Site Index Values	72
3.3.2.2 Linear Models Developed Using Chapman Richards Three Parameter Model	73
3.4 Discussion.....	74
3.4.1 Anamorphic Modeling Discussion.....	74
3.4.2 Linear Models to Predict Red Spruce Site Index.....	77
3.4.2.1 Models that Predict Red Spruce Site Index Using Carmean et al. (1989) Site Index Values	77
3.4.2.2 Models that Predict Red Spruce Site Index Using Three Parameter Chapman Richards Site Index Values.....	79
3.5 Conclusions.....	81
3.6 Tables and Figures	82
3.7 Works Cited	93
Chapter 4: Conclusions	97

List of Tables

Chapter 2:

Table 2.1. Regional group data including the individual plots within each regional group and their associated mean values for all three plots combined.....	42
Table 2.2. Plot chronology statistics for the 18 individual dendroclimatic plots. Plot level statistics are listed according to their corresponding regional group.....	43
Table 2.3. Coefficients and their corresponding p-values for regression models that use temperature climatic variables in predicting red spruce growth for regional groups. Coefficients are listed in order of importance in the model.....	44
Table 2.4. Coefficients and their corresponding p-values for regression models that use moisture climatic variables in predicting red spruce growth for regional groups. Coefficients are listed in order of importance in the model.....	45
Table 2.5. Average annual climatic values for the reference period and future growth periods. Future climate values are estimated from RCP 4.5 data.....	46
Table 2.6. Coefficients and their corresponding p-values for regression models that use temperature climatic variables in predicting red spruce growth.....	47
Table 2.7. Coefficients and their corresponding p-values for regression models that use moisture climatic variables in predicting red spruce growth.....	48

Chapter 3:

Table 3.1. Height models and corresponding statistics for models that use suppression corrected age values or DBH to predict total tree height of central Appalachian red spruce.....	82
Table 3.2. Best performing models using stepwise regression with forward selection and subset regression. Models were created using associated species site index values, climatic variables, and geographic variables. Best performing models were identified by low AICc values and having all significant predictors in each model.....	83
Table 3.3 Linear modeling variable legend. Climatic and geographic variables considered and used for linear site index modeling.....	84
Table 3.4. Correlation between site index variables for site index modeling including height, DBH (diameter at breast height), true age, and suppression corrected age.....	85
Table 3.5. Red spruce suppression summary data showing average number of suppression periods and length of suppression. Ring width measurements for suppressed and free growth periods are also provided.....	86

List of Figures

Chapter 2:

- Figure 2.1. Map showing the study area on the Monongahela National Forest in West Virginia. Dendroclimatic plots are indicated with black dots.....49
- Figure 2.2. Chronologies for each region and aspect. Chronologies in solid gray lines are from regional groups with north facing plot aspects. Chronologies in dashed black lines are from groups with south facing plot aspects.....50
- Figure 2.3. Significant predictors of the regression models are shown below for regional groups using temperature climatic variables. Predictors displayed in black indicate a negative correlation with red spruce growth, while indicators in light gray indicate a positive correlation with red spruce.....51
- Figure 2.4. Significant predictors of the regression models are shown below for regional groups using moisture climatic variables. Predictors displayed in Black indicate a negative correlation with red spruce growth, while indicators in light gray indicate a positive correlation with red spruce growth. Adjusted R2 values are listed for each growth model. Adjusted R2 values are listed for each model.....52
- Figure 2.5. Projected red spruce growth by regional group using temperature variables. Error bars indicate a 95% confidence interval of the base growth rate. All changes in growth that lie outside of the error bars indicate significant changes in growth. Growth projections were created with future climate data that was estimated using climate change scenario RCP 4.5.....53
- Figure 2.6. Projected red spruce growth by regional group using moisture variables. Error bars indicate a 95% confidence interval of the base growth rate. All changes in growth that lie outside of the error bars indicate significant changes in growth. Growth projections were created with future climate data that was estimated using climate change scenario RCP 4.5.....54
- Figure 2.7. Coefficients and their corresponding p-values for regression models that use temperature climatic variables in predicting red spruce growth. Coefficients are listed in order of importance in the model. N.S. Indicates no models are significant in predicting growth with the selected climate variable. Analysis timeframe was from 1947 to 2017. Note: C is the model constant. V are model predictors. B is the beta coefficient for each model predictor. c.f. Fig. 5.1 for specific monthly and (or) seasonal variables.....55
- Figure 2.8. Coefficients and their corresponding p-values for regression models that use moisture climatic variables in predicting red spruce growth. Coefficients are listed in order of importance in the model. N.S. Indicates no models are significant in predicting growth with the selected

climate variable. Analysis was conducted between 1947 to 2017. Note: C is the model constant. V are model predictors. B is the beta coefficient for each model predictor. c.f. Fig. 5.2 for specific monthly and (or) seasonal variables.....56

Chapter 3:

Figure 3.1. Map of the plots where site index sampling occurred. Sampling was conducted on the Monongahela National Forest in West Virginia.....	87
Figure 3.2. Chapman Richards three parameter height model and guide curves with age-height data points used to develop the model. The model curve is marked with a solid black line, guide curves are marked with dashed lines, sample points are marked with dots.....	88
Figure 3.3. Meyer model and guide curves with age-height data points used to develop the model. The model curve is marked by a solid black line, guide curves are marked with dashed lines, and sample points are marked with dots.....	89
Figure 3.4. Meyer model and guide curves with DBH-height data points used to develop the model. The model curve is marked with a solid black line, guide curves are marked with dashed lines, and sample points are marked with dots.....	90
Figure 3.5. Chapman Richards three parameter height model and guide curves with true age and height data points used to develop the model. The model curve is marked with a solid black line, guide curves are marked with dashed lines, sample points are marked with dots.....	91
Figure 3.6. Meyer model and guide curves with true age and height data points used to develop the model. The model curve is marked by a solid black line, guide curves are marked with dashed lines, and sample points are marked with dots.....	92

Chapter1: General Introduction and Literature Review

1.1 Restoration Importance

Restoration of limited forest resources is critical for the future of many forest species. Forest restoration activities and planning rely on sound silvicultural methods when deciding how to manage land to promote desired species. Silvics vary for every tree species, as every tree species has different growing and light requirements and reacts to treatments differently. A changing climate will create difficult scenarios in the future for the restoration and promotion of certain species. Several restoration methods are used when considering future climate issues. Restoration methods such as adaption, promotion of resiliency, and mitigation, all share a common goal of maintaining the selected species but use different management techniques (Magruder et al., 2013; Lof et al., 2019).

Silviculture treatments, such as thinnings and release harvests, have proven effective methods in promoting the growth of many species throughout North America. Treatments that reduce residual tree densities can improve tree growth and promote resilience to climate change through increased tree vigor (McGuire et al., 2010; Chhin, 2018). Carbon sequestration is an excellent ecosystem service forests provide and will continue to be more important in the future to mitigate atmospheric carbon accumulation. Increases in the growth and health of managed forests can facilitate greater carbon gains through sequestration (Millar et al., 2007). Using silviculture, managers can sustainably harvest forests that provide long term benefits for the ecosystem and the forest products industry (Rentch et al., 2007).

1.2 Importance of Red Spruce

Red spruce (*Picea rubens*) has been an important timber species throughout much of the northeastern part of North America. This species has been valued for its harvestable resources and the ecosystem services it provides. The species historic value was mainly for structural lumber, pulp fiber, and musical instrument components (Hart, 1959; Burns 1990). However, current non-timber values for

red spruce are becoming more important and will continue to become more important as red spruce provides critical ecosystem services. Endangered and threatened organisms such as the Cheat Mountain Salamander (*Plethodon nettingi*) rely on red spruce forests for survival (Pauley, 2008). Another important ecosystem service red spruce associated forests offer is the ability to sequester large amounts of carbon (Diochen et al., 2009). Expansion of red spruce would extend these non-timber benefits of the forest cover type. Spruce restoration and research are needed to restore this species back to more than just a fraction of its original extent. Red spruce in the central Appalachians historically covered around 600,000 hectares, the species current extent is limited to approximately 10,000 hectares (Rentch et al., 2010; Thomas-Van Gundy and Sturtevant, 2014). The benefits of this important tree species highlight the importance of maintaining and encouraging the expansion of red spruce forest cover. This literature review chapter will outline important factors that will help aid the restoration of this once common timber species.

1.3 Red Spruce Silvicultural Characteristics

High shade tolerance is an important characteristic of red spruce that allows seedlings and saplings to persist in the understory for extended periods of time (D'Arrigo et al., 2012; Saladyga, 2017). Red spruce is a long-lived tree species that can live up to 400 years (Hart, 1965). Despite the longevity of this tree species, the larger stem diameters are usually around 61 cm and seldom reach 76 cm (Burns, 1990). Total height of red spruce can reach 35 meters in the central Appalachians (Burns 1990). Red spruce can grow on a variety of sites and soil conditions, including poor sites that are not productive for the growth of competing tree species (Hart, 1965).

Red spruce seldom reproduces from coppice methods (D'Amato et al., 2013). Red spruce primarily reproduces from seed sources and can produce seed when around 30 years old. Seed dispersal is facilitated by wind and gravity and can extend up to 100 meters from the parent tree (Dumais &

Prevost, 2007). Regeneration and spread of spruce cover is limited by the distance of seed travel and seed source (Griscom et al., 2011). Seed germination is best in cool and moist sites with large decaying woody debris and softwood litter (Dumais and Prevost, 2007). These germination requirements are characteristic of the undisturbed understory of spruce forests in the Central Appalachians.

Predation from herbivores has little impact on red spruce regeneration because they are of low palatability to many species including white-tailed deer. Deer tend to favor hardwood species for browse. Browse resistance may offer a competitive advantage for red spruce regeneration over competing species such as red maple and yellow birch (Griscom et al., 2011). In contrast, competition from other plant species limits spruce regeneration. Rhododendron is a common understory species found throughout West Virginia. Rhododendron stems can grow into dense thickets and create regeneration problems for red spruce (Adams & Stephenson 1989). Beech root sprouts that develop in canopy caps created by beech bark disease grow fast and may end up filling canopy gaps with infected beech saplings instead of favorable red spruce regeneration (Van Miegroet et al., 2007; Rentch et al., 2016).

Red spruce growth productivity and efficiency is impacted by a variety of factors. One important growth factor for red spruce especially in central West Virginia is age. Being a highly shade tolerant species, red spruce can reach a considerably old age as evidenced by dendrochronological studies. Dendrochronology allows researchers to determine age and growth characteristics of trees using samples such as increment cores (Speer, 2010). Red spruce has a negative relationship with age and productivity. As age increases, red spruce has lower photosynthesis rates, and foliar efficiency also decreases (Day et al., 2001). Older red spruce trees can exhibit more symptoms of decline than younger and understory red spruce affected by similar stressors (Adams & Stephenson, 1989; Goelz et al., 1999). Age of suppressed red spruce is important as older red spruce are less responsive to releases and will not be able to optimize growth. Managers must consider this growth characteristic when planning

restoration efforts involving release events (Seymour & Kenefic, 2002). In addition to age, tree structure can be important when considering red spruce productivity and efficiency. Studies have shown that red spruce experience decreased growth efficiency with a crown size that is too large (Seymour & Kenefic, 2002; DeRose & Seymour, 2009).

Red spruce dominated forests are important for storage and sequestering of atmospheric carbon. A red spruce forest can store a large amount carbon and much of the carbon stored is in locations other than wood fiber. Over half of the carbon stored in spruce forests is located in organic and mineral soil horizons (Kosiba et al., 2018). Extensive soil carbon was lost in the past due to harvests followed by wildfires. Soil carbon can be substantially drained from the ecosystem just from harvesting (Diochon et al., 2009). After a forest is harvested, microbes in the soil continue to break down carbon at rates faster than rates which organic matter can be replenished (Fahey et al., 2005). When managing a red spruce forest for carbon storage, the rotation age length may exceed the biological rotation length (Diochon et al., 2009). Diochon et al. (2009) found that soil organic carbon decreases by over 50 percent over for a 30-year period, after a clear-cut harvest on red spruce stands. It takes 100 years to replenish soil carbon to pre-harvest conditions (Diochon et al., 2009). Losses in soil organic matter can reduce moisture holding capacity and may hinder red spruce seeds ability to germinate (Dumais and Prevost, 2007). When forest managers are determining future harvests and treatments, soil carbon should be considered to ensure carbon loss is minimized.

1.4 History of Management

Until the mid-1800s and into the 1930s the state of West Virginia, and particularly the area now designated as the Monongahela National Forest, was dominated by red spruce associated forest types. This mountainous area is known for having steep terrain over a large portion of the region. Much of the forests were difficult to extract timber resources from in the early logging period for this region (White

et al., 2014). As logging and railroad technology developed, harvesting crews were able to increase production throughout the eastern US forests (Adams & Kochenderfer, 2015). Logging railroads allowed logging operations to extract large volumes of harvested timber out of the mountains and into West Virginia timber boom towns such as Cass, Richwood, and Spruce. Timber boom towns processed the raw forest materials into value added products such as lumber, furniture, and pulp (Rentch et al., 2007). Timberlands were generally large and usually owned by coal, railroad, or timber barrens. Timber was harvested from these lands with little regard for the environment or for future stand health. Common harvesting methods consisted of clear-cut type harvesting or high-grade selection harvesting (White et al., 2014). Silviculture was not practiced when making large scale forest management decisions. The main objective that forests served was for unsustainable commercial production. Because of unsustainable harvesting, there were few mature forest stands available for harvesting by the 1930s. Most of the mature and un-harvested timber in the central Appalachians was located in areas that were out of reach from logging railroads. Forest stands in excessively rocky, steep, or high elevations, were saved from early harvesting due to their low merchantability and difficult access (White et al., 2014).

Red spruce forests are known for storing large amounts of organic matter both above and below the forest floor. Red spruce forests create a thick layer of organic matter on the forest floor and incorporate organic matter into soil horizons (Pauley, 2008; Diochon et al., 2009). A closed canopy and regional climate keep the organic layer moist. If allowed to dry, the thick organic layer can be susceptible to wildfires if ignited, this vulnerable fuel source can fuel extensive forest fires. Logging operations during the 1800's to the early 1900's in this area left tremendous amounts of slash in the recently cleared forests, either scattered or in slash piles. Post logging conditions consisting of a dry organic layer and evergreen slash that was a readily available fuel found throughout the harvested landscape. Logging railroads used to harvest the regions timber were a major spark source that started wildfires in this area (Rentch et al., 2007; White et al., 2014). Coal fired locomotives, such as the shay

locomotive, were used on logging railroads throughout the central Appalachians, and while in use, locomotives created sparks and embers that would ignite the readily available post-harvest fuels and organic layers. Once ignited there was little effort involved with stopping ignited wildfires. Logging and wildfires collectively disturbed an estimated 97% of central Appalachian red spruce's home range throughout the 1800's and 1900's, with an estimate of over 580,000 hectares of forest disturbed over the historical exploitation period (Thomas-Van Gundy & Sturtevant, 2014). Logging followed by wildfire resulted in disturbance conditions not optimal for the growth of red spruce saplings and seedlings, which led to optimal conditions for hardwood species, which offer considerable competition for red spruce (McGuire et al., 2010; Rentch et al., 2016). Many competing hardwood species that have replaced red spruce's dominance such as red maple and beech readily reproduce through coppice regeneration in the form of stump sprouts. Stump sprouts have growth advantages from established roots and can outcompete seedling regeneration (Smith, 1996).

In addition to intensive forest exploitation, land clearing for agricultural purposes also affected red spruce and other woody species negatively. Forest land was converted to grazing lands for cattle which favored the growth of cool season grasses, not woody plants (Rentch et al., 2007; Gundy et al., 2012; Griscom et al., 2011). Privately owned forest lands experienced minimal silvicultural treatments or management that promoted the growth of red spruce. Publicly owned timberlands however, such as the Monongahela National Forest (MNF), did experience timber stand treatments/improvements which promoted the growth of red spruce (Thomas-Van Gundy & Sturtevant, 2014). These treatments involved girdling or applying herbicide to individual trees competing with red spruce stems. Selection harvests conducted on privately owned forest lands that acted as a release event, promoting residual red spruce growth and recruitment. Privately owned lands that endured secondary harvests likely experienced high grading, which leaves behind undesirable timber species and poor-quality trees. Red spruce forestlands have also experienced disturbance from mining operations (Brown, 1962). Surfsce

mines consequently destroyed red spruce habitat. Remnants of old surface mines can be observed frequently within areas of the central Appalachians that were once dominated by red spruce. Surface mines consequently destroyed red spruce habitat. Surface mines can offer red spruce restoration opportunities.

1.5 Issues effecting Red Spruce Management and Restoration

1.5.1 Red Spruce and a Changing Climate

Climate change is a major factor that land managers must consider when focusing on red spruce restoration. With a warming climate and altered precipitation regime in the future, it is difficult to predict exactly how red spruce will be affected. Literature points to growth declines and or advances associated with climate change (Soule, 2011; Koo et al., 2014; Kosiba et al., 2018).

Dendroclimatology involves analyzing tree core ring measurements and comparing annual ring measurements to climate data for that year and location. Using dendroclimatology, scientists can determine how climate affects the growth of woody plants. Studies have shown both positive and negative responses to increased temperatures (Schwartz et al., 1997; Soule et al., 2011; White et al., 2014). The results of dendroclimatic studies allow us to determine the impacts historic climate had on tree growth. Dendroclimatic results also allow us to make estimates on how the species of interest could potentially respond to future predicted climate values.

Red spruce responds differently to temperature depending on time of year and growing season (Koo et al., 2014; Kosiba et al., 2018). Radial growth of southern red spruce trees shows negative growth relationships with excessive heat, this negative impact on spruce growth can be observed in the following growing season and is noted with a narrow growth ring (Kosiba et al., 2017). The southern extent of red spruce in the Appalachians is restricted by maximum summer temperatures (White et al.,

2014). In the northern extent of red spruce's range, it appears that the species is not restricted by warm temperatures and red spruce growth has increased with increasing temperatures, particularly at higher elevations (Soule et al., 2011; Kosiba et al., 2018). Warming summer temperatures may extirpate spruce from lower latitudes and elevations, especially in the southern portion of its range (White et al., 2014).

A warmer climate will result in an extended growing season by lengthening growing degree days. Longer growing seasons and an increase in average mean temperature may allow red spruce to increase carbon capture and also increase respiration (Soule, 2011). This extra carbon production could lead to growth increases as long as growth declines from high summer temperatures are not severe (Kosiba et al., 2018). Early spring growing conditions can increase tree growth (Mathias & Thomas, 2018). Being an evergreen, red spruce can photosynthesize whenever conditions are suitable (Pallardy, 2007). Due to this growth advantage, warmer winters and springs may make the species more productive. Winter thaws that lead to red spruce conducting photosynthesis can help the tree sequester extra carbon, but sudden freezing events can damage spruce trees through frost damage (Mosseler et al., 2000).

Precipitation extremes may be a more important growth variable than temperature. Spruce can be more sensitive to water availability in terms of water shortages, but excess moisture in the spring has a negative impact on southern red spruce growth (Berry & Smith, 2012; White et al., 2014). Magnitude of effects caused by climate change and precipitation vary between elevations, and are usually more severe at lower elevations (Griscom et al., 2011). Loss of snowpack can contribute to red spruce declines through the loss of growing season moisture from snow melt and also through loss of insulation leading to root damage (Socci and Templer, 2008).

A warming climate has increased the competitiveness of many competing hardwood species frequently associated with red spruce. The future climate could offer competing tree species, particularly hardwoods a competitive advantage and potentially lead to a decline in red spruce forest cover (Kosiba et al., 2017). Silviculture and management activities such as thinning and single tree selection harvests offer options to land managers that may promote the growth of spruce through harvests that create release events for residual red spruce (Millar et al., 2007).

A significant concern regarding central Appalachian red spruce is the loss of suitable lands for restoration. This loss of land is not from deforestation, but from the warming of seasonal temperatures and an altered hydrologic cycle. Climate change models predict that as future conditions persist there will be less suitable locations available for red spruce restoration in the future (Walter et al., 2017). Forest lands that may be marginal candidates for restoration of the species in the present, may no longer be viable restoration locations in the future due to climate change (Walter et al., 2017; Rentch et al., 2007). Locations with the greatest probability for red spruce restoration success should be selected first. This method of selection will ensure limited resources are allocated to restoration efforts in areas that will likely be able to support red spruce in the future years (Rentch et al., 2007). Walter (2017) predicts that even under optimistic climate projections, the health of red spruce forests will depend on well executed restoration efforts. Common restoration efforts for central Appalachian red spruce include seedling plantings, understory competition treatment, and harvests/gap establishment to promote or release red spruce regeneration. Human disturbance in spruce forests could intensify red spruces response to climate change. Large canopy altering events such as harvests can intensify the species sensitivity to climate change (Dumais & Prevost, 2007; White et al., 2014).

1.5.2 Red Spruce and Pollution

In addition to climate change, pollution is a critical factor affecting many aspects of red spruce health and growth. Air pollution in the form of sulfur dioxide, nitrogen dioxide, and carbon dioxide resulting from combustion of fossil fuels such as coal has negatively affected red spruce growth historically (McLaughlin et al., 1987; Dumais & Prevost, 2007; Soule, 2011). Air pollution may be more important than climate change in the future when looking at the growth and health of red spruce. Red spruce at all elevations experience negative growth from air pollution, however, higher elevation spruce has a higher sensitivity to air pollution (Koo et al., 2014). Acid deposition, commonly in the form of acid rain, is responsible for red spruce declines in the past (McLaughlin et al., 1987; Dumais & Prevost, 2007; Soule, 2011; Berry & Smith, 2014). Acid rain is a form of precipitation having a low PH value and is commonly associated with sulfur and nitrogen ions (Boyle, 1983). Acid rain consequently lowers soil PH which, if too low, can negatively affect plant growth. Acid rain causes other growth problems through soil leaching (Boyle, 1983). Calcium is an important nutrient lost through soil leaching (Dumais and Prevost, 2007; Kosiba et al., 2018). When calcium shortages occur, red spruce can become more susceptible to winter injuries such as frost damage and crown dieback, resulting in growth and health declines in the future (McLaughlin et al., 1987; Dumais & Prevost 2007; Soule, 2011). Similarly, soil organisms can also be negatively impacted from air pollution and acid deposition. A decline in soil organisms can impede leaf litter decomposition and impact nutrient cycling (Lukina et al., 2017). However, air pollution levels have declined since the Clean Air Act of 1970 (Driscoll et al., 2001). Red spruce growth has improved from lower levels of pollution and the increase in growth is expected if pollution levels continue to decline (Soule, 2011; Koo et al., 2014; Mathias & Thomas, 2018).

1.6 Red Spruce and Site Index

Site index is a common metric used to explain forest stand productivity. Site index is commonly expressed as height of an overstory tree at a base age, usually of 50 years base age in eastern North America (Mathiasen et al., 2006). Site index values can be compared and used to determine areas that will be most productive for growth of specific trees (Geyer and Lynch, 1987). There are a few common methods to develop site index curves. One of the more basic and commonly used methods for creating site index figure uses an anamorphic height equation with corresponding guide curves (Nigh and Love, 1999). Polymorphic site index equations and curves are another commonly used method used to explain site index. This method uses a different curve equation for each site index value curve (Nigh and Love, 1999; Carmean et al., 2001; Newton, 2008).

There has been research on red spruce and site index development for northern and southern populations of red spruce (McClintock and Bickford 1957; Hoar and Young 1965; Griffin and Johnson 1980; Carmean et al, 1989; Nicholas and Zedaker, 1992; Seymour and Fajvan, 2001). All of the site index curves available for red spruce use historical data collected in the northern or southern portion of red spruces range. Traditional site index development methods require that sampled trees for site index creation require that the tree to have lived in free growing conditions in the overstory (codominant or dominant crown class) (Nigh and Love, 1999). Due to red spruces extreme shade tolerance and slow growth characteristics, red spruce frequently encounters periods of suppression (Rentch et al., 2007). Because of this growth characteristic, red spruce are not good candidates for traditional site index methods. Using diameter to predict height of red spruce is one way that previous studies have accounted for the growth suppression of red spruce when developing site index curves (Meyer 1942; Nicholas and Zedaker, 1992). Using only free growth and replacing suppression periods with corresponding free growth periods has also been used to develop red spruce site index when the trees

encounter suppression (Seymour and Fajvan, 2001). One of the more common and recent red spruce site index curves are from the Carmean et al. (1989) publication. This site index uses true age to predict height but uses outdated data collected in the 1920s (Meyer, 1929).

Linear models have been developed that predict site index values of timber species using the site index values of associated species (Carmean, 1979; Steel and Clutter, 1986). Having linear models that can predict site index where a species is currently absent from the overstory is an important way for land managers to determine potential productivity of forest lands for a species. Linear modeling that uses site index values of commonly associate timber species such as yellow birch and red maple to predict red spruce site index could be useful in the central Appalachians. Because much of the historic central Appalachian red spruce forest lands are now dominated by hardwoods, linear modeling to predict red spruce site index using associated species could be used to estimate land productivity in terms of site index. There have been no linear models created for central Appalachian red spruce that use associated species to predict red spruce site index values.

There are currently no site index curves available for central Appalachian red spruce. The development of a site index curve that uses trees sampled from the central Appalachians would be useful and important. Site index curves developed for central Appalachian red spruce will better explain forest productivity in terms of site index values than site index curves created with data taken from northern or southern populations of red spruce. Linear modeling that uses associated species site index values to predict red spruce site index would be beneficial for predicting central Appalachian red spruce productivity where the species is currently absent from the overstory.

1.7 Red Spruce Restoration Research and Findings

Obtaining acceptable regeneration is a critical and challenging step in forest restoration. A large part of silviculture deals with managing a forest to create regeneration for the next cohort of trees

(Smith, 1996). Suppressed red spruce can change their crown structure to sustain growth under heavy canopy cover (Dumais & Prevost, 2007). Many of the over story red spruce observed in the forest today started out as a suppressed seedlings. Release events are needed to allow spruce regeneration to reach dominance in the canopy (Fraver & White, 2005; Rentch et al., 2016). Release events through small canopy gaps are effective for red spruce recruitment; in contrast, full sunlight, created from large disturbances negatively affects regeneration (Dumais & Prevost, 2007). Many spruce trees require more than one release to reach co-dominate or dominant status (Rentch et al., 2010; Amos-Binks & MacLean, 2016).

Red spruce has unique management and restoration requirements. A common management practice that promotes red spruce forest cover is timber stand improvements or harvesting in a way that creates canopy gaps (Rentch et al., 2010; Rentch et al., 2016). Small canopy gaps are preferred over large gaps, as the species can be sensitive to full sunlight exposure (Rentch et al., 2016). Full sunlight from large gaps may cause temperature and water related stress. If merchantable, single tree selection harvesting and shelterwood harvesting are effective management tools to promote the growth of the next generation of red spruce (Seymour and Hunter, 1992; Dumais and Prevost, 2007; Rentch et al., 2010). Selective harvests should create small gaps and removed trees should be undesirable species and trees that are overtopping existing regeneration (Rentch et al., 2010). Red spruce are shallow rooted and prone to windthrow when residual stand densities are low after a harvest; windthrow should be considered when planning management activities (Hart, 1959). Harvests may not be permitted in some locations restricted by endangered species such as the Cheat Mountain Salamander (CMS). Harvests should be minimized in suitable CMS habitat. Stands with suppressed red spruce stems can benefit from forest stand improvements such as thinnings that remove competition from hardwood species and promote the growth of red spruce (Rentch et al., 2010; Thomas-Van Gundy & Sturtevant, 2014). Carbon sequestration and the ability of red spruce stands to store large amounts of carbon

should be taken into consideration when planning restoration activities. Disturbance events including harvesting will lead to the carbon loss from loss of stems and from loss of soil organic matter which is critical for maintaining soil moisture and establishing red spruce regeneration (Van Miergroet, et al., 2007). Planning for loss of organic matter should be considered when determining rotation lengths (Diochon et al., 2009).

Restoration plantings can be used to expand red spruce habitat. Locating suitable locations to install red spruce plantings is critical and adequate planning efforts must go into this planning step (Walter et al., 2017). Existing hardwood and mixed spruce-hardwood stands where red spruce once historically occupied, could benefit from plantings. Hardwood stands with spodic soils located within the central Appalachians can be used to identify lands that were once dominated by red spruce (Nauman et al., 2015). These soil characteristics may help isolate stands suitable for enrichment plantings after partial harvests. Restoration activities will likely be more successful at higher elevations (Thomas-Van Gundy & Sturtevant, 2014). Higher elevation areas will provide more favorable climatic conditions and also allow red spruce to be more competitive (Kosiba et al., 2017). Planting spruce seedlings in recently partially harvested hardwood stands can be an effective method of introducing red spruce back into forests where it has been absent for decades (Dumais et al., 2018). It is important to plant seedlings in light gaps where they can benefit from full sunlight before over story canopy closure. Once canopy closure occurs, release activities may be necessary in the future to promote growth of the established planted seedlings.

1.8 Thesis Structure

In addition to chapter 1 (literature review chapter), my thesis will also contain two research chapters (Chapter 2 and Chapter 3) and a general conclusions chapter (Chapter 4). Chapter 2 of my thesis is a research chapter that reports on my research efforts and results related to the dendroclimatic

research portion of my thesis. Chapter 2 will highlight historical dendroclimatic relationships for central Appalachian red spruce. Chapter 2 will also provide predicted future changes in growth with predicted climate conditions to determine potential growth impacts that a changing climate could have on central Appalachian red spruce. Chapter 3 will report on research and results related to the site index modeling portion of my thesis. Anamorphic models that use age or diameter with height will be developed and compared to predict height and estimate site index values of central Appalachian red spruce in Chapter 3. Linear models developed to predict red spruce site index values using associated species site index values along with climatic and geographic variables will also be created and compared in Chapter 3 of my thesis. Chapter 4 of my thesis will be a general conclusion chapter, where major results from Chapters 2 and 3 will be highlighted and discussed to showcase their importance and potential implementation.

1.9 Conclusion

An increase in red spruce habitat will create more endangered wildlife species habitat, sequester larger amounts of atmospheric carbon, promote the growth of an important timber species, and increase aesthetic values for the landscape. Determining how climate and other factors have affected the growth of red spruce can potentially help land managers make critical management decisions when selecting future restoration locations and methods. Development of a site index curve for central Appalachian red spruce could be beneficial and eliminate the need to rely on site index curves that were created with data collected using northern or southern red spruce populations. Linear models that estimate site index values of central Appalachian red spruce using associated spruces could be useful to explain productivity of lands where red spruce is currently absent from the overstory.

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Chapter 2: Dendroclimatic Analysis of Central Appalachian Red Spruce

2.1 Introduction

Red spruce (*Picea rubens*) is a unique and important tree in eastern North America. The species was once very common in the central Appalachian Mountains but is now found in much smaller numbers than in the past (Rentch et al. 2016). Forest disturbance resulting primarily from anthropogenic causes such as fire and logging have been large contributors to the decline of red spruce. The restoration of red spruce in the central Appalachians is necessary and justifiable as red spruce forests provide many ecosystem services. The endangered cheat mountain salamander (*Plethodon nettingi*) is endemic to red spruce associated forests in the state of West Virginia and within the central Appalachians (Pauley, 2008). Increases in spruce cover may benefit cheat mountain salamander populations and may promote the expansion of the threatened Virginia northern flying squirrel (*Glaucomys sabrinus*) which relies on red spruce associated forests for food sources (Trapp et al., 2017).

An important factor that should be considered when planning red spruce restoration is climate. Understanding how climate impacts growth would be helpful for future planning and resource allocation. In addition, determining how climate change may affect spruce growth in the future could help guide restoration efforts to areas within the central Appalachians with the highest probability of spruce survival (Rentch et al., 2007; Walter et al. 2017).

Dendrochronology is the science of dating tree rings by examining historical growth characteristics of trees (Speer 1971). Dendroclimatology is a more specific subdiscipline of dendrochronology where scientists use tree rings and past climate data to determine what climate factors have impacted tree growth (Fritz 1976). Results from dendroclimatic studies can be used to plan restoration activities and identify the suitability of future species in terms of climate change resilience (Chhin 2015). A dendroclimatic study that analyzes red spruce growth across the central Appalachians

may highlight areas where red spruce growth will yield favorable growth rates with future climate change. Dendroclimatic studies on red spruce have been conducted but these studies are generally limited to red spruce in the northern and southern portion of the range of red spruce. Studies in the central Appalachians were mainly focused on other growth factors such as acid deposition, disturbance, and air pollution, but not specifically climate (Rentch et al., 2007; Mathias and Thomas 2018).

Dendroclimatic studies conducted in the northeastern United States that analyze red spruce, generally have similar results. Air pollution and associated acid rain historically contributed to growth declines in red spruce, but recent trends in air pollution reduction have resulted in growth increases (Kosiba et al. 2018). Red spruce growth at the northern portion of their range have shown growth increases with warmer temperatures and increased CO₂, but extremely warm temperatures may result in growth declines (Dumais and Prévost 2007; Kosiba et al. 2017). Future excessive summer temperatures from climate change may result in declines of spruce growth which are more noticeable at lower elevations (Gavin et al. 2008). Red spruce at high elevations have benefited overall from warming mean temperatures which may make the species better suited than its competitors at high elevations in the future (Kosiba et al. 2017). Maintaining diversity in spruce associated forests could mitigate future expected climatic induced declines in growth (Teets et al. 2018).

Red spruce near its southernmost range in the southern Appalachians has different growth responses to climate variables than spruce at the northern portion of its range (Berry and Smith, 2014; Koo et al., 2014; White et al., 2014; Walker et al, 2017). This difference in growth response may hint that the species could respond differently to climate in the isolated central Appalachian portion of its range. Increasing summer temperatures are having negative impacts on growth within red spruces range in the southern Appalachians; future increases in temperature will likely reduce suitable habitat to higher elevations (Koo et al. 2014). Moisture stress is an additional factor that could contribute to spruce decline in the future (Berry and Smith 2014). Southern Appalachian red spruce relies on cloud

cover for supplementary moisture from condensation that is necessary for growth (Johnson and Smith 2006). Cloud cover is important for sustaining spruce growth during the summer growing season as clouds mitigate negative growth effects associated with extreme summer temperature by limiting direct solar radiation and moisture loss (Berry and Smith 2014). Climate change predictions have estimated a reduction in cloudy days during the growing season in the southern Appalachians, this reduction in cloud cover will also result in a reduction in moisture and habitat suitability in the south, particularly at lower elevations (Berry and Smith 2012). Although moisture deficits can be growth limiting to southern red spruce populations, excess moisture leading to anaerobic soil conditions, in the spring can have negative effects on growth; this could become even more of a factor considering future climate predictions (White et al. 2014). Overall, predictions of red spruce's growth response to increasing temperatures and moisture limitations forecast the reduction in suitable southern Appalachian red spruce habitat in the future (Walter et al. 2017).

There are limited studies of central Appalachian red spruce that utilize dendroclimatic analysis. Previous studies have established that the historical reach of red spruce extended to lower elevations than does its current range (Thomas-Van Gundy et al., 2012). These lower elevation areas could be suitable for red spruce restoration activities, but restoration on currently marginal lands in terms of suitability could yield unfavorable results with future climate change (Rentch et al. 2007; Walter et al. 2017). Models have been created to help locate suitable lands for future red spruce restoration activities; these models predict that restoration activities at higher elevations generally will result in better success (Thomas-Van Gundy and Sturtevant 2014). A recent study published in 2018 found that central Appalachian red spruce has shown positive growth responses in the past 30 years due to decreases in air pollution and acid precipitation events (Mathias and Thomas 2018). Mathias and Thomas (2018) also found that increases in July summer temperatures and increased CO₂ levels have had a fertilizer effect on red spruce growth. Future research that identifies climate variables that have

significant impacts on red spruce growth in the central Appalachians may contribute to our understanding of the species and help promote its habitat expansion.

Two primary objectives were established for this portion of my thesis which involves dendroclimatic analysis of central Appalachian red spruce. The first objective is to conduct growth-climate analysis and determine climate growth relationships for central Appalachian red spruce using historic climate data. The creation of models that explain red spruce growth using significant climate variables as growth predictors will be included in the first objective. The second objective is to project red spruce growth with future climate change predictions. Projected growth will be compared to historic growth and used to estimate how central Appalachian red spruce growth may be affected by climate change.

2.2 Methods

2.2.1 Field Sampling Design

Most of the red spruce remaining in the central Appalachian Mountains occurs in West Virginia and furthermore on lands within the Monongahela National Forest (MNF). To take advantage of the large latitudinal range of red spruce forests in the MNF, this study included red spruce trees located throughout the extent of the national forest. Eighteen plots were randomly selected using Arc GIS and the random sample tool located within the data management Arc toolbox (Theobald et al. 2007). The study area that was eligible for plot selection was determined by a forest type cover map obtained from the state of West Virginia's GIS clearinghouse website (Byers et al. 2013). The map is titled *Red Spruce Cover in West Virginia 2013* and was created using a compilation of state and federal stand inventory

data. All forested land with a minimum of 10 percent estimated red spruce cover according to the red spruce forest cover layer, was included for random plot placement (Figure 2.1).

Six regional groups were established for the 18 individual climate plots (three climate plots per regional group). Regional groups organized individual plots based on their latitude and aspect. The regional groups are as follows: North Latitude and North Aspect (NLNA), North Latitude and South Aspect (NLSA), Central Latitude and North Aspect (CLNA), Central Latitude and South Aspect (CLSA), South Latitude and North Aspect (SLNA), and South Latitude and South Aspect (SLSA). Regional grouping of plots by latitude ensures that plots within close spatial proximity are grouped together. Separating regional groups further by aspect ensures that variance in climate response is preserved as trees on north and south facing slopes may react differently to climate variables. Table 2.2 shows a breakdown of the individual plots within each region along with corresponding mean values.

Once random plots were determined using ArcGIS, Garmin Oregon 650 GPS units were used to navigate to the 18 climate plots for this study. Plot center was established using a GPS unit and marked with a temporary stake. Ten codominant and dominant red spruce trees were sampled within the 0.0337 hectare circular plot. A random bearing was established for each plot. Sampling started with using the random bearing and then proceeding clockwise until the first 10 red spruce trees in the dominant or codominant size class were reached and sampled. If the entire plot did not have 10 red spruce trees in the codominant or dominant size class, an additional 10 meters was added to the plot radius and sampling continued starting with the previous random bearing and proceeding clockwise. If necessary, additional 10-meter segments were added to the plot radius until a total of 10 trees were sampled. Because red spruce trees were scarce at a few plots, a sample size of 10 was selected to minimize spatial variability of growth within the sampled trees.

Sampling of red spruce trees at each of the 18 plots involved extracting two increment cores taken at breast height (1.3 meters from the ground). Increment cores were taken 180 degrees from each other and perpendicular to the slope of the ground at the plot. Increment cores were extracted only from red spruce trees that were in the codominant and dominant crown classes. Sampling trees in this crown class would help ensure that tree growth responses to climate would be more noticeable as suppressed size classes may show less of a response to climate due to competition and suppression effects. Trees with noticeable defects or disease were not sampled. Additional data including diameter at breast height (DBH), total height, crown height, and bark depth, were collected for each sampled tree. Tree height and crown height was obtained using a Haglof ultrasonic hypsometer. Bark depth was determined using a bark depth gauge and recorded to the nearest millimeter.

Since plot sizes were not uniform due to the variability of spruce density across the central Appalachians, stand densities were quantified for each sampled tree rather than just at plot center. Basal area was determined around each cored tree. Basal area estimations were conducted using a 2.296 metric BAF wedge prism. Ideal basal area calculation would be conducted using the pith of the sampled tree as plot center. Since the center of the sampled tree could not be used as a plot center for basal area measurements, a basal area plot was taken three feet from the sampled tree's pith. To maintain randomness, a random bearing was established for the basal area measurement around each tree. Basal area for red spruce species was noted as well as basal area of competing species and total basal area.

2.2.2 Sample Processing and Dendrochronological Analysis

Extracted increment cores were stored in large paper straws and labeled according to the plot number and tree sample number. Cores were then air dried in the field and finally oven dried in the lab. Properly dried increment cores were mounted to wooden core mounts, pressed, and dried. Mounted

cores were allowed to dry while pressed to maintain straight and undamaged cores. Mounted cores were then sanded using an electric palm sander. All cores were sanded to a minimum grit level of 400. Sample cores that showed growth suppression were sanded to a grit level of 800.

Sanded increment cores were then visually cross dated by using the list method of Yamaguchi (1990). A dissecting microscope was used to provide magnification when cross dating cores. Tree cores were marked by highlighting, false, missing, and narrow rings (Yamaguchi, 1990). Tree cores were cross dated at the plot level using the list method, taking into account marker rings. Marker years can be observed as years where the ring width is notably narrow or wide relative to the surrounding tree rings. Once cores were visually cross dated, they were then scanned with an EPSON V600 scanner at a resolution of 2400 dots per inch (D.P.I).

Scanned cores were then processed in tree ring analysis program Coorecorder (version 9.0). Coorecorder was used to measure all tree ring widths for each increment core. Missing rings were noted in Coorecorder and tree rings were assigned an accurate age. Individual chronologies were grouped together in the computer program CDendro (version 9.0) to form plot level chronologies. Tree cores were then statistically cross dated using the computer program COFECHA (version 6.06). COFECHA compares individual tree chronologies to the plot master chronologies and identifies potential errors (i.e., missing rings or false rings) associated with the initial visual crossdating process. Individual chronologies with low correlations to the master chronology could have crossdating errors such as missing rings or improper age of the outermost ring (Grissino-Mayer 2001). Logical suggestions in COFECHA were considered and used to identify missing rings in a few instances. Once chronologies were statistically cross dated, plot master chronologies were then standardized in computer program ARSTAN version 6.05P (Holmes et al. 1986). ARSTAN is used to standardize chronologies to isolate climate related growth responses while removing and or minimizing growth responses related to competition and other non-climatic factors (Chhin 2015). Residual chronologies were used for plot level

chronologies in ARSTAN. Residual chronologies consist of plot level growth chronologies that have autocorrelation removed which removes growth trends caused by non-climatic factors such as between tree competition. Cubic smoothing splines are generally used for shade tolerant species in closed canopy stands and trees that have experienced periods of suppression (Cook and Peters 1981). Cubic smoothing splines of 50 years were used for chronologies with average lengths of approximately 100 years. For several plots which consisted of younger cohorts of sampled trees, a cubic smoothing spline of a shorter length of 40 or 30 years was used. Expressed Population Signal (EPS) is one of the many statistics ARSTAN provides in its output; EPS provides a measure of how well the chronology explains variance within the population of trees (Magruder et al. 2013). EPS of 0.80 is a benchmark that should be reached for dendroclimatic analysis on red spruce species (Kosiba et al. 2017). A total of 17 of the 18 climate plots reached minimum EPS values of 0.80. Plot 103 did not reach an EPS value of 0.80. ARSTAN recommended that an additional 3 trees would need to be sampled to reach an EPS level of 0.80. Red spruce densities were low at plot 103 and there are longer distances between sampled trees when comparing this plot to others. This increase in distance between sampled trees could be a reason why these trees are showing less climatic growth responses on a plot level. An additional 10 trees were cored at plot 103 in hopes of reaching acceptable EPS values in ARSTAN. The additional trees resulted in an EPS of over 0.85 for the final plot 103 chronology. Residual tree-ring chronologies generated by ARSTAN were used to represent the individual plots because the residual chronology had the strongest mean sensitivity and EPS values. Residual tree-ring chronologies have autocorrelation removed. Since all 18 inventory plots now had a standardized chronology with an EPS of at least 0.80, dendroclimatic analysis could be conducted. Regional chronologies were developed for all six regional groups (Fig. 2.2). Regional chronologies consisted of averaging each of the individual plots' residual chronologies. Averaged regional chronologies only included averages for time periods where individual chronologies maintained EPS signals above 0.80.

2.2.3 Dendroclimatic Analysis

Growth – climate analysis (dendroclimatic analysis) consists of analyzing the relationship of tree ring widths to climate variables (Fritz 1976). Historic climate data for this project was obtained from Oregon State University's PRISM website (prism.oregonstate.edu). Climate data was obtained for each of the 18 climate plots by using each plot's geographical coordinates (i.e. latitude and longitude) in PRISM's data collection system. Historical climate data obtained from PRISM is spatially interpolated from the actual weather stations that have been collecting climate data such as daily temperature and precipitation since 1895 (Oregon State University, 2013). Monthly climatic data included total precipitation, mean temperature, minimum temperature, and maximum temperature. Climate moisture index (CMI) is a function of precipitation and temperature which takes into account water losses through evapotranspiration (Hogg 1997). CMI was calculated with monthly data obtained from PRISM. Six regional groups (NLNA, NLSA, CLNA, CLSA, SLNA, and SLSA) were established for the 18 individual climate plots (3 plots per regional group). The six regional groups were separated based on their latitude and aspect following the same sampling design as the original inventory plots. Regional climate values were derived from averaging climate values from the 3 individual plots within each regional group.

Growth climate analysis was conducted using Dr. Chhin's Rscript in the computer program R Studio (Chhin et al., 2008). Growth-climate analysis consisted of comparing red spruce growth to monthly and seasonal (3 consecutive months) climate variables and creating multiple linear regression models using stepwise analysis (with forward selection) and only including significant predictors with low AIC values. Multiple linear regression models use seasonal and monthly climate variables that are statistically significant predictors of spruce growth. Stepwise regression models considered both monthly and seasonal climate values in analysis. If significant monthly and seasonal climate values

overlapped, the larger predictor of the two values was retained in the model and the predictor with the lower prediction power was dropped from the regression models. Seasonal variables were considered for regression models as sometimes seasonal variables can show relationships that monthly variables may not. Regression equations to predict spruce growth were developed for each regional group. Historic growth-climate analysis also considered climate conditions for the previous growing season as climate conditions during the previous growing season can have impacts on current growth. This lag effect of tree growth was important to consider when determining climate conditions critical to red spruce growth. Growth-climate analysis was conducted to find significant relationships between residual chronologies for each regional group and the corresponding regional climate variables including minimum temperatures, maximum temperatures, mean temperatures, precipitation, and climate moisture index.

Growth-climate analysis was conducted using a common chronology length of 76 years (year 1941-2017). This time frame was determined when a second member of a regional group lost acceptable EPS signals and an average residual chronology could no longer be constructed.

2.2.4 Future Growth Projections

Future climate data for the 18 climate plots were obtained using computer program ClimateNA (Wang et al. 2006). ClimateNA provides spatially interpolated future climate data that is custom tailored to different emissions scenarios. The climate scenario referred to as Representative Concentration Pathways (RCP) 4.5 was used to make future climate predictions. The climate scenario RCP 4.5 is thought of as a middle of the road scenario in terms of future projected greenhouse trajectories (Wang et al. 2016). Individual climate estimations were averaged for each regional group and would be used with regional chronologies to predict future growth. Table 2.5 shows average future predicted climate values for each of the regional groups in the central Appalachians. Future climate projections indicate

an overall warming of mean, minimum, and maximum temperatures with an increase in precipitation and decrease in climate moisture index.

The historic growth-climate regression equations were then used to project spruce growth on a regional level. Monthly and seasonal projected climate values were included in the regression models to make estimations of future tree growth with the selected climate variables. Climate variables used to project future growth included: mean temperature, minimum temperature, maximum temperature, precipitation, and climate moisture index.

Growth projections were conducted on a yearly basis and then averaged over four, 20-year, periods: 2021-2040, 2041-2060, 2061-2080, and 2081-2100. Projected growth for each time period was then compared to average growth during a 20-year reference period of 1981-2000. The reference period of 2081-2000 was selected because it was a common timeframe shared by all cores and the time period also occurred before many climate change concerns were highlighted. Projected future percent change in growth was determined for each of the time periods for each regional group and also for all regional groups combined. Projected change in growth for all groups combined may be used to estimate future growth change for central Appalachian red spruce. Growth projections for regional groups could be used to determine areas that may produce favorable red spruce growth in a changing climate. Future projections were compared to 95% confidence intervals of the growth rate during the reference period for each regional group. All changes in growth for the future time periods which surpass positive and negative growth changes within the 95% confidence interval are considered a significant change in growth.

2.3 Results

2.3.1 Historical Growth-Climate Results

All 6 regional plots show negative growth relationships related to mean summer temperatures in the previous growing season(t-1) (Fig.2.3, Table 2.3). All 6 regional groups share August (t-1) (as the sole monthly or part of the seasonal climate variable) as negatively related to growth. Regional groups NLNA, CLSA, and SLNA, all share the late summer seasonal window (t-1) (June, August, and September) as negatively associated with growth. Groups SLNA and CLNA share the summer seasonal window (t-1) (June, July, and August) which are also negatively associated with growth. Mean temperatures during the fall and early winter seasonal period (t-1) (October, November, and December) are positively associated with growth across all 6 regional groups. A regression model ($R^2 = 0.225$) that uses mean temperature values was developed for all 6 regional groups which had 2 statistically significant growth predictors. The most important predictor of growth was mean late fall seasonal temperatures (t-1) (October, November, and December) which had a positive growth association. The second most important predictor in the model for all regions combined was seasonal summer mean temperatures (t-1) (July, August, and September) which had negative growth associations.

Comparing regional growth to maximum temperatures yielded regression models with largest adjusted R^2 values compared to all of the climate variables (Fig. 2.3, Table 2.3). Maximum seasonal summer temperatures (encompassing different seasonal combinations of June, July, August, and September) for the previous growing season (t-1) were important predictors for growth declines in the following growing season. All 6 regional groups shared at least July and August maximum temperatures as part of their three-month seasonal predictor. NLNA and CLNA both shared June as the third month associated with spruce growth declines in the following year. While regional groups NLNA, CLSA, SLNA, and SLNA, all shared September (t-1) as the third month for their significant 3-month seasonal window.

Regional groups NLNA, NLSA, CLSA, and SLSA, all shared the 3-month seasonal window of fall to early winter (October, November, and December) of the previous year (t-1) as a positive associated growth predictor. Group CLNA included maximum February temperature (t-1) as a positive related growth predictor. The regression model to predict spruce growth using maximum temperatures ($R^2 = 0.338$) for all regional groups combined had seasonal summer (July, August, and September) (t-1) maximum temperatures as the most important predictor in the model. Fall and early winter seasonal (October, November, and December) (t-1) maximum temperatures were second most important predictors in the regression model. The third most important and last predictor in the regression model includes spring seasonal (April, May, and June) (t-1) maximum temperatures.

Growth is positively associated with minimum monthly seasonal fall and early winter temperatures (October, November, and December) (t-1) (Fig. 2.3, Table 2.3). Regional groups NLNA, NLSA, SLNA, and SLSA, all shared this period as a significant predictor in their regional regression models. Site CLSA had just minimum temperatures for the month of December (t-1) as a significant predictor for spruce growth. The regression model developed to predict growth using minimum temperatures ($R^2 = 0.110$) for all 6 regional groups combined had one significant, positively related, predictor which is minimum temperatures for the fall and early winter seasonal period (t-1) (October, November, and December).

Precipitation had fewer significant predictors associated with radial growth compared to the other moisture variable (Climate Moisture Index) (Fig. 2.4, Table 2.4). Groups CLNA and CLSA both experienced a seasonal negative growth relationship with precipitation during the months of July, August, and September (t). Plots SLNA and SLSA experience a monthly negative relationship with precipitation during the month of August (t). Regional groups located within the northern latitude portion of the MNF experience significant growth increases with high precipitation during June, July, and August (t-1). The regression model to explain spruce growth across all regional groups combined using

precipitation ($R^2 = 0.143$) has two predictors: 1) seasonal summer period (t-1) (June, July, August) is positively associated with growth and the most important predictor, and 2) the second most important predictor is seasonal fall precipitation (t) (August, September, October) which is negatively associated with spruce growth.

Climate moisture index values for the summer (t-1) showed positive relationships with red spruce growth for 4 of the 6 sites (NLNA, NLSA, CLSA, and SLSA) (Fig. 2.4, Table 2.4). NLNA, NLSA, and SLSA, share the summer seasonal (t-1) months of June, July, and August, while CLSA shares the months of July and August with the previously listed groups. High climate moisture index values in the late summer to early fall (t) is negatively associated with growth on 3 of the 6 sites (CLNA, CLSA, SLNA). CLSA and SLNA include the seasonal early fall months (t) (August, September, and October) as significant growth predictors. Regional group CLNA includes the seasonal late summer months (t) (July, August, and September) as significant predictors in its regression model. The regression model created to predict spruce growth across all regional groups combined with CMI values ($R^2 = 0.178$) has the seasonal summer period (t-1) (May, June, July) as the most important predictor. The second most important, negatively associated, growth predictor was the seasonal fall and early winter period (t) (October, November, December).

2.3.2 Future Climate Projection Results

Future predicted growth when considering expected mean monthly temperatures show significant changes in growth for all regional groups except regional group CLNA (Fig. 2.5). NLNA shows trends of a negative change in future growth with a significant decline in growth change for the time period 2061-2080. Regional group NLSA shows positive trends in growth change with significant changes in growth during time periods 2061-2080 and 2080-2100. Largest growth declines are predicted for regional group CLSA, where significant negative changes in growth are expected for all 4

future time periods (from 2020-2100). Regional group SLNA is projected to have negative changes in growth with significant declines occurring in time periods 2041-2060, 2061-2080, and 2081-2100. SLNA future growth also follows negative trends and significant growth declines are predicted for all 4 time periods. The overall change in growth for all regional groups shows significant growth declines for time periods 2041-2060, 2061-2080, and 2081-2100. Trends in projected growth show the largest declines in growth during the time period 2061-2080, with less negative growth during the last growing period (2081-2100).

Predicting growth using projected maximum monthly temperatures show similar trends as mean temperature but with overall larger declines (Fig. 2.5). Group NLNA experienced a negative change in growth for all future time periods with significant growth declines in time periods 2041-2060, 2061-2080, and 2081-2100. NLSA showed negative trends in change in growth but significant declines in growth is only projected for time period 2081-2100. Regional group CLNA shows significant negative changes in projected growth for all 4 time periods (2021-2040, 2041-2060, 2061-2080, and 2081-2100). The largest declines in growth are expected to occur at plots in the CLSA group. The CLSA group had significant growth declines for all 4 time periods with a maximum change in growth during period 2061-2080 where growth is expected to decline by over -14%. Groups NLSA and CLNA overall have smaller predicted growth declines when compared to the other regional groups. Predicted growth using maximum monthly temperature for all regional groups combined will result in an overall growth decline with significant growth declines in the latter 3 time periods (2041-2060, 2061-2080, and 2081-2100).

A positive growth trend is observed when projecting future growth with minimum monthly temperatures as the climate predictor (Fig. 2.5). Southernmost groups (SLNA and SLSA) show the largest positive change in predicted growth with growth changes being significant for all 4 time periods. Groups NLSA and CLSA follow the positive future growth trend but only have significant changes in growth during the last time period (2081-2100). CLNA also has a positive change in future growth when

projected using minimum temperature, significant growth changes are predicted for the last three time periods (2041-2060, 2061-2080, and 2081-2100). Regional group NLNA shows no significant changes in projected growth using minimum temperatures as a predictor. Future projected growth for all regional groups combined using future predicted minimum monthly temperatures shows significant overall growth increases in all 4 time periods (2021-2040, 2041-2060, 2061-2080, and 2081-2100).

Projecting spruce growth using future precipitation as a predictor yield overall negative changes in growth (Fig. 2.6). Groups CLSA and SLNA both have significant negative changes in projected growth for all 4 time periods (2020-2040, 2041-2060, 2061-2080, and 2081-2100). SLNA also has an overall negative trend in change in growth, with significant growth declines predicted in time periods 2041-2060, 2061-2080, and 2081-2100. CLNA has no significant changes in growth for the future 80 years using precipitation as a predictor. NLNA is the only regional group that shows a positive change in projected growth, significant growth increases can be observed in time periods 2041-2060, 2061-2080, and 2081-2100. NLNA has negative trends in projected growth with one significant decline in change in growth during 2061-2080. The overall trend in change in projected growth using future predicted precipitation for all regional groups combined will result in negative growth changes, with significant growth declines in the last 3 time periods (2041-2060, 2061-2080, and 2081-2100).

Projected growth using future climate moisture index appears to yield overall positive trends in change in future growth (Fig. 2.6). Predicted growth changes are positive but it is important to note that all predicted changes in growth for all time periods and regional groups lie within the 95% confidence interval of the base growth rate. This means the null hypothesis (there is no change in future growth predicted by climate moisture index) is accepted.

2.4 Discussion

2.4.1 Historical Growth-Climate Analysis

Historical monthly maximum temperatures are the most important predictors of spruce growth, as these models had the highest R^2 values overall for historic growth-climate analysis. The overall regional historical dendroclimatic model that predicts red spruce growth using maximum monthly temperatures has an R^2 value of 0.338. Summer maximum temperatures (t-1) (July, August, and September) were negatively associated with spruce growth during the following year (t). This is likely the result of increased respiration which deplete carbohydrate reserves necessary for next year's growth (Pallardy, 2007; McGuire et al., 2010). Fall (t-1) (October, November, and December) and spring (t) (April, May, and June) seasonal predictors are positively associated with red spruce growth the following year (t). Increases in maximum temperatures during these seasonal periods further increase the number of suitable days within the growing season to photosynthesize (Kosiba et al. 2018). Increases in growing season length allows trees to store more carbohydrates and establish better buds for next year's growth (Kolowski and Pallardy 1996).

The growth models created that use mean temperature to predict growth share similarities with the models that used maximum temperatures. The model created to predict overall red spruce growth with mean temperature (adjusted $R^2 = 0.225$) uses two significant seasonal periods. The first and most important seasonal period is the fall and early winter season (t-1) (October, November, and December) there is a positive relationship between mean fall temperatures (t-1) and growth. This is likely a result of an extended growing season which allows red spruce to increase carbohydrate production and storage, while also establishing better buds for next year's primary growth (Kolowski and Pallardy 1996). Increasing mean temperatures, especially in the late fall and winter growing season, result in milder winters. Milder winters will result in less xylem cavitation from warmer non-growing season

temperatures which allows better productivity in terms of water use efficiency in the future (Holst et al. 2008). Summer (t-1) (July, August, and September) is the other significant predictor used in the model, in which there is a negative relationship with high mean summer (t-1) temperatures and growth. High mean summer temperatures can induce moisture deficiencies from evapotranspiration and deplete carbohydrate reserves from higher respiration rates causing temperature induced moisture stress (Mcguire et al., 2010; Berry and Smith, 2014; Schwab et al., 2018). These moisture deficiencies can result in negative growth the following year (Dumais and Prévost 2007).

Minimum temperatures appear to have less of an effect on historic growth when compared to mean and maximum temperatures. The model created to predict growth using minimum monthly temperatures ($R^2 = 0.122$) only had one significant predictor which was the fall seasonal period (t-1) (October, November, and December). There was a positive relationship with fall temperatures meaning that increases in minimum fall temperatures (t-1) result in increased growth the following year. This could be the result of an extended growing season for red spruce into the fall as long as other growth variables produce favorable growing conditions (Gunderson et al., 2012; Koshiba et al. 2018). Mathias and Thomas (2018) found that warming temperatures at the beginning or end of the growing season extremes result in increased growth in central Appalachian red spruce which agrees with my positive fall temperature results. Butnor et al. (2019) found that warmer spring temperatures allowed red spruce bud break to occur earlier in the growing season and resulted in a positive growth response. While these results are similar to mine, my results indicate that red spruce is more responsive to fall temperature changes. My historic growth-climate analysis results suggested that central Appalachian red spruce benefited from extended growing seasons, but the growth benefits may be outweighed by growth declines associated with extreme summer temperatures or severe fall precipitation events. Northern aspect plots in the northern and southern latitude regions experienced negative growth relationships with increasing summer minimum temperatures (t-1). This makes sense because red

spruce at northern aspects are generally more acclimated to cooler and moist conditions. Increasing minimum temperatures on these northern aspects likely are leading to moisture losses that could be associated with growth decreases while southern (Fekedulegn et al., 2003).

The negative association between fall moisture and growth during the present growing season (t) could be the result of crown damage from heavy fall snowfall or high wind events associated with precipitation events, although this could be argued for any precipitation event (Peterson, 2000; Griscom et al. 2014). White et al. (2014) found that spring precipitation events could have negative impacts on spruce growth. This study showed agreement with both of my precipitation trends, but my study shows that red spruce was more sensitive to fall precipitation rather than spring. Another explanation may be that excessive moisture, especially within the soil, could potentially lead to unfavorable anoxic conditions as 5 of the 18 plots have soils with poorly drained soils (White et al. 2014). North latitude, south aspect red spruce did not respond negatively to increased moisture events; it is possible that plots in this regional group are not affected by excess precipitation because their soils are well drained or because the south facing aspect facilitates evaporation (Parker, 1982).

Negative relationships with spruce growth and summer (t-1) mean and maximum temperatures show spruces' susceptibility to drought stress and high respiration (McGuire et al. 2010). Studies have shown that southern red spruce populations have negative dendroclimatic relationships between high summer temperatures and radial growth (Koo et al., 2014; Ribbons et al., 2014). These findings agree with my results that monthly maximum temperatures in the summer result in spruce growth declines.

Koshiba et al. (2018) found that increasing mean summer temperatures resulted in a positive growth response. This result was opposite of my findings that central Appalachian red spruce will have overall negative growth responses to increasing mean summer temperatures. The study of Koshiba et al. (2018) was conducted on red spruce trees in the northern portion of its range. However, Mathias

and Thomas (2018) found that increasing summer temperatures had positive effects on central Appalachian red spruce growth, but only when combined with additional CO₂ enrichment. These results disagree with my findings, but I did not consider CO₂ levels and fertilization effects in my study which may have caused the difference in results.

Summer temperatures are not as severe in the northern portion of red spruce's range and the species is likely not yet at its temperature maximum as compared to red spruce at its southern most range (White et al. 2014). Red spruce at the northern latitudes of my study (NLNA and NLSA) show growth increases with increased mean and maximum spring temperatures which could be due to microsite effects due to the small difference in latitude and elevation between plots. Another explanation for these results is that northern red spruce are not as sensitive to increasing temperatures as red spruce towards the southern limits (White et al., 2014).

2.4.2 Growth Projection

Future growth projections provide some insight on how spruce will perform with future climate predictions. Growth projections using future mean and maximum temperatures suggest that future climate conditions will not favor red spruce growth. These results support predictions that red spruce habitat will decrease with future climate change (Rentch et al. 2007; Walter et al. 2017). Growth declines related to mean and maximum temperature in the future could be caused from increased respiration in summer months (Ribbons 2014). Koo et al. (2014) found that increasing temperatures will also lead to growth declines in southern Appalachian spruce, and these predictions align with my growth projections. However, my results using future minimum temperatures show opposite changes. Growth increases are predicted due to increasing minimum temperatures. These future increases will be the result of an extended growing season which will allow spruce to put on more radial growth, provided

that maximum temperatures do not have a larger effect on growth (Gunderson et al. 2012; Kosiba et al. 2018; Mathias and Thomas 2018).

Modeled precipitation levels are expected to reduce growth in the future. Growth declines from precipitation could be the result of reduced moisture during the growing season (Berry and Smith 2012). Declines could also be a result of storm damaged from a predicted increase in severe weather events (Peterson 2000). My future growth projections using climate moisture index indicate that there will be no change in future growth. This result was not expected as red spruce growth is expected to decline with mean temperature, maximum temperatures, and precipitation, in the future. A reasonable explanation for this result is that although future growth will be negatively impacted by increasing summer temperatures and precipitation events, an extended growing season from increased minimum temperatures may allow red spruce to compensate for the other high temperature and moisture stressors (Gunderson et al., 2012). Kosiba et al. (2018) found that spring and fall temperatures were most important at predicting growth, which help support this result. NLSA and CLNA regional groups show the least overall growth declines when considering future maximum and mean temperatures. These two regional groups showed either growth increases or no change with minimum temperature, precipitation, and climate moisture index. These results may indicate that locations either in central latitudes on north aspects or northern latitudes on south aspects will be the best for red spruce growth in the future. An important fact to note is that the large significant declines in growth associated with mean and maximum temperature or precipitation do not occur until the third time period of 2061-2080. If greenhouse emissions are mitigated and reduced, less severe growth declines could be observed.

2.5 Conclusion

Central Appalachian red spruce experience growth declines associated with increased mean and maximum summer temperatures. Increasing minimum temperatures have positive impacts on red spruce growth by expanding the nontraditional growing season. Fall precipitation events have negative growth impacts on red spruce. Growth declines from future precipitation events and increasing summer temperatures may be mitigated by the positive growth impacts resulting from an expanded growing season in the future. Future predicted growth declines are the lowest for red spruce in the northern latitude portion on south facing aspects of the central Appalachians. Restoration efforts in the future should consider future growth projections for central Appalachian red spruce when planning future restoration activities.

2.6 Tables and Figures

Table 2.1. Regional group data including the individual plots within each regional group and their associated mean values for all three plots combined

Regional Group	Label	Elevation (m)	Temp (Celsius)	Precip (mm)	CMI	Plots Within Group	Soil Drainage Class	Diameter (cm)		Height (m)		Plot Basal Area (m ² /ha)	
							Class	avg	SE	avg	SE	avg	SE
North Latitude, North Aspect	NLNA	1087	7.74	115.98	6.33	008, 016, 147	Poor, Excessive, Poor,	44.01	1.35	23.30	0.34	31.91	1.32
North Latitude, South Aspect	NLSA	1091	7.74	115.98	6.33	101, 115, 130	Well, Poor, Poor,	41.91	1.02	23.12	0.59	21.20	2.95
Central Latitude, North Aspect	CLNA	1272	7.14	125.98	8.06	030, 085, 128	Mod. Well, Poor, Well,	44.59	1.36	23.80	0.65	26.02	1.55
Central Latitude, South Aspect	CLSA	1115	6.93	122.24	7.34	013, 061, 103	Well, Mod. Well, Mod. Well,	47.58	2.09	23.09	0.50	25.56	2.03
South Latitude, North Aspect	SLNA	1206	7.82	113.18	8.05	023, 113, 121	Well, Mod. Well, Well,	40.96	5.10	24.20	0.26	29.47	4.18
South Latitude, South Aspect	SLSA	1204	8.24	131.59	7.50	040, 106, 142	Well, Mod. Well, Well,	43.80	1.81	24.10	0.15	32.53	1.10

Footnote: Avg is the average value of the three individual plots values. SE is the associated standard error values for the averaged data. Precip is the abbreviation for annual average precipitation in millimeters during a 1981 to 2000 reference period. CMI shows the average annual climate moisture index during the 1981 to 2000 reference period. Temp is the average annual temperature during the 1981 to 2000 reference period. Soil Drainage shows the expected soil drainage class from data obtained from USGS Soil Survey: websoilsurvey.nrcs.usda.gov. Mod. Well indicates soils in a moderately well drainage class. The soil drainage classes range from excessively well drained to very poorly drained.

Table 2.2. Plot chronology statistics for the 18 individual dendroclimatic plots. Plot level statistics are listed according to their corresponding regional group.

Group	Site	Interval	Total Trees (radii)	Mean Ring Width (mm)	Absent Rings (%)	Mean Sensitivity	Autocorrelation	Between Tree Correlation	EPS	EPS≥ 0.80 Year (trees)
North Latitude North Aspect (NLNA)	147	1936-2018	10 (20)	1.938	0.0000	0.1449	-0.0430	-0.0136	0.87	1936(6)
	16	1945-2018	10 (20)	2.440	0.0000	0.1467	-0.0650	-0.0174	0.84	1945(5)
	8	1947-2017	11 (19)	2.240	0.0000	0.2108	-0.0430	0.0103	0.90	1929(5)
North Latitude South Aspect (NLSA)	115	1935-2018	10 (20)	2.188	0.0000	0.1510	-0.0460	-0.0203	0.83	1949(7)
	130	1941-2018	10 (20)	2.105	0.0600	0.1243	0.1058	0.0342	0.84	1941(8)
	101	1944-2018	10 (20)	2.183	0.0000	0.1299	-0.0520	0.0396	0.83	1944(8)
Central Latitude North Aspect (CLNA)	30	1968-2017	10 (19)	1.930	0.0000	0.1371	-0.0360	-0.0389	0.80	1968(10)
	85	1923-2018	11 (22)	1.908	0.0000	0.2159	-0.1330	0.1308	0.82	1923(10)
	128	1926-2018	10 (20)	1.271	0.0722	0.1801	-0.0060	0.1338	0.86	1900(7)
Central Latitude South Aspect (CLSA)	103	1926-2018	20 (40)	1.725	0.1906	0.1247	-0.0020	-0.0206	0.86	1926(14)
	61	1930-2018	10 (19)	1.228	0.1130	0.1424	0.0527	0.0418	0.80	1930(10)
	13	1939-2018	10 (20)	2.672	0.0614	0.1426	-0.0600	0.0845	0.85	1939(7)
South Latitude North Aspect (SLNA)	106	1919-2018	10 (19)	1.719	0.0521	0.1690	0.0855	0.0513	0.87	1919 (7)
	40	1921-2018	11 (22)	1.743	0.0485	0.1582	0.0618	0.0781	0.80	1921(11)
	121	1936-2018	10 (20)	1.656	0.0540	0.1697	-0.0330	0.0790	0.84	1936(8)
South Latitude South Aspect (SLSA)	113	1914-2018	10 (20)	1.664	0.2043	0.1698	-0.0180	0.0313	0.86	1922(7)
	23	1953-2018	10 (19)	2.143	0.0000	0.1167	0.0255	0.0748	0.85	1953(8)
	142	1930-2017	10 (20)	1.498	0.1980	0.2015	-0.2680	-0.0688	0.83	1930(9)

Footnote: EPS is abbreviated and represents expressed population symbol. EPS≥0.80 Year is the earliest year when the individual chronology reaches an EPS of 0.80 or higher; corresponding tree count is listed in parenthesis next to the EPS≥0.80 year and indicates the number of trees required with the listed starting year to reach EPS levels above 0.80.

Table 2.3. Coefficients for regression models that use temperature climatic variables in predicting red spruce growth for regional groups. Coefficients of model predictors are listed in order of importance in the model.

Mean Temperature									
Regional Group	C	V1	B1	V2	B2	V3	B3	V4	B4
North Latitude, North Aspect (NLNA)	1.5892	-0.0621	-0.427	0.0257	0.299	0.0298	0.221		
North Latitude, South Aspect (NLSA)	0.9900	-0.0264	-0.283	0.0218	0.281	0.0150	0.225	0.0194	0.227
Central Location, North Aspect (CLNA)	1.5433	0.0221	0.349	-0.0375	-0.318	0.0171	0.269		
Central Latitude, South Aspect (CLSA)	1.9754	-0.0653	-0.500	0.0274	0.369				
South Latitude, North Aspect (SLNA)	1.8869	-0.0561	-0.341	0.0284	0.330				
South Latitude, South Aspect (SLSA)	1.9105	-0.0688	-0.422	0.0335	0.341	0.0179	0.213		
All Latitudes and Aspects	1.6272	0.0270	0.387	-0.0434	-0.366				
Maximum Temperature									
Regional Group	C	V1	B1	V2	B2	V3	B3	V4	B4
North Latitude, North Aspect (NLNA)	1.5570	-0.0615	-0.546	0.0227	0.301	0.0351	0.315		
North Latitude, South Aspect (NLSA)	1.5161	-0.0431	-0.398	0.0201	0.302	0.0131	0.258	0.0102	0.203
Central Latitude, North Aspect (CLNA)	1.5456	0.0112	0.352	-0.0272	-0.302	0.0080	0.266		
Central Latitude, South Aspect (CLSA)	1.8506	-0.0588	-0.578	0.0207	0.304	0.0129	0.188		
South Latitude, North Aspect (SLNA)	1.8628	-0.0473	-0.440	0.0234	0.315				
South Latitude, South Aspect (SLSA)	2.2192	-0.0638	0.508	0.0279	0.330				
All Latitudes and Aspects	1.6523	-0.0536	-0.583	0.0210	0.341	0.0207	0.228		
Minimum Temperature									
Regional Group	C	V1	B1	V2	B2	V3	B3	V4	B4
North Latitude, North Aspect (NLNA)	1.3611	0.0262	0.313	-0.0294	-0.234				
North Latitude, South Aspect (NLSA)	1.0358	0.0247	0.317						
Central Latitude, North Aspect (CLNA)	1.0920	0.0221	0.338						
Central Latitude, South Aspect (CLSA)	1.0624	0.0096	0.258						
South Latitude, North Aspect (SLNA)	1.1434	0.0262	0.323	-0.0362	-0.277	0.0301	0.299		
South Latitude, South Aspect (SLSA)	1.0431	0.0263	0.296						
All Latitude and Aspects	1.0362	0.0238	0.349						

Note: C is the model constant. V are model predictors for each climate variable. B is the beta coefficient for each model predictor. c.f. Fig. 2.3. For specific monthly and (or) seasonal variables.

Table 2.4. Coefficients for regression models that use moisture climatic variables in predicting red spruce growth for regional groups. Coefficients of model predictors are listed in order of importance in the model.

Precipitation					
Regional Group	C	V1	B1	V2	B2
North Latitude, North Aspect (NLNA)	0.9940	0.0004	0.304	-0.0004	-0.275
North Latitude, South Aspect (NLSA)	0.8171	0.0003	0.323	0.0005	0.243
Central Latitude, North Aspect (CLNA)	0.9841	-0.0003	-0.284	0.0003	0.270
Central Latitude, South Aspect (CLSA)	1.1311	-0.0004	-0.308		
South Latitude, North Aspect (SLNA)	1.0731	-0.0005	-0.243		
South Latitude, South Aspect (SLSA)	1.0884	-0.0007	-0.272		
All Latitudes and Aspects	0.9671	0.0003	0.321	-0.0003	-0.265

Climate Moisture Index					
Regional Group	C	V1	B1	V2	B2
North Latitude, North Aspect (NLNA)	1.0198	0.0036	0.334	-0.0034	-0.266
North Latitude, South Aspect (NLSA)	0.9720	0.0028	0.319		
Central Latitude, North Aspect (CLNA)	0.9168	-0.0023	-0.265	0.0032	0.259
Central Latitude, South Aspect (CLSA)	0.9878	0.0027	0.268	-0.0030	-0.249
South Latitude, North Aspect (SLNA)	1.0273	-0.0028	-0.231		
South Latitude, South Aspect (SLSA)	0.9618	0.0028	0.264		
All Latitudes and Aspects	0.9827	0.0032	0.358	-0.0029	-0.264

Note: C is the model constant. V are model predictors for each climate variable. B is the beta coefficient for each model predictor. c.f. Fig. 2.4 for specific monthly and (or) seasonal variables. Predictor V1 is the most important predictor for each model.

Table 2.5. Average annual climatic values for the reference period and future growth periods for each regional group and all groups combined. Future climate values are estimated from RCP 4.5 data.

Mean Temperature (Celsius)							
Time Period	NLNA	NLSA	CLNA	CLSA	SLNA	SLSA	All
1981-2000	7.74	8.00	6.60	6.93	7.83	8.24	7.55
2021-2040	9.47	9.34	8.51	8.82	9.38	9.81	9.22
2041-2060	10.10	10.10	9.16	10.08	10.04	10.47	10.48
2061-2080	10.73	10.64	9.22	9.48	10.64	11.07	9.88
2081-2100	11.69	10.66	9.79	10.12	10.67	11.10	10.51
Maximum Temperature (Celsius)							
Time Period	NLNA	NLSA	CLNA	CLSA	SLNA	SLSA	All
1981-2000	13.39	13.59	12.03	12.79	13.47	14.12	13.23
2021-2040	15.59	16.93	14.12	14.89	15.04	15.31	15.08
2041-2060	16.28	16.89	14.74	15.53	15.64	15.90	15.72
2061-2080	16.98	16.23	15.44	16.22	16.37	16.64	16.42
2081-2100	16.98	15.54	15.46	16.24	16.35	16.61	16.43
Minimum Temperature (Celsius)							
Time Period	NLNA	NLSA	CLNA	CLSA	SLNA	SLSA	All
1981-2000	2.10	2.41	1.17	1.07	2.17	2.36	1.88
2021-2040	3.35	3.22	3.00	2.85	3.82	4.42	3.44
2041-2060	3.93	3.80	3.56	3.43	4.44	5.04	4.03
2061-2080	4.52	4.38	4.06	3.93	4.90	5.51	4.55
2081-2100	4.52	4.39	4.13	3.99	4.99	5.60	4.60
Precipitation (mm)							
Time Period	NLNA	NLSA	CLNA	CLSA	SLNA	SLSA	All
1981-2000	115.98	123.22	125.98	122.24	133.18	131.59	125.37
2021-2040	124.95	125.77	126.55	122.19	125.16	125.53	125.02
2041-2060	127.82	128.69	126.85	123.38	124.43	124.67	125.97
2061-2080	129.53	130.58	129.33	125.22	126.73	126.91	128.05
2081-2100	137.79	138.94	138.58	134.10	135.24	135.09	136.62
Climate Moisture Index (cm)							
Time Period	NLNA	NLSA	CLNA	CLSA	SLNA	SLSA	All
1981-2000	6.33	6.93	8.06	7.34	8.05	7.50	7.37
2021-2040	6.01	6.17	7.11	6.24	6.52	6.49	6.44
2041-2060	5.92	6.03	6.76	6.00	6.07	6.03	6.14
2061-2080	5.76	5.88	6.66	5.80	5.93	5.87	5.99
2081-2100	6.54	6.67	7.57	6.70	6.79	6.71	6.83

Footnote: NLNA = North Latitude North Aspect, NLSA = North Latitude South Aspect, CLNA = Central Latitude North Aspect, CLSA = Central Latitude South Aspect, SLNA = South Latitude North Aspect, SLSA = South Latitude South Aspect.

Table 2.6. Coefficients and their corresponding p-values for regression models that use temperature climatic variables in predicting red spruce growth. Coefficients are listed in order of importance in the model. N.S. Indicates no models are significant in predicting growth with the selected climate variable. Analysis timeframe was from 1947 to 2017.

MEAN TEMPERATURE														
REGION	PLOT	C	V1	B	V2	B	V3	B	V4	B	V5	B	V6	B
NLNA	8	2.1429	-0.0873	-0.4659	0.0329	0.2897	0.0275	0.2711						
CLSA	13	1.9237	-0.0575	-0.3899	0.0197	0.2672								
NLNA	16	2.1604	-0.0640	-0.4959	0.0334	0.4299	0.0221	0.3167	-0.0212	-0.2102				
SLNA	23	0.8702	0.0193	0.2531										
CLNA	30	0.8463	0.0348	-0.2531	0.0195	-0.2388	-0.0201	-0.2376						
SLSA	40	1.4016	-0.0431	-0.3315	0.0268	0.2369								
CLSA	61	2.5372	-0.1000	-0.4740	0.0274	0.3258								
CLNA	85	0.5453	0.0290	0.2776	0.0228	0.2553								
NLSA	101	0.5677	0.0295	0.3452										
CLSA	103	2.2287	-0.0508	-0.3138	0.0130	0.2902	0.0126	0.2400	-0.2226					
SLSA	106	2.4854	-0.0952	-0.4438	0.0361	0.2753								
SLNA	113	1.5554	-0.0859	-0.3895	0.0565	0.3011								
NLSA	115	1.8685	-0.0568	-0.3972	0.0268	0.3074								
SLNA	121	2.4645	-0.0914	-0.3889	0.0386	0.3353								
CLNA	128	1.3752	0.0371	0.3598	-0.0441	-0.3587	0.0263	0.2488	0.0210	0.2313				
NLSA	130	1.9509	-0.0731	-0.4316	0.0293	0.3740	0.0308	0.3516						
SLSA	142	1.3614	-0.0463	-0.3668	0.0389	0.3278	0.0225	0.2204						
NLNA	147	1.3007	-0.0363	-0.2169	0.0217	0.2279								
ALL	ALL	1.7561	-0.0575	-0.4728	0.0265	0.3753	0.0157	0.2512						
MAXIMUM TEMPERATURE														
REGION	PLOT	C	V1	B	V2	B	V3	B	V4	B	V5	B	V6	B
NLNA	8	1.9246	-0.0754	-0.5097	0.0276	0.2717	0.0292	0.1980	0.0238	0.2402	-0.0326	-0.2671	0.0138	0.1841
CLSA	13	1.2007	0.0249	0.3637	-0.0315	-0.3142								
NLNA	16	2.0877	-0.0471	-0.4601	0.0230	0.3231	-0.0292	-0.3449	0.0207	0.2976				
SLNA	23	N.S.												
CLNA	30	-0.4027	-0.0170	-0.3629	0.0148	-0.2388	0.0450	-0.2376	0.0335					
SLSA	40	1.4898	-0.0439	-0.4032	0.0281	0.2981								
CLSA	61	2.5698	-0.0857	-0.5268	0.0335	0.3205								
CLNA	85	1.9085	-0.0518	-0.3912	0.0233	0.2811	0.0195	0.2502	-0.0248	-0.2581	0.0180	0.2289		
NLSA	101	1.4216	-0.0160	-0.2083	0.0195	0.2824	-0.0191	-0.2389						
CLSA	103	2.3401	-0.0624	-0.4965	0.0122	0.2928								
SLSA	106	2.6705	-0.0865	-0.5305	0.0336	0.2967								
SLNA	113	1.9489	-0.0826	-0.5113	0.0363	0.2442	0.0203	0.2119						
NLSA	115	1.9385	-0.0497	-0.4356	0.0230	0.3068								
SLNA	121	1.8801	-0.0708	-0.4851	0.0283	0.2874	0.0226	0.2245						
CLNA	128	1.2127	0.0143	0.3007	-0.0281	-0.2979	0.0261	0.2378						
NLSA	130	1.8350	-0.0568	-0.4605	0.0202	0.353	0.0257	0.3382						
SLSA	142	2.0906	-0.0598	-0.4008	0.0229	0.2797	0.0207	0.2110						
NLNA	147	1.4972	-0.0482	-0.4314	0.0333	0.2993								
ALL	ALL	1.6075	-0.0515	-0.5469	0.0186	0.3019	0.0130	0.2020	0.0086	0.1817				
MINIMUM TEMPERATURE														
REGION	PLOT	C	V1	B	V2	B	V3	B	V4	B	V5	B	V6	B
NLNA	8	N.S.												
CLSA	13	1.2413	0.0207	0.2946	-0.0455	-0.3943	0.0301	0.2574						
NLNA	16	1.3846	0.0255	0.3626	-0.0288	-0.3225	0.0184	0.2370						
SLNA	23	0.9626	0.0178	0.2920										
CLNA	30	1.1810	0.0418	0.3944	0.0213	0.3913	-0.0233	-0.3597	-0.0289	-0.2775	0.0213	0.2570		
SLSA	40	0.9715	0.0253	0.2583	-0.0139	-0.2802	0.0143	0.2295						
CLSA	61	1.1562	0.0233	0.2543										
CLNA	85	1.0855	0.0270	0.3198										
NLSA	101	0.7597	0.0178	0.2346	0.0243									
CLSA	103	1.1529	0.0175	0.2915	0.0243	0.2756								
SLSA	106	N.S.												
SLNA	113	1.3073	0.0323	0.3242	-0.0470	-0.2960	0.0251	0.2392						
NLSA	115	1.3703	0.0272	0.3149	-0.0299	-0.2643								
SLNA	121	1.0810	0.0380	0.3487										
CLNA	128	1.8119	0.0245	0.3003	0.0301	0.3089	-0.0478	-0.3226	0.0273	0.2268				
NLSA	130	1.2451	0.0286	0.3291	0.0231	0.2580	-0.0203	-0.2471						
SLSA	142	N.S.												
NLNA	147	N.S.												
ALL	ALL	1.3068	0.0270	0.3989	-0.0226	-0.2296								

Table 2.7. Coefficients and their corresponding p-values for regression models that use moisture climatic variables in predicting red spruce growth. Coefficients are listed in order of importance in the model. N.S. Indicates no models are significant in predicting growth with the selected climate variable. Analysis was conducted between 1947 to 2017.

Climate Moisture Index														
REGION	PLOT	C	V1	B	V2	B	V3	B	V4	B	V5	B	V6	B
NLNA	8	1.0946	0.0071	0.5559	-0.0081	-0.2829	-0.0092	-0.2412	-0.0076	-0.2288	-0.0047	-0.1937	0.0053	0.1872
CLSA	13	1.0166	-0.0053	-0.4405	0.0020	0.2297								
NLNA	16	0.9938	0.0076	0.3163	-0.0055	-0.2848								
SLNA	23	1.0379	-0.0072	-0.2576										
CLNA	30	1.0916	-0.0056	-0.3967										
SLSA	40	1.0125	-0.0041	-0.3123	0.0047	0.2578								
CLSA	61	1.0632	-0.0040	-0.2635	0.0069	0.2630	-0.0084	-0.2330						
CLNA	85	0.9101	0.0049	0.4646										
NLSA	101	0.9734	0.0021	0.3466										
CLSA	103	0.9446	0.0058	0.3855	-0.0056	-0.2310								
SLSA	106	0.9373	0.0048	0.3139										
SLNA	113	0.9323	0.0042	0.3571										
NLSA	115	0.9852	-0.0077	-0.3615	0.0066	0.3457								
SLNA	121	1.0119	-0.0045	-0.2726	0.0055	0.2369								
CLNA	128	1.0145	0.0034	0.2509	-0.0038	-0.2369								
NLSA	130	0.9953	0.0079	0.4154	-0.0038	-0.2941								
SLSA	142	0.9642	0.0038	0.2651										
NLNA	147	1.0268	-0.0076	-0.3525	0.0057	0.3086	-0.0060	0.2396						
ALL	ALL	0.9988	0.0031	0.3364	-0.0037	-0.3279								
Precipitation														
REGION	PLOT	C	V1	B	V2	B	V3	B	V4	B	V5	B	V6	B
NLNA	8	1.1320	0.0008	0.5113	-0.0004	-0.2669	-0.0010	-0.2647	-0.0005	-0.2579				
CLSA	13	1.0821	-0.0006	-0.4131	0.0002	0.2406								
NLNA	16	1.0289	0.0007	0.2737	-0.0004	-0.2717								
SLNA	23	1.0952	-0.0008	-0.2570										
CLNA	30	1.2948	-0.0005	-0.3818	-0.0007	-0.0989								
SLSA	40	1.1664	-0.0004	-0.2944										
CLSA	61	1.2369	-0.0006	-0.3488										
CLNA	85	0.7792	0.0005	0.4242										
NLSA	101	N.S.												
CLSA	103	0.7948	0.0006	0.3511										
SLSA	106	0.7961	0.0005	0.2845										
SLNA	113	0.8186	0.0004	0.2932										
NLSA	115	0.9824	-0.0009	-0.3570	0.0007	0.3380								
SLNA	121	1.1681	-0.0005	-0.2660										
CLNA	128	0.8595	0.0004	0.2648										
NLSA	130	1.0087	0.0008	0.3973	-0.0004	-0.2816								
SLSA	142	1.1805	-0.0005	-0.2778										
NLNA	147	1.0705	-0.0007	-0.2767	0.0006	0.3154	-0.0008	-0.2715	-0.0007	-0.3259	0.0005	0.2664		
ALL	ALL	1.0584	-0.0005	-0.3613	0.0006	0.3221								

Figure 2.1. Map showing the study area on the Monongahela National Forest in West Virginia. Dendroclimatic plots are indicated with black dots. Map was created using ARC-MAP Version 10.5.

Figure 2.2. Average ring width chronologies by regional group for northern, central, and southern latitudes of central Appalachian red spruce. Each regional group chronology consists of average ring width values from standardized chronologies of the three separate climatic group chronologies.

Figure 2.3. Significant predictors of the regression models are shown below for regional groups using temperature climatic variables. Predictors are displayed over a two year seasonal window and include monthly and three month seasonal climate variables. The two year seasonal window includes climate variables from April (t-1) of the prior year to October (t) of the current year in regression models. Models with multiple predictors list them in order of importance (1 = most important predictor). Predictors displayed in black indicate a negative relationship with red spruce growth, while indicators in light gray indicate a positive correlation with red spruce growth. Adjusted R² values are listed for each model.

Month - Mean Temperature

Regional Group	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ²
North Latitude, North Aspect (NLNA)		3			1		2													0.233
North Latitude, South Aspect (NLSA)	3				1		2											4		0.254
Central Latitude, North Aspect (CLNA)				2			3				1									0.178
Central Latitude, South Aspect (CLSA)					1		2													0.294
South Latitude, North Aspect (SLNA)				1			2													0.189
South Latitude, South Aspect (SLSA)					1		2													0.254
All Latitudes and Aspects					2		1													0.225

Month - Maximum Temperature

Regional Group	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ²
North Latitude, North Aspect (NLNA)		3			1		2													0.304
North Latitude, South Aspect (NLSA)	3				1		2						4							0.255
Central Latitude, North Aspect (CLNA)				1			3			2										0.149
Central Latitude, South Aspect (CLSA)					1		2											3		0.401
South Latitude, North Aspect (SLNA)					1		2													0.210
South Latitude, South Aspect (SLSA)					1		2													0.298
All Latitudes and Aspects		3			1		2													0.338

Month - Minimum Temperature

Regional Group	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ²
North Latitude, North Aspect (NLNA)					2		1													0.093
North Latitude, South Aspect (NLSA)																				0.088
Central Latitude, North Aspect (CLNA)																				0.102
Central Latitude, South Aspect (CLSA)																				0.054
South Latitude, North Aspect (SLNA)				2			1										3			0.178
South Latitude, South Aspect (SLSA)																				0.072
All Latitudes and Aspects																				0.110

Figure 2.4. Significant predictors of the regression models are shown below for regional groups using moisture climatic variables. Predictors are displayed over a two year seasonal window and include monthly and three month seasonal climate variables. The two year seasonal window includes climate variables from April (t-1) of the prior year to October (t) of the current year in regression models. Models with multiple predictors list them in order of importance (1 = most important predictor). Predictors displayed in Black indicate a negative relationship with red spruce growth, while indicators in light gray indicate a positive correlation with red spruce growth. Adjusted R² values are listed for each model.

Month – Precipitation

Regional Group	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ²
North Latitude, North Aspect (NLNA)				1										2						0.143
North Latitude, South Aspect (NLSA)				1			2													0.121
Central Latitude, North Aspect (CLNA)																1				0.117
Central Latitude, South Aspect (CLSA)																				0.083
South Latitude, North Aspect (SLNA)																				0.046
South Latitude, South Aspect (SLSA)																				0.062
All Latitudes and Aspects				1														2		0.143

Month - Climate Moisture Index

Regional Group	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ²
North Latitudes, North Aspect (NLNA)				1										2						0.161
North Latitudes, South Aspect (NLSA)																				0.089
Central Latitude, North Aspect (CLNA)											2						1			0.098
Central Latitude, South Aspect (CLSA)					1													2		0.134
South Latitude, North Aspect (SLNA)																				0.044
South Latitude, South Aspect (SLSA)				1																0.052
All Latitudes and Aspects				1														2		0.178

Figure 2.5. Projected red spruce growth by regional group using temperature variables. Error bars indicate a 95% confidence interval of the base growth rate. All changes in growth that lie outside of the error bars indicate significant changes in growth. Growth projections were created with future climate data that was estimated using climate change scenario RCP 4.5.

Figure 2.6. Projected red spruce growth by regional group using moisture variables. Error bars indicate a 95% confidence interval of the base growth rate. All changes in growth that lie outside of the error bars indicate significant changes in growth. Growth projections were created with future climate data that was estimated using climate change scenario RCP 4.5.

REGION		Plot	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ² _{adj}
North Latitude North Aspect	8	3				1		2														0.27
	16	3				1		2										4				0.37
	147					1													2			0.10
North Latitude South Aspect	101																		1			0.11
	115					1		2														0.21
	130	2			1			3														0.34
Central Latitude North Aspect	30											1	3	2								0.05
	85							2											1			0.14
	128	4					2	1					3									0.28
Central Latitude South Aspect	13				1		2	1														0.19
	61					1		2														0.26
	103				4		1				2			3								0.26
South Latitude North Aspect	23														1							0.02
	113					1												2				0.26
	121					1			2													0.25
South Latitude South Aspect	40				1														2			0.18
	106					1		2														0.24
	142	3					1		2													0.19
ALL	ALL	4				1		2											3			0.34

		Month - Min Temperature																			
REGION	Plot	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ² adj
North Latitude North Aspect	8																				NA
	16	3																			0.20
	147																				NA
North Latitude South Aspect	101																				0.10
	115																				0.11
	130																				0.19
Central Latitude North Aspect	30																				0.35
	85																				0.09
	128																				0.25
Central Latitude South Aspect	13																				0.16
	61																				0.05
	103																				0.14
South Latitude North Aspect	23																				0.07
	113																				0.18
	121																				0.11
South Latitude South Aspect	40																				0.15
	106																				NA
	142																				NA
ALL	ALL																				0.14

Figure 2.8. Significant predictors of the regression models are shown below for individual plots using moisture climatic variables. Predictors are displayed over a two-year seasonal window and include monthly and three-month seasonal climate variables. The two-year seasonal window include climate variables from April (t-10) to October (t) in regression models. Models with multiple predictors list them in order of importance (1 = most important predictor). Predictors displayed in black indicate a negative correlation with red spruce growth, while indicators in grey indicate a positive correlation with red spruce growth. Adjusted R² values are listed for each

Month - Climate Moisture Index

REGION	Plot	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ² _{adj}
North Latitude North Aspect	8	5		1				6			2			4					2		0.46
	16			1															2		0.15
	147			2										3					1		0.28
North Latitude South Aspect	101			1																	0.05
	115			2															1		0.22
	130			1															2		0.24
Central Latitude North Aspect	30				1																0.21
	85			1																	0.20
	128				1														2		0.11
Central Latitude South Aspect	13		2																1		0.24
	61			2					3									1			0.19
	103					1													2		0.21
South Latitude North Aspect	23																		1		0.05
	113				1																0.11
	121			2															1		0.11
South Latitude South Aspect	40			2															1		0.14
	106				1																0.09
	142			1																	0.06
ALL	ALL				1														2		0.23

Month – Precipitation

REGION	Plot	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	R ² _{adj}
North Latitude North Aspect	8				1						3				2				4		0.31
	16				1														2		0.12
	147				1									4	2		5		3		0.36
North Latitude South Aspect	101																				NA
	115				2														1		0.20
	130				1														2		0.22
Central Latitude North Aspect	30	2			1																0.14
	85				1																0.17
	128					1															0.06
Central Latitude South Aspect	13			2															1		0.21
	61																		1		0.11
	103						1														0.11
South Latitude North Aspect	23																		1		0.05
	113					1															0.07
	121																		1		0.06
South Latitude South Aspect	40																		1		0.07
	106				1																0.07
	142																		1		0.06
ALL	ALL				1														1		0.22

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Chapter Three: Site Index Modeling of Red Spruce

3.1 Introduction

Site index can be a valuable tool at quantifying productivity of forest stands. Site index is used to explain how tall a selected tree will be at a base age. Base ages used to quantify site indexes are generally 50 years in the eastern, 25 in the southern, and 100 years in the western portions of North America (Mathiasen et al., 2006). Site index allows forest managers to determine how suitable and or productive forest stands may be. Site index can be one metric considered when determining feasibility of lands for forest management activities (Geyer and Lynch, 1987). Site index is a common input used in forest models such as Forest Vegetation Software (FVS) where growth models take into account site index values when estimating future tree growth (Dixon and Keyser, 2008). Having reliable site index values could allow for more accurate prediction of future tree growth.

Basic site index methods involve sampling dominant and or codominant trees that have remained in that canopy class throughout their entire life to ensure free growth (Nigh and Love, 1999). Sampled trees are aged by dendrochronological methods and their total height is determined. This age-height data can then be processed to estimate site productivity in terms of tree height at a base age. Trees selected for site index development must be free from defect and have quality form. Two common methods used to develop site indexes for tree species are polymorphic and anamorphic.

Polymorphic methods involve sampling trees incrementally throughout the entire stem of the tree. Sampling trees incrementally throughout the stem allows researchers to identify the exact age of the tree at the selected height throughout the tree. Knowing a tree's height at its base age is critical in modeling site index using polymorphic site index equations. One method of sampling for polymorphic models is felling trees and removing cross sections from the trees stem at common intervals such as two meters (Carmean et al, 2001). This method of sampling is destructive and involves killing the sampled

tree. Less destructive methods involve collecting periodic height measurements throughout a tree's life. For example, height data can be collected every 5 or 10 years for an extended period at least covering a base age of 25 or 50 years (Newton, 2008; Homagain et al., 2011; Coble and Lee, 2006).

Anamorphic methods are not as effective as polymorphic site index models (Lee, 1999). Anamorphic data are easier to collect as all that are required is height measurement and tree age. Despite the lack of destructive sampling, some anamorphic site index models still contain some sort of height measurement taken at a known age (Coble and Lee, 2006). Because of this requirement, anamorphic site index studies are usually conducted on plantation species or with samples that have data of the tree's height at or near a base age (Newton, 2008; Homagain et al., 2011).

Site index models are primarily developed for shade intolerant species in even aged stands. There have been few site index models developed for shade tolerant species growing in uneven aged stands, such as red spruce (*Picea rubens*) (Carmean et al., 1989; Nicholas and Zedaker 1992). Red spruce usually encounters suppression during its lifetime. In particular, central Appalachian red spruce frequently experiences suppression periods as it transitions through canopy classes (Rentch et al., 2007). Frequent growth suppression and shade tolerance makes red spruce a poor candidate for traditional site index research per standard protocols. Some site index research has been conducted to account for the shade tolerance of red spruce and growth suppression regime. One novel method of accounting for suppression in red spruce was developed by Seymour and Fajvan (2001). This method involves using free growth age of the tree instead of the true age of the tree by replacing time periods during lengths of suppression on tree cores with free growth age of the same length following the suppressed period. Another novel method of accounting for suppression in red spruce was used by Nicholas and Zedaker (1992) and developed by Meyer (1942). This method uses diameter to predict height in shade tolerant species instead of age. Researchers used diameter to predict tree height as they observed that shade tolerant trees of a given height had a similar diameter with a variety of ages. High age variations in

similar diameter classes was due to trees shade tolerance and different suppression regimes. Both, age correction from suppression and use of diameter instead of age, are different methods to address the shade tolerance of red spruce when predicting height and site index.

Carmean et al. (1989) developed a site index curve for red spruce in the northern portion of the species range. This site index was developed using data that were collected in the early parts of the twentieth century in Maine, Vermont, and New Hampshire (Meyer, 1929). Carmean et al's (1989) red spruce site index model uses a Chapman Richards growth model utilizing five parameters with age and height to predict site index of even-aged, red spruce. This model is not suitable to predict site index for central Appalachian red spruce as central Appalachian red spruce typically encounter suppression and climatic conditions that are different than red spruce at northern latitudes. The suppression correction method developed by Seymour and Fajvan (2001) does account for suppression in red spruce and would be suitable to use for central Appalachian red spruce. Using their suppression correction method with the Carmean et al. (1989) equation still is not ideal as the Carmean et al. (1989) model was developed with historic, northern red spruce data. This suppression corrected method could be effective for accounting for growth suppression in the development of a site index model for central Appalachian red spruce.

The previously described models have been established to explain age-height or age-diameter relationships for red spruce and quantify these relationships into site index values. The extent of the limited red spruce site index research has focused on red spruce at the northern and southern portions of its range (McClintock and Bickford 1957; Hoar and Young 1965; Griffin and Johnson 1980; Carmean et al, 1989; Nicholas and Zedaker, 1992; Seymour and Fajvan, 2001). No site index models are currently available for central Appalachian red spruce. A model used to estimate red spruce height and site index values for central Appalachian red spruce could be a valuable tool for estimating red spruce growth and selecting locations where restoration activities would be most productive. Using red spruce site index

estimations could allow land managers to make land suitability decisions when identifying possible locations for red spruce restoration activities such as plantings.

Models have been created to predict site quality and quantify site quality using metrics other than height at a base age. Forest site quality index (FSQI) have been used in the Appalachian Mountains to quantify site quality (Meiners et al. 1984). FSQI is a land ranking system that ranks forest lands in terms of productivity by assessing geographic features that impact soil moisture such as aspect, slope, and landscape position (Meiners et al. 1984; Sturtevant and Seagle, 2004). Other models have been created that use climate specific variables and geographic FSQI related variables to predict other spruce species site index in northern latitudes (Wang and Klinka, 1995). Jiang et al (2014) developed models to predict site index for conifers in the eastern United States (including red spruce) using climate variables. Using combinations of geographic and climatic variables on a site level may be an effective method of predicting central Appalachian red spruce site index.

Much of the forest land in the central Appalachians that was once dominated by red spruce is now dominated by associated hardwood species such as red maple (*Acer rubrum*) and yellow birch (*Betula alleghaniensis*) (Burns and Honkala, 1990; Rentch et al., 2010; Thomas-Van Gundy & Sturtevant, 2014). There have been no studies published that predict the site index of red spruce using site index values of associated species. Steel and Clutter (1986) developed linear models to predict site index values of western timber species using the site index values of associated western timber species. Older studies conducted in the eastern United States have developed models that use site index of common timber species to predict the site index of associated commercial timber species (Doolittle, 1959; Foster, 1959; Olsen and Lino, 1959). Carmean (1979) created linear models to predict site index values between 12 common timber species in the mid-western United States. Site index of red spruce may be an important factor to influence the decision-making process when selecting land for future restoration activities. Developing models that can estimate red spruce site index using associated hardwood species

could be an effective method of assessing the suitability of forested land for potential red spruce management activities.

The primary objective of my research was to develop anamorphic site index curves for central Appalachian red spruce using easily acquired data including height, diameter, and age. The other objective of my research was to develop models to predict red spruce site index at sites where dominant or codominant red spruce are absent from the overstory. These models would use site index values of common associated hardwood species and easily obtainable climatic and geographic data to predict the site index of red spruce. Models to predict red spruce site index where the species is currently absent would be an important tool in pinpointing optimal locations for future red spruce restoration activities.

3.2 Methods

3.2.1 Field Sampling Methods

Field sampling occurred on the Monongahela National Forest (MNF) in the state of West Virginia. Random sampling locations were determined by using the random sample tool within the data management Arc toolbox in ArcGIS (Theobald et al. 2007). Random points were placed on portions of the MNF that contained at least 10% estimated red spruce canopy cover using the red spruce landcover dataset obtained from the state of West Virginia's GIS clearinghouse website (Byers et al., 2013). A total of 150 random sample points were established in order to meet a sampling goal of 100 plots. A total of 83 plots were sampled because some plots had absence of spruce cover (Fig. 3.1). Additionally, some sites were located in wilderness areas where sampling was not permitted. Some random sample points were also located on private property or remote locations that could not be safely accessed for sampling.

Garmin Oregon 650 GPS units were used to navigate to the randomly selected sample points. Once at the random sample point, a temporary plot marker was installed, and sampling occurred. Sampling was conducted using a circular plot with a 10-meter radius (0.02337-hectare area) and sampling was conducted using a random azimuth. From plot center, a random azimuth was determined, and a 10-meter tape was extended from the plot center along the random azimuth. Sampling was then conducted from the random azimuth on a clockwise rotation until all samples were collected. The first red spruce tree that was encountered in this clockwise sweep that was larger than 10.16 centimeters (4 inches) diameter at breast height (DBH) (1.37 meters from ground) was determined to be the primary red spruce. The primary red spruce was the spruce tree that was to be destructively sampled for developing polymorphic red spruce site index models for a future study. Once the primary spruce was selected, sampling continued clockwise until the next red spruce in the codominant or dominant canopy class occurred. This red spruce in the codominant or dominant size class was designated the secondary red spruce and its data would be used for anamorphic site index modeling. In addition, the first black cherry (*Prunus serotina*), American beech (*Fagus grandifolia*), yellow birch, and red maple, occurring in the dominant or codominant canopy class were sampled for site index conversion modeling. If one of the trees selected for sampling had visible signs of poor health, defects, or crown damage the tree was not sampled, and the next suitable tree of that species was selected. Two increment cores were extracted at breast height on the secondary red spruce and for each sampled hardwood tree. Increment cores were taken perpendicular to slope on opposite sides of the tree. Total height, crown height, bark thickness, crown class, and diameter at breast height (DBH), was recorded for each tree.

3.2.2 Laboratory Methods

Extracted increment cores were stored in large paper straws and labeled according to the plot number and tree sample number. Cores were then oven dried in a laboratory oven. Once dry,

increment cores were mounted to wooden core mounts and pressed. Once mounted, cores were then sanded using an electric palm sander. All cores were sanded to a minimum grit level of 400. Red spruce cores that showed growth suppression and all hardwood species cores were sanded further to a grit level of 800.

Sanded increment cores were then visually crossdated using a dissecting microscope (Speer, 1971). Starting, ending, decadal, and narrow, rings were marked for each sample core. Each core was dated by ensuring narrow, marker rings were the same age on both cores extracted from the tree. Starting and ending years of each core were noted to determine true age of the sample core. Suppression periods within the red spruce increment cores were identified and noted. Red spruce samples were processed according to the suppression correction methods developed by Seymour and Fajvan (2001). Periods of growth suppression were measured with a micrometer to a precision of 0.01 millimeters. Age of suppression was noted, and the micrometer was used to measure the exact distance as the suppressed period on the free growth period following the suppression. The age of the corresponding length of free growth was noted. A suppression corrected age was then determined for the increment core by replacing the suppression period age with the following free growth age. A total of 39 of the 83 sampled trees required suppression corrected ages, as they experienced at least one suppression period at breast height. Average ring width measurement was noted for each suppression period. Average 10-year ring width measurements were noted for periods preceding and following suppression periods. Average ring width for suppression periods was 200% lower than periods of free growth before suppression. Average ring width for suppression periods was 300% lower than free growth periods following suppression release events. Table 3.5 shows average ring width measurements of suppressed and free growth periods to justify the suppression correction methods.

Once cores were visually dated, they were then scanned with a high-resolution scanner at a resolution of 2400 dots per inch (D.P.I). Scanned images of each core were then processed in

CooRecorder (Version 9.0) by measuring and dating each annual growth ring. The pith estimation tool was used in CooRecorder to estimate rings to the pith on samples that did not reach the pith.

CooRecorders' pith estimation value was used for future predicted age values for all cores that did not contain the pith of the tree.

3.2.3 Height Modeling

Nonlinear regression was conducted in SYSTAT (Version 13.2) using the Gauss-Newton method to determine a suitable three parameter Chapman Richards model to predict red spruce height using age-height combinations of 83 sampled overstory red spruce trees (Richards, 1959). The three parameter Chapman Richards model is as follows:

$$Height = 1.37 + B1(1 - e^{B2*Age})^{B3}.$$

The independent variable is red spruce suppression corrected "age" at breast height, and the dependent variable is total height. An additional three parameter Chapman Richards model was also developed using true age to predict height. A Meyer model was also created to estimate red spruce height with suppression corrected age (Meyer, 1940). Non-Linear regression using the Gauss-Newton method in SYSTAT was used to solve for the two regression parameters for the Meyer model. This model uses suppression corrected age in conjunction with two regression parameters to estimate height, the model equation is as follows:

$$Height = 1.37 + B1(1 - e^{B2*Age}).$$

The independent variable of the original Meyer model uses DBH, but my model replaces DBH with suppression corrected age at breast height. An additional Meyer model was also created that uses true age to predict height. Adjusted R^2 , model bias, and PRESS statistic, were calculated for both models, to determine and compare model performance. PRESS statistic is a leave one out cross-validation statistic

that sums up predicted, squared, residual errors. Lower PRESS statistics indicate better performing models. A residual vs fitted plot was examined to ensure errors were normally distributed. Guide curves were established for the models to predict height at varying site classes. Guide curves were created incrementally by using the 95% confidence interval asymptote value difference to create guide curves at intervals from the original curve (Mathiasen et al., 2006). Guide curves and the height model were then plotted in Microsoft Excel (Version 2010) to make an age-height figure to predict site index values.

An additional model was created to predict red spruce height using nontraditional methods. This model was a Meyer model that uses tree diameter at breast height (1.3 meters from the ground) to predict total height of central Appalachian red spruce (Meyer, 1940). The two regression parameters in the Meyer model were solved by using DBH as the independent variable and total height as the dependent variable, the model equation is as follows:

$$Height = 1.37 + B1(1 - e^{B2*DBH}).$$

Non-linear regression was conducted in SYSTAT (Version 13.2) using the Gauss-Newton method to solve for the regression parameters. Adjusted R^2 , model bias, and PRESS statistic, were calculated for the model, to determine the model's performance. A residual vs fitted plot was examined to ensure errors were normally distributed. Because this model does not use age, there is no base age to classify tree site index values. A base diameter of 35 centimeters was instead used as the base to estimate site index values which is consistent with previous studies (Meyer, 1940; Nicholas and Zedaker, 1992). The height model using DBH was then plotted in Excel and guide curves were created to allow for site index estimation. Guide curves were created by using the 95% confidence interval value to add and subtract from the original asymptote values.

3.2.4 Predicting Red Spruce Site Index with Associated Species

An objective of my research efforts was to develop linear models that can estimate red spruce site index values where the species is absent from the overstory. Preliminary examination of red spruce site index and associated species site index showed a linear trend and justified linear model development. Linear models were created using the site index values for two of the most popular species found in the sample plots (yellow birch and red maple). Linear models were also created using just climate and or geographic variables to predict red spruce site index to determine which variables are important for estimating site index. Models considering site index of associated species, climatic variables, and geographic variables, were also created. Linear modeling was conducted in the statistical program JMP (version 14.0 Pro). Site index values of associate species were determined using the site index models of Carmean et al. (1989). Linear models were created with red spruce site index as the dependent variable. Models were created using two site index values for red spruce. The first red spruce site index values were determined using the red spruce equation of Carmean et al. (1989). The second red spruce site index values were estimated by using the three parameter Chapman Richards model and guide curves created in this study. Twenty-three climatic variables (30-year mean values from 1981 to 2010) considered for modeling were obtained from Oregon State University's PRISM website (prism.oregonstate.edu, 02/20/2020) (Daly et al, 2001). Geographic variables were determined using data collected during field sampling such as slope, latitude and longitude coordinates, elevation, and aspect. Table 3.3 shows a list of the climatic and geographic variables considered for linear site index modeling.

Linear models were created using several methods for comparison of best models to predict spruce site index. The first method of modeling used stepwise regression with forward selection using minimum AICc values. Akaike information criterion for small sample sizes (AICc) estimates how well

models perform relative to each other and applies penalties to each model predictor; models with small AICc values are considered the best. A best model was determined for each input category (associated species site index values, climatic values, and geographic values,) and for all categories combined. The combined model considers only variables that were significant predictors in the prior category models. Linear models were also created using subset regression in JMP to predict red spruce site index values. A total of 8,656,936 models were constructed in JMP that considered associated species, climatic variables, and geographic variables (31 variables total). Best models were determined by minimum AICc values and significant P-values for individual model predictors and the entire model. Adjusted R^2 (R^2_{adj}) values and PRESS statistics were determined for each model to help demonstrate model performance. Residual vs. fitted plots were then constructed to ensure normal distribution of errors. Linear models were compiled in a table to showcase strengths and weaknesses of each model.

3.3 Results

3.3.1 Central Appalachian Red Spruce Height Model and Figure Results.

The solved three parameter Chapman Richards equation for central Appalachian red spruce that uses suppression corrected age to predict height is as follows: $Height = 1.37 + 26.301 (1 - e^{-0.0064 * Age})^{-0.248}$ (Table 3.1, Model 1)). The R^2_{adj} value for this model was 0.553 (Table 3.1, Model 1). Model bias was calculated to be -0.259 with a 95% confidence interval of -3.096 to 2.579, which indicates no model bias as the 95% confidence interval includes 0. A PRESS statistic of 1287.007 was determined for this model. This model predicts height values well (Fig. 3.2) and had normally distributed errors with no major outliers using red spruce samples. The solved three parameter Chapman Richards equation that uses total age to predict height is as follows: $Height = 1.37 +$

$23.563 (1 - e^{-0.033*Age})^{-0.478}$ Table 3.1, Model 4). The R^2_{adj} value for this model was 0.490 and the bias was -2.476 with a confidence interval of -3.558 to -1.393 which indicates model bias.

The Meyer model that uses suppression corrected age is as follows: $Height = 1.37 + 28.587(1 - e^{-0.015*Age})$ (Table 3.1, Model 2). This nonlinear model and guide curves were plotted to create a figure to estimate site index values using age-height data (Fig. 3.3). The R^2_{adj} value for this model is 0.548. Model bias was calculated to be 0.033 with a 95% confidence interval of -0.836 to 0.293, which means this model is not biased as 0 falls within the confidence interval. The press statistic for this model was calculated to be 1275.88. This model predicts height of the red spruce samples well (Fig 3.3), with no outliers, and a normal distribution on the residual vs fitted plot. The solved Meyer model that uses true age to predict height is as follows: $Height = 1.37 + 24.546(1 - e^{-0.020*Age})$ (Table 3.1, Model 5). Model 5 has and R^2_{adj} value of 0.470 and has a bias of -0.084 with a confidence interval from -1.003 to 0.834, which indicates no model bias.

The Meyer Model that uses DBH to predict height with solved regression parameters is: $Height = 1.37 + 32.381(1 - e^{-0.028*dbh})$ (Table 3.1, Model 3). This models R^2_{adj} value is 0.560. Model bias was calculated as -0.040 with a 95% confidence interval of -1.09 to 0.29 which means the model has no bias as 0 falls within the bias confidence interval. This model had a low PRESS statistic of 804.85. This height model and guide curves were plotted to establish a figure (Fig. 3.4) that can be used with easily collected field data to estimate site index values at a base diameter. A base diameter of 35 centimeters is used to replace base age which is traditionally used in determining site index. This model predicts height well (Fig. 3.4) with no outliers and a normally distributed residuals vs fitted plot.

3.3.2 Predicting Red Spruce Site Index Using Associated Species, Climatic, and Geographic Variables

3.3.2.1 Linear Models Developed for Carmean et al. (1989) Site Index Values

Linear models (Table 3.2) were constructed using associated species site index values, climatic variables, and geographic variables, to predict red spruce site index values estimated from Carmean et al. (1989, Page88). A linear model using yellow birch site index (Model #1, $R^2_{adj}=0.22$, AICc=227.67) was determined to be the best predicting model for associated hardwood species using stepwise regression with forward selection and selecting the model with the lowest AICc values. Using stepwise regression with forward selection, a linear model was created to predict red spruce site index using strictly climatic variables (Model #2, $R^2_{adj}=0.25$, AICc=508.67). This model includes the following climatic variables when estimating red spruce site index: growing degree days above 0 degrees Celsius (DD_0), number of frost-free days (NFFD), frost free period (FFP), and 30-year extreme maximum temperature (EXT). There were no significant models that were able to predict red spruce site index values using only geographic variables. The combined model created using stepwise regression with forward selection (Model #3, $R^2_{adj}=0.31$, AICc=338.19) uses yellow birch site index, DD_0, NFFD, FFP, and EXT, as significant predictors in predicting red spruce site index.

The best model using subset regression to predict red spruce site index using Carmean et al. (1989) values was a linear model that included geographic, climatic, and hardwood site index variables. This linear model (Model #6, $R^2_{adj}=0.54$, AICc=222.17) uses longitude, mean annual temperature (MAT), heating degree days above 18 degrees Celsius (DD_18), NFFD, mean annual radiation (MAR), red maple site index, and yellow birch site index, to predict red spruce site index. The second-best model using subset regression in terms of AICc (Model #7, $R^2_{adj}=0.31$, AICc= 223.17) uses yellow birch site index

value with latitude, mean warmest month temperature (MWMT), extreme monthly temperature difference (TD), and DD_0.

Models were created that used red maple site index values along with climate and geographic variables did not perform as well as yellow birch models. Models using red maples were still created for potential management situations where yellow birch could be absent from forest stands. The best performing model that uses red maple site index in terms of AICc is Model #5 (Model $R^2_{adj}=0.09$, AICc= 234.51) just uses red maple site index to predict red spruce site index. Model #4 (Model $R^2_{adj}=0.26$, AICc= 358.619) is the next best performing model in terms of AICc. This model uses red maple site index, NFFD, FFP, and EXT, to predict red spruce site index.

3.3.2.2 Linear Models Developed Using Chapman Richards Three Parameter Model

Modeling was conducted to estimate red spruce site index values from the suppression corrected three parameter Chapman Richards figure using associated species site index values, climatic values, and geographic values (Table 3.2, Figure 3.2). Top performing models were determined by their AICc values. The best performing model created using stepwise regression with forward selection with associated species uses yellow birch site index value (Model #10, $R^2_{adj}=0.17$, AICc= 296.99). The best performing model created using only climate variables (Model #11, $R^2_{adj}=0.09$, AICc= 234.51) uses MAT, MWMT, DD_18, NFFD, beginning date of frost-free period (bFFP), FFP, and extreme 30-year minimum temperature (EMT), to estimate red spruce site index. A model was also created that uses only yellow birch and significant climate variables to predict red spruce site index values (Model # 12, $R^2_{adj}=0.25$, AICc= 417.84). This combined model uses yellow birch site index, MAT, bFFP, and FFP, as predictors. A model was also created that uses red maple site index (Model #13, $R^2_{adj}=0.15$, AICc=434.25) to predict red spruce site index, but the model did not perform as well as models that use yellow birch site index for predictor variables.

Linear models were also created to predict red spruce site index values estimated from the three parameter Chapman Richards function using subset regression methods. The best performing linear model in terms of AICc was model # 14 ($R^2_{adj}=0.309$, AICc=270.201). This model uses yellow birch site index, Frost Free Period (FFP), TD, growing degree days (DD5), DD_0, and latitude, to predict red spruce site index values. The second-best model (Model #15, $R^2_{adj}=0.56$, AICc=286.75) uses red maple site index, yellow birch site index, MAT, MCMT, TD, DD_18, bFFP, and FFP, as predictors. This model has a slightly larger AICc value but has the largest Adjusted R^2 value of all models created to estimate red spruce site index values using my three parameter Chapman Richards figure (Figure 3.2). I created a linear model using just red maple site index and climate variables to estimate red spruce site index values (Model #16). Model #16 has a larger AICc value (AICc = 421.73) than models using yellow birch site index values but has a high adjusted R^2 value of 0.47. This model uses red maple site index, MAT, MWMT, DD_18, NFFD, bFFP, FFP, and EMT, as predictors.

3.4 Discussion

3.4.1 Anamorphic Modeling Discussion

My three parameter Chapman Richards model (Table 3.1, Model #1) predicts height well using the suppression corrected age of red spruce from breast height samples. This model had competitive adjusted R^2 values and PRESS statistics with the other two Meyer models that use suppression corrected age or DBH (Models #2 and #3) (Table 3.1). The three parameter Chapman Richards model (Table 3.1, Model #4; Fig 3.5) that uses true age is not a good model as it contains bias and a lower Adjusted R^2 value when compared to model #1. My three parameter Chapman Richards model that uses suppression corrected age and guide curves (Fig. 3.2) could be easily used in the field by plotting total height and suppression corrected age to make site index estimations for central Appalachian red spruce.

Carmean et al (1989) created site index equations for red spruce near its northern range, using a Chapman Richards 5 parameter model. Their study utilized polymorphic red spruce data collected in the 1920's (Meyer, 1929). Their model was effective at predicting red spruce site index values for northern red spruce as it utilized actual tree heights at a base age of 50 to create a model with high R^2 values ($R^2=0.99$)(Carmean et al., 1989). I tried to solve for the Chapman Richards 5 parameter model using age, height, and estimate site index values, but SYSTAT was not able to successfully converge on a solution. I only had height-age data from temporary plots to create site index estimations, so I was limited to making models that did not require known heights of the tree at a base age such as the Chapman Richards three parameter model. This model has been used to estimate tree height using age (Cao, 1993). I chose to use suppression corrected age to estimate height as it is important to use free growth age of a tree when estimating site index. If suppressed age is used it can result in misrepresentation of site index values by underestimating site index values that would occur under free growth conditions (Seymour and Fajvan, 2001). My correlation analysis results also highlight that suppression corrected age has a greater correlation to height than true age, which justifies the use of suppression corrected age for site index development (Table 2.3).

The Meyer model was originally created to predict heights of shade tolerant species that frequently experience growth suppression throughout their life cycle (Meyer, 1929). Meyer observed that age was not associated with growth on these suppressed species and developed his model that uses DBH to predict height instead of age, to account for suppression (Meyer, 1929). The first Meyer model I created uses suppression corrected age to predict height (Table 3.1, Model #2). I used suppression corrected age as the independent variable in this model in place of DBH to account for growth suppression in my red spruce samples. This model performed well and was comparable but performs slightly worse when comparing R^2_{adj} values. The Meyer model that uses true age to predict height (Table 3.1, Model # 4) does not perform as well as the model that uses suppression corrected age

(Table 3.1, Model #2) as the model that uses true age (Model #4) has a higher PRESS value and a lower R^2_{adj} value which indicate a poorer performing model. These results suggest that suppression corrected age is closer related to height than true age. These results are supported by their correlation coefficient in Table 3.4, which shows that suppression corrected age has a higher correlation with height than true age.

Using diameter to predict height worked well and produced a model that was competitive with the traditional age-height models. Diameter of the red spruce trees was utilized as the independent variable as a way to account for frequent periods of suppression. The adjusted R^2 value and PRESS statistic of this model was the best of the three models I developed but the difference between all three models was minimal (Table 3.1). Nicholas and Zedaker (1992) used the Meyer equation to estimate red spruce heights using diameter for southern Appalachian red spruce in North Carolina and southern Virginia. Their model worked well for their sampled red spruce and they chose to use this model as their sampled trees were much older than a base age of 50 and had experienced growth suppression (Nicholas and Zedaker, 1992). Comparing regular R^2 values, it appears my model ($R^2=0.59$, Regular $R^2=0.62$) for central Appalachian red spruce would perform comparable to Nicholas and Zedaker's (1992) model for southern Appalachian red spruce. My models adjusted R^2 value of 0.56 indicated that there is a strong relationship between DBH and height. This relationship is strong as my sampled trees have slow radial growth rates due to frequent suppression and competition. The relationship between DBH and height would likely deteriorate if management was introduced resulting in faster than average growth of the red spruce trees. Using diameter-height data in the field to estimate tree height at a base diameter instead of age, would be fast and eliminate the need to core trees to determine an age. Communicating site index values using base diameters would be difficult as site index for eastern North American species usually reports site index values at base ages of 25 or 50 years, not by base diameters (Mathiasen et al., 2006). Because there are limited models that quantify site productivity in terms of

site index using base diameters it would be hard to justify widespread use site index models that use diameter-height data instead of age-height data.

Both models created using suppression corrected age-height data predicted height of central Appalachian red spruce well. The three parameter Chapman Richards height model and guide curve figure (Fig. 3.2) which uses suppression corrected age at breast height is likely the best and most useful model of the three, as this model equation is more commonly used (Cao, 1993). Figure 3.2 can be used in the field for quick estimations of site index for central Appalachian red spruce. My models and figures may be more appropriate to use with anamorphic data to estimate central Appalachian red spruce site index than previous site index models that use red spruce samples in the northern and southern portions of its range (Nicholas and Zedaker, 1992; Carmean et al, 2001)¹.

3.4.2 Linear Models to Predict Red Spruce Site Index.

3.4.2.1 Models that Predict Red Spruce Site Index Using Carmean et al. (1989) Site Index Values

The overall best model (model #6, Table 3.2) in terms of AICc uses both red maple and yellow birch site index along with climatic and geographic variables. Although this is the best model, it may not be the easiest to use as this model has climatic predictors for which data must be acquired to determine red spruce site index values. This model also requires the presence of at least one red maple and yellow birch tree in the overstory to estimate red spruce site index values. This requirement may make this equation unfit for stands that have only red maple or only yellow birch in the overstory. I also developed models that use yellow birch or red maple site index. Red maple is the most common tree in West Virginia and is predicted to become more common in the overstory in the future (Morin et al., 2013). Mesophication of eastern forests from historical fire suppression creates microenvironment conditions that favor and promote red maples population increase (Nowacki and Abrams, 2008). Due to

this trend, my model (model #4) using just red maple site index and climate values should be considered for use in the future.

AICc values were generally lower for models created using subset regression than models using stepwise regression with forward selection. In a situation where yellow birch is only present in the overstory, model #7 (Table 3.2) should be used to predict red spruce index values. If time and resources allow, site index predictions should use linear model #6 that uses red maple site index value, yellow birch site index value, and climate values. This model should be used if possible as it is the best model in terms of AICc and R^2_{adj} values. Climatic variables (MAT, DD_18, NFFD, MAR) used in this model are temperature related. These results suggest that red spruce height growth could be limited by growing season length, which would suggest that red spruce height growth responds similar to temperature conditions as radial growth does (Koo et al., 2014). This model along with others, uses DD_18 (heating degree days) as an important predictor of red spruce productivity. This makes sense as Schagberg (2000) found that red spruce photosynthesis rates greatly increase when temperatures are above 17 Celsius during the nontraditional growing season. Wang et al. (2005) created equations to predict site index values for white spruce that included soil moisture values dependent on climate variables such as mean temperature, precipitation, and radiation. I did not consider soil conditions when developing equations, but my best performing equation does include climatic variables that impact soil conditions that Wang et al. (2005) considered such as MAT and MAR. Jiang et al. (2015) predicted site index values for eastern conifers (red spruce was included). In their models the most important predictors in estimating site index values were climate variables and specifically annual variables that measure gross temperatures such as growing degree days (Jiang et al., 2015). Model #6 does include variables that measure gross temperatures such as heating degree days and frost-free period which are similar to inputs in Jiang et al.'s (2015) models.

3.4.2.2 Models That Predict Red Spruce Site Index Using Three Parameter Chapman Richards

Site Index Values

The best model (model #14, Table 3.2) to predict red spruce site index based on AICc criteria uses 5 predictors which included yellow birch site index, climatic, and geographic variables. This model should be used whenever possible, but in the event of yellow birch absence in the overstory model #16 (Table 3.2) can be used. This model (Tab 3.2, Model #16) uses red maple site index with 5 climatic and geographic predictors to estimate red spruce site index along with MAT, MWMT, DD_18, NFFP, bFFP, FFP, and EMT. Model #16 has a much larger AICc value than model #14 but has a larger adjusted R^2 value (Table 3.2). Model #16 could be the most important models in the future as it uses red maple which is the most common species in West Virginia (Morin et al., 2013). The best overall model in terms of R^2_{adj} (model #15, Table 3.2) uses both red spruce site index and yellow birch site index values with climatic and geographic variables. This model has a slightly higher AICc value but has a much larger R^2_{adj} value than model #14 (Table 3.2). This model requires presence of both yellow birch and red maple in the overstory, which may not be possible in many situations. Because of this dual species requirement, models that require only one species (model #14 and #16, Table 3.2) may be more suitable to apply on a larger scale. Most publications only develop models using one associated species as the predictor which can be more readily implemented (Carmean, 1979; Steele and Clutter, 1986)

Two variables in this model (heating degree days and frost-free period) are similar to the variables used in Jiang et al (2015) to develop eastern conifer site index models. Mean annual temperature is another important predictor in this model. Sharma et al. (2012) also used mean annual temperature in their linear model to predict site index values of Norway spruce in addition to associated species and soil characteristics.

Linear modeling to predict site index of traditional timber species using site index values of associated species do not typically use climate data. Past research has included climate and soil for spruce species such as white spruce and Norway spruce (Wang et al. 2005; Sharma et al, 2012). My linear models to predict red spruce site index values are important as there have been no models ever published that predict red spruce site index using linear models and associated species. Jiang et al. (2014) did develop models that use climate variables similar to my models to estimate conifer site index but not specifically red spruce. The models I created that only utilize associated species site index values do not perform as well as models that use climate and or geographic variables in addition. Red spruce growth, especially towards its elevational extremes, can be limited by temperature and moisture (White et al. 2014; Koo et al. 2014; Walter et al. 2017). Growth responses from climatic or moisture limitations may help explain why linear models that include climate and geographic variables perform the best.

My linear models that predict site index of red spruce using my Chapman Richards three parameter function may be the best models to use as the site index values for red spruce using the Carmean et al (1989) publication may not be accurate. Red spruce that were sampled for the Carmean et al (1989) publication were located toward the northern portion of the range of red spruces (Burns and Honkala, 1990). Studies have shown that northern red spruce are not as affected by climate as central and southern red spruce (Koo et al. 2014; White et al., 2014; Walter et al., 2017; Kosiba et al., 2018; Mathias and Thomas, 2018). Data used to develop the Carmean et al (1989) site index model was collected in the 1920's (Meyer, 1929). Red spruce sampled in Meyers' 1929 study had different growing conditions and had probably not experience growth limitations from acid rain (Johnson, 1983; Kosiba et al. 2018). Because of the different growing conditions that the spruce in Meyers' 1929 study experienced, the Carmean et al. (1989) red spruce site index is probably not very representative of central Appalachian red spruce. My linear models use data that was only collected in the central Appalachians and should be more effective at predicting red spruce site index in the central Appalachian

region. Linear models that use associated species, climatic, and geographic variables, are critical for estimating site index in the central Appalachians as much of red spruces' home range is now dominated in forest cover other than red spruce (Thomas-Van Gundy et al., 2014; Nauman et al., 2015). In locations where red spruce is absent, these linear models could be useful for estimating site productivity in terms of height growth for red spruce. Being able to quantify locations with predicted site index values for red spruce would be a major advantage in selecting lands for future restoration activities to ensure management activities occurs on good sites to optimize return on investment and success (Geyer and Lynch, 1987).

3.5 Conclusion

My site index model that uses the three parameter Chapman Richards height model with guide curves could be useful for estimating central Appalachian red spruce site index values. This figure can allow foresters to estimate red spruce site index values in the field with easily collected age-height data for stands that have a red spruce component in the overstory. My Chapman Richards three parameter site index curves that use suppression corrected age may be more appropriate to use with anamorphic data to estimate central Appalachian red spruce site index values than previous site index models created for southern and norther populations of red spruce. For situations where red spruce is absent from the overstory, my linear models that use associated species could be helpful tools for estimating potential red spruce site index values. If resources allow, models that have the best AICc values should be used, but models with fewer parameters may be easier to implement in the field. The ability to estimate red spruce site index using linear models with associated species could help quantify land productivity in terms of red spruce site index where the species once existed. Predicted red spruce site index values could be used to refine lists of potential forest stands for red spruce restoration projects.

3.6 Tables and Figures

Table 3.1. Height models and corresponding statistics for models that use suppression corrected age values or DBH to predict total tree height of central Appalachian red spruce.

Model	Model #	Model Equation	R ² _{Adj}	PRESS	Bias - meters	Lower 95% C.I.	Upper 95% C.I.
Chapman Richards 3 Parameter Using Suppression Corrected Age to Predict Height	1	$Height = 1.37 + 26.301 (1 - e^{-0.0064*Age})^{-0.248}$	0.553	1287.007	-0.079	-0.944	0.786
Meyer Model Using Suppression Corrected Age to Predict Height	2	$Height = 1.37 + 28.587(1 - e^{-0.015*Age})$	0.548	1275.880	0.034	-0.836	0.903
Meyer Model Using DBH to Predict Height	3	$Height = 1.37 + 32.381(1 - e^{-0.028*DBH})$	0.560	804.850	-0.402	-1.096	0.293
Chapman Richards 3 Parameter Using True Age to Predict Height	4	$Height = 1.37 + 23.563 (1 - e^{-0.033*Age})^{-0.478}$	0.490	2608.81	-2.476	-3.558	-1.393
Meyer Model Using True Age to Predict Height	5	$Height = 1.37 + 24.546(1 - e^{-0.020*Age})$	0.470	1514.236	-0.084	-1.003	0.834

Table 3.2. Best performing models using stepwise regression with forward selection and subset regression. Models were created using associated species site index values, climatic variables, and geographic variables. Best performing models were identified by low AICc values and having all significant predictors in each model. Reference Table 3.3 for a legend of the abbreviated variables included in the following model.

Site Index Values	Regression Method	Model Number and Variables	Model Equation	AICc Value	R ² _{Adj}	P-Value	Press Statistic	
Carmean et al. 1989 Red Spruce Site Index Equation Estimates	Stepwise Regression with Forward Selection	Hardwood SI.	1	Si= 36.547+(0.35821*YB.SI.)	227.668	0.217	0.0003	2261.559
		Climate	2	Si= 266.162+(-0.064*DD_0)+(0.832*NFFD)+(-1.194*FFP)+(-4.717*EXT)	508.660	0.248	<0.0001	368.792
		Hardwood SI. and Climate	3	Si= 251.592+(0.280*YB.SI.)+(-0.069*DD_0)+(-0.895*NFFD)+(00.00*FFP)+(4.782*EXT)	338.193	0.307	0.0005	2190.021
		RM.SI. and Climate	4	Si= 92.981+(0.189*RM.SI.)+(0.576*NFFD)+(-0.817*FFP)+(-1.0*EXT)	358.619	0.258	0.0010	3104.815
		RM.SI. only	5	Si= 44.653+(0.20*RM.SI.)	234.510	0.095	0.0139	2978.384
	Subset Regression	BEST AICc -All Variables	6	Si= 2637.187+(20.950*Longitude)+(-48.561*MAT)+(-0.164*DD_18)+(0.273*NFFD)+(2.312*MAR)+(0.170*RM.SI.)+(0.323*YB.SI.)	222.172	0.548	<0.0001	870.841
		2 nd Best AICc- All Variables	7	Si= -417.048+(14.048*Latitude)+(-9.829*MWMT)+(5.724*TD)+(-0.132*DD_0)+(0.274*YB.SI.)	223.494	0.319	0.0004	2150.950
		3 predictor model only	8	Si= -3424.443+(34.626*SHM)+(-26.628*RM.SI.)+(0.307*YB.SI.)	228.694	0.298	0.0003	2089.359
	RM best AICc -All variables	9	Si= 641.727+(0.193*RM.SI.)+(12.689*MCMT)+(13.926*TD)+(-0.038*DD_18)+(0.859*NFFD)+(-2.033*FFP)+(-17.045*EXT)	390.007	0.095	0.0004	3733.512	
Chapman Richards Three Parameter Site Index Estimations	Stepwise Regression with Forward Selection	Hardwood	10	Si= 32.118+(0.0454*YB.SI.)	296.998	0.167	0.0009	5163.987
		Climate	11	Si= 2966.430+(-82.319*MAT)+(18.527*MWMT)+(-0.188*DD_0)+(0.816*NFFD)+(-7.601*bFFP)+(-5.322*FFP)+(8.287*EMT)	611.270	0.265	<0.0001	7234.620
		Combined	12	Si= 1024.460+(0.471*YB.SI.)+(-1.936*MAT)+(-4.925*bFFP)+(-2.256*FFP)	417.842	0.248	0.0008	4966.192
		RM	13	Si= 38.839+(0.335*RM.SI.)	434.251	0.148	0.0017	5996.427
	Subset Regression	Best AICc – All Variables	14	Si= -724.677+(0.236*YB.SI.)+(0.689*FFP)+(-0.058*DD5)+(-0.154*DD_0)+(22.516*Latitude)	270.201	0.309	0.0002	3389.645
		Best AICc – RM and YB	15	Si= 2250.182+(0.355*RM.SI.)+(0.572*YB.SI.)+(-90.307*MAT)+(28.537*MCMT)+(24.537*TD)+(-0.201*DD_18)+(-6.238*bFFP)+(2.565*FFP)	286.750	0.556	<0.0001	2808.421
		RM-Best AICc –All Variables	16	Si= 3277.033+(0.345*RM.SI.)+(-95.591*MAT)+(22.809*MWMT)+(-0.219*DD_18)+(0.703*NFFP)+(-8.511*bFFP)+(-5.605*FFP)+(8.376*EMT)	421.727	0.466	<0.0001	4568.323
		YB-Field Variables only	17	Si= -4683.004+(0.414*YB.SI.)+(44.376*Latitude)+(-37.604*Longitude)	418.765	0.217	0.0011	5029.613

Footnote: Si (Site index), YB.SI.(Yellow Birch Site Index), RM.SI.(Red Maple Site Index), MAT(Mean Annual Temperature), MWMT (Mean Warmest Month Temperature), MCMT (mean coldest month temperature), TD (MWMT-MCMT), SHM (summer heat-moisture index), DD_0 (degree days above 0 degrees Celsius, chilling degree days), DD5 (degree days above 5 degrees Celsius, Growing degree days), DD_18 (degree days below 18 degrees Celsius, heating degree days), DD18 (degree days above 18 degree Celsius, cooling degree days), NFFD(number of frost free days), FFP (frost free period), bFFP (day of the year on which FFP begins), eFFP (day of the year on which FFP ends), EMT (extreme minimum temperatures over 30 years), EXT (extreme maximum temperature over 30 years), MAR (mean annual solar radiation).

Table 3.3 Linear modeling variable legend. Climatic and geographic variables considered and used for linear site index modeling.

Directly calculated annual variables:	
MAT	mean annual temperature (°C),
MWMT	mean warmest month temperature (°C),
MCMT	mean coldest month temperature (°C),
TD	temperature difference between MWMT and MCMT, or continentality (°C),
MAP	mean annual precipitation (mm),
MSP	May to September precipitation (mm),
AHM	annual heat-moisture index $(MAT+10)/(MAP/1000)$
SHM	summer heat-moisture index $((MWMT)/(MSP/1000))$
Derived annual variables:	
DD_0	degree-days below 0°C, chilling degree-days
DD5	degree-days above 5°C, growing degree-days
DD_18	degree-days below 18°C, heating degree-days
DD18	degree-days above 18°C, cooling degree-days
NFFD	the number of frost-free days
FFP	frost-free period
bFFP	the day of the year on which FFP begins
eFFP	the day of the year on which FFP ends
PAS	precipitation as snow (mm) between August in previous year and July in current year
EMT	extreme minimum temperature over 30 years
EXT	extreme maximum temperature over 30 years
Eref	Hargreaves reference evaporation (mm)
CMD	Hargreaves climatic moisture deficit (mm)
MAR	mean annual solar radiation (MJ m ⁻² d ⁻¹)
RH	mean annual relative humidity (%)
Geographic variables:	
Slope	Average % slope
Latitude	Latitude - decimal degrees
Longitude	Longitude - decimal degrees
Slope-Aspect	Azimuth with Cosine transfer (Stage and Sales, 2007)
Elevation	Elevation in meters

Table 3.4. Correlation between site index variables for site index modeling including height, DBH (diameter at breast height), true age, and suppression corrected age.

Variable 1	Variable 2	Correlation	P-Value
True Age	Height	0.474	0.0002
Suppression Corrected Age	Height	0.670	<0.0001
True Age	DBH	0.442	0.0007
Suppression Corrected Age	DBH	0.645	<0.0001
Height	DBH	0.795	<0.0001
Suppression Corrected Age	True Age	0.844	<0.0001

Table 3.5. Red spruce suppression summary data showing average number of suppression periods and length of suppression. Ring width measurements for suppressed and free growth periods are also provided.

Average number of suppression period for each tree.	Average length of suppression	Average suppressed ring width	Average 10-year ring width before suppression	Average 10-year ring width after suppression
1.27	34.94 years	0.46 mm	1.11 mm (241 % wider than suppressed ring width)	1.62 mm (352 % wider than suppressed ring width)

Footnote: Average suppressed ring width for sampled trees is 241% more narrow than the 10-year free growth period before the suppression event, and 352% more narrow than the 10- year post suppression period after the suppression event.

Figure 3.2. Chapman Richards three parameter height model and guide curves with suppression corrected age and height data points used to develop the model. The model curve is marked with a solid black line, guide curves are marked with dashed lines, sample points are marked with dots.

Figure 3.3. Meyer model and guide curves with suppression corrected age and height data points used to develop the model. The model curve is marked by a solid black line, guide curves are marked with dashed lines, and sample points are marked with dots.

Figure 3.4. Meyer model and guide curves with DBH and height data points used to develop the model. The model curve is marked with a solid black line, guide curves are marked with dashed lines, and sample points are marked with dots.

Figure 3.5. Chapman Richards three parameter height model and guide curves with true age and height data points used to develop the model. The model curve is marked with a solid black line, guide curves are marked with dashed lines, sample points are marked with dots

Figure 3.6. Meyer model and guide curves with true age and height data points used to develop the model. The model curve is marked by a solid black line, guide curves are marked with dashed lines, and sample points are marked with dots

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Chapter 4: General Conclusions

4.1 General Conclusions

Dendroclimatic results from Chapter 2 highlight central Appalachian red spruces negative growth relationship with increasing mean and maximum summer temperatures. Increasing mean and maximum temperatures with predicted climate change will have negative impacts on red spruce growth. Growth declines from increasing future summer temperatures could be alleviated by growth increases resulting from an extended growing season. Future growth declines for central Appalachian red spruce is projected to be the least severe at northern Latitudes of the central Appalachians on southern aspects and at central latitudes on north facing aspects. My growth projection results can be used for future planning of restoration activities to select locations less likely to experience growth declines for best chances of red spruce survival and success. Future dendroclimatic studies that focus on central Appalachian red spruce at lower elevations would be useful to compare against my results to determine if lower elevation red spruce are at a higher risk of future decline, or if the dendroclimatic growth responses are comparable to my results.

My three parameter Chapman Richards site index curves can be easily implemented in the field to estimate red spruce site index for central Appalachian red spruce. My site index curve was created using recently obtained data from central Appalachian red spruce and may be a better alternative for forest managers to use as opposed to red spruce models created with data collected from northern or southern red spruce populations. My linear models developed to estimate red spruce site index using associated species, climatic, and geographic variables are important as a large portion of central Appalachian red spruces range has been replaced with associated species. Linear site index models using associated species could be important to help determine future areas where red spruce

restoration activities will be most productive and or successful. Future research involving stem analysis of central Appalachian red spruce will be utilized to create better performing site index models.

Linear models I developed to predict central Appalachian red spruce site index values that use associated species with climatic and geographic variables performed the best. This makes sense as my dendroclimatic results from chapter two show that central Appalachian red spruce is responsive to climatic and geographic conditions. Chapter two dendroclimatic results highlight red spruces positive growth relationship with an increased growing season. Similarly, many of the linear site index models listed in Chapter three uses degree days as significant predictors. Top performing linear site index models in chapter three use mean annual temperature as a significant predictor which supports my findings in Chapter 2, that central Appalachian red spruce growth is sensitive to mean temperatures. My dendroclimatic findings and site index models should be used and considered by forest managers in the future when planning red spruce restoration activities in the central Appalachians.