NEW DENDROCHRONOLOGICAL APPROACHES TO IDENTIFYING CLIMATE DRIVERS IN NORTHERN CONIFERS

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NEW DENDROCHRONOLOGICAL APPROACHES TO
IDENTIFYING CLIMATE DRIVERS IN NORTHERN CONIFERS

A THESIS SUBMITTED TO THE
DEPARTMENT OF GEOGRAPHY AND
HONORS COLLEGE

BY
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BURLINGTON, VT
MAY 2016
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ABSTRACT

The Northern Forest is a complex, heterogeneous environment which is undergoing changes in response to anthropogenic forcing factors. It is, therefore, necessary to quantify how trees have responded to environmental conditions in the past and may respond in the future. Traditional tree-ring width analysis enables the creation of temporally-expansive, annually-resolved records of yearly variability in tree growth. These tree-ring archives are well suited for researching which climate drivers have impacted forest growth most significantly and for identifying changes in the temporal stability of the climate signal over the 20th and 21st century. To perform this analysis, tree-ring width chronologies were developed for an eastern hemlock (*Tsuga canadensis*) stand, located at the Abbey Pond site in East Middlebury, Vermont, and red spruce (*Picea rubens*) stand, located in the Cape National Research Area (NRA) site, near Goshen Four Corners, Vermont, using increment cores sampled in 2010. A subset of each chronology was analyzed using blue intensity analysis (BIA), a novel dendrochronological technique which has been developed as a proxy for maximum latewood density (MXD) analysis. MXD has been utilized extensively in summer temperature reconstructions as it is capable of capturing a stronger, summer temperature signal. This study represents the first attempt to use BIA with eastern hemlock and red spruce trees and the first study within the US Northeast to incorporate BIA into dendroclimatological analysis. A combination of temperature, precipitation, and novel climate datasets were assembled to explore the drivers of growth of each forest stand. Several climate datasets, namely total percent cloudiness, total percent possible sunshine, and sunshine hours, to the best of our knowledge, have not been incorporated into past dendrochronology studies conducted in Vermont or the Northeastern US. Linear mixed model analysis was used to determine how much variability in annual growth could be attributed to climate drivers. 34% of the variance ($R^2 = 0.34$) in the Abbey Pond TRW chronology was accounted for using summer (JJA) precipitation and June PDSI as predictors of growth. 35% of the variance in the Abbey Pond BIA chronology was accounted for using minimum September temperatures and total percent cloudiness (TPC). Previous year temperatures in July and August and present year minimum temperatures in September accounted for 33% of the annual variance in the Cape NRA TRW chronology. Minimum spring temperatures were only able to account for 6.8% of the annual variance in the Cape BIA chronology.
CHAPTER 1: LITERATURE REVIEW

Introduction

Forests are undergoing rapid changes in response to anthropogenic pressures upon the landscape. Factors such as climate change, land-use change, acid-deposition, and the introduction of invasive species have altered the pre-industrial ecological status-quo. In New England, increased temperatures, precipitation amount, and a lengthening of the growing season will alter the rate of forest growth within the Northern Forest (Huntington et al. 2009; Groffman et al. 2012). Dendrochronology, the study of tree rings, offers researchers an annually resolved, long-term archive that can be used to assess how climate drivers have influenced forest growth via the relationship between climate and the annual variations in a tree-ring width.

In addition to identifying the principal climate drivers, it is necessary to explore how these drivers’ significance has evolved in response to an evolving ecological landscape. Northern environments are especially complex and present challenges for tree-ring research. Unlike environments in the US Southwest and Fennoscandia, many environmental factors (both exogenous and endogenous to the forest stand) are represented in Northern Forest tree-ring chronologies. We will evaluate which climate drivers contribute most significantly to forest productivity and determine the amount of annual variability which cannot be ascribed to climate drivers (e.g. acid deposition, stand dynamics, stochastic variability, etc.). A novel method of tree-ring analysis, blue intensity analysis (BIA), will be used in conjunction with tree-ring widths. Blue intensity analysis may prove to be a powerful technique for extracting a stronger climate signal than ring-widths. Additionally, less explored climate variables will be used to assess how the relationship between annual growth and climate has evolved over the last century.
Part I: The Landscape

The Northern Forest

Northern Forests, including those in Vermont, are composed of deciduous trees at lower elevations which transition into conifers at higher elevations (Siccama 1974; Beckage et al. 2008). Common species at lower to middle elevations include beech (*Fagus grandifolia*), eastern hemlock (*Tsuga canadensis*), ash (*Fraxinus americana*), and maple species (*Acer saccharum* and *Acer rubrum*) (Siccama 1974). At higher elevations, red spruce (*Picea rubens*) and balsam fir (*Abies balsamea*) dominate forest stands (Siccama 1974). The structure and composition of Vermont’s forests is characterized by a transitionary zone called the northern hardwood-boreal forest ecotone (NBE), which is located along the elevation gradient of the Green Mountains (Siccama 1974; Siccama et al. 1982; Beckage et al. 2008). Past research classified the transitional zone into three subdivisions with hardwoods dominating at lower elevations, the middle elevations possessing a mix of hardwoods and conifers, and the highest elevations containing conifer-dominate stands (Siccama 1974). The high elevational subdivision is characterized by the disappearance of mountain maple (*Acer spicatitmun*) and hobble-bush (*Viburnum alnifolium*) from the forest understory (Siccama 1974). These assessments of the transitional zone, characterized the NBE as being highly defined with the deciduous to spruce-fir transition occurring at 760-880m in Vermont and boreal species dominating at elevations >880m (Siccama et al. 1982; Cogbill and White 1991). However, recent, large-scale landscape analysis has determined that this traditional conception of the NBE fails to account for ~20-40% of the transitional areas. (Foster and D'Amato 2015). Transitional areas varied from a linear transition between hardwood and boreal species to a lack of a discernable ecotone (Foster and D'Amato 2015).
Multiple environmental factors are predicted to influence the structure and composition of the Northern Forests. For example, studies have evaluated the overarching dynamics causing changes in the NBE’s location. Using global climate models, researchers have predicted a northward migration of southern tree species in response to climate change, which may correspond to a upward movement in the NBE (Iverson et al. 2008). Beckage et al. (2008) predicted an upslope shift in the NBE, allowing for the upward migration of deciduous trees, based upon forecasts of climatological (e.g., warming temperature) and associated ecological factors. However, subsequent research found that the upper and lower edges of the ecotone predominantly shifted downward between 1991-2010, with only 13% and 15% of the upper and lower ecotone edges having migrated upslope (Foster and D’Amato 2015). The conflicting accounts of the NBE migration highlights the complex climatological and ecological factors which influence the distribution and competition between northeastern tree species. When performing research in the Northern Forests, the NBE can serve as a landscape wide barometer to predict how habitat suitability for species in northeastern forests is evolving. The NBE also reflects the competition between conifer and deciduous species which occurs within Northern Forests. Within the context of assessing climate’s impact upon growth, competition between species is effectively noise that will obscure the climate signal.

*Red spruce*

Red spruce (*Picea rubens*) is a conifer found throughout the northeastern United States in cool, moist climates (Burns and Honkala 1990). The species is shade tolerant, relatively long lived (>400 years), and grows to a medium size (Burns and Honkala 1990). Within the northern extent of its distribution, the species becomes abundant in spruce-fir stands from 790 m up to
1370 m in elevation (Burns and Honkala 1990). Within the Green Mountains, spruce-fir forests begin to emerge from the hardwood-broadleaf forest stands around 792m (Siccama 1974). Red spruce can be suppressed within the understory, with low rates of growth for decades before being released into the upper canopy (Burns and Honkala 1990). Historically, the migrations of conifers near their northern latitudinal limits tend to be restricted by low temperatures with red spruce possessing a unique ecological niche due to its latent photosynthetic capabilities (Martin-Benito and Pederson 2015).

*Eastern hemlock*

Eastern hemlock (*Tsuga canadensis*) is a long-lived conifer (>800 years) found throughout the northeastern and mid-Atlantic United States in regions with cool, humid climates drainage (Burns and Honkala 1990). The species reaches maturity in 250-300 years with the typical adult growing ~30 m tall (Burns and Honkala 1990). The species is shade tolerant and produces an acidic litter layer which limits understory growth within eastern hemlock stands (Burns and Honkala 1990; Paradis et al. 2007). The species’ shade tolerance and slow rate of growth can allow for trees to remain suppressed for 200 or more years (Burns and Honkala 1990). In the United States, eastern hemlock are presently suffering population declines and increased rates of mortality due to the an invasive species, the hemlock woolly adelgid (HWA) (Paradis et al. 2007). The HWA is an insect which feeds off the sap in the needles of the eastern hemlock, resulting in a decline in crown vigor and potentially death, notably among smaller, less established hemlock trees (Orwig and Foster 1998; Foster and D'Amato 2015).
Impacts of climate change on northern forests

Global climate change has continually altered climatological and ecological dynamics within the Northern Forests. Since the mid-1950s, the growing season has lengthened by an average of 2.6 days per decade (Groffman et al. 2012). Precipitation has increased by 7% - 14% within the same time period (Huntington et al. 2009). Measurements at the Hubbard Brook Experimental Forest in New Hampshire recorded a greater change in precipitation with a 13 – 28% increase over the span of 50 years (Groffman et al. 2012). Data from general circulation models (GCMs) indicate temperatures across New England will rise 2.1° C – 2.9° C by 2035 – 2064 (Huntington et al. 2009). Yet, under high and low emissions projections for 2080, northern New England is projected to have lower rates of precipitation and temperature change relative to coastal regions (Horton et al. 2014). In addition, the rate of climate change in montane regions is typically slower due to the effects of topography and may stay within the bounds of historically observed rates (Loarie et al. 2009).

Understanding the influence of changes in moisture availability in the Northern Forest is especially important because drought has been identified as an important stressor on tree growth (Pederson et al. 2014; Martin-Benito and Pederson 2015). While the northeastern United States is typically thought of as a mesic region, periods of drought (e.g. the drought of the mid-1960s) do occur. Dendroclimatological evidence shows that this period was the longest and most intense event in the northeastern US during the 20th and 21st centuries (Pederson et al. 2013). The impact of drought on forest ecosystem dynamics cannot be underestimated. In a recent large-scale analysis of tree-ring chronologies from sites across the eastern United States, Pederson et al. (2014) demonstrated that broadleaf forests can be significantly affected by drought and that severe events are capable of causing a synchronous disturbance at spatially extensive scales.
In a separate study which focused on the greater Northeastern United States, Martin-Benito and Pederson (2015) identified moisture availability as the dominant climatic driver within broadleaf forests (Martin-Benito and Pederson 2015). Specifically, low overall precipitation amounts, despite a cooler, northern climate, increased drought sensitivity within forests (Martin-Benito and Pederson 2015). This presents an interesting situation for broadleaf forests within Vermont as both the amount of precipitation and regional temperatures are expected to increase in the near-term, influencing broadleaf forest growth in an inverse manner. Martin-Benito and Pederson (2015) speculated, based upon existing estimates of changes in annual precipitation, that the net impact would be increased growth. This could enhance the ability of broadleaf species, such as sugar maple, to compete with conifers in mixed, lower-elevation forest stands.

Beginning in the 1960s, red spruce underwent a decline in growth that has been attributed an increased vulnerability to foliar winter injury events and a reduction in the species’ capacity to recover following injury (Cook and Johnson 1989; Kosiba et al. 2013; Engel et al. 2016). Species distribution modeling based on climate change projections has predicted that red spruce will experience a reduction in habitat area as the species climate envelope is diminished (Iverson et al. 2008). However, recent landscape analysis has found that the NBE has shifted downward, despite predictions of upwards movement (Foster and D’Amato 2015). The recovery of red spruce was hypothesized to have been prompted by improved air quality and warmer winters coupled with an increased pressure from environmental stressors placed upon hardwood competition (Foster and D’Amato 2015). Recent evidence suggests that red spruce has experienced an unprecedented rebound in the last decade (Kosiba et al. 2013), yet the extent to which climate change has contributed to red spruce growth has not yet been fully quantified.
Eastern hemlock is characterized as a moisture-sensitive species and has been used previously in multiple paleoclimatic reconstructions and investigations of past moisture in the eastern United States (Pederson et al. 2012; Pederson et al. 2013; Belmecheri et al. 2014). It is unclear how a changing climate will affect this species, but indirect effects due to increasing temperatures during the winter season may leave the species vulnerable to the hemlock woolly adelgid (*Adelges tsugae*) as this invasive pest expands further northward into northern New England (Paradis et al. 2007).

**Red spruce, acid deposition and winter injury events**

Since its identification in the 1960s (Likens et al. 1972), acid deposition has had significant repercussions on forest health in the Northeastern United States through the depletion of forest calcium (Ca) pools (DeHayes et al. 1999). Anthropogenic emissions of nitrogen (N) and sulfur (S) combine to produce acid rain which mobilizes soil-extractable aluminum (Al), leaching Ca-cations from the soil (DeHayes et al. 1999; Halman et al. 2011). Declines in tree health as a result of acid deposition have been documented in numerous species including red spruce, sugar maple (*Acer saccharum* Marsh.), mature paper birch (*Betula papyrifera* Marsh.) and heart-leafed paper birch (*B. papyrifera var. cordifolia* (Regel) Fern.) (Halman et al. 2011). Calcium has been identified as a regulator of a tree’s physiological response to environmental stressors (Halman et al. 2008; Schaberg et al. 2011). Red spruce possess the ability to engage in photosynthetic activity during the winter season if temperatures are sufficiently warm, with the trade-off of an increased risk of foliar injury if low temperatures return suddenly (average injury temperature of -41.7°C) (DeHayes et al. 1999; Schaberg et al. 2011). Calcium regulates the
toggling of red spruce’s winter photosynthesis capacity; a reduction in calcium diminishes the species’ ability to respond to changes in temperature (DeHayes et al. 1999).

A number of studies have characterized the decline of red spruce in relation to acid deposition. An assessment of 37 red spruce chronologies distributed throughout Vermont and New Hampshire attributed critical load exceedance of nitrogen and sulfur as the cause of significant variations in the mean BAI growth from the 1950s to the present (Engel et al. 2016). The critical load for pollutants represents the threshold beyond which calcium leaching will occur (Engel et al. 2016). Studies have found that red spruce’s recovery from winter injury events changes across an elevational gradient with higher-elevation stands (>920 m) influenced by suboptimal growing conditions (e.g. greater cloud cover, thinner soil, etc.), and low-elevation stands (<765 m) suffering from competition by hardwood species (Kosiba et al. 2013). Red spruce trees on Bolton Mountain, Vermont were impacted by sub-decadal winter injury events, predominantly in the high altitude trees, which resulted in a significant decline in productivity during subsequent recovery periods (Gavin et al. 2008). However, recent evidence indicates that red spruce may be experiencing a growth resurgence due to yet unidentified causes (Kosiba et al. 2013).

**Part II: Methods of Dendrochronological Exploration**

*Dendrochronology*

Dendrochronology, the study of tree rings, is a scientific discipline that utilizes tree-ring analysis to derive information about past climate and the environment. Tree-ring chronologies are an annually resolved, long term archive which record periods of influence caused by
individual tree age-effects, climate, endogenous (inter-stand dynamics) and exogenous (extra-stand influences) events, as well as other non-quantifiable influences (i.e., noise) (Pilcher et al. 1990). While multiple factors may influence tree productivity, a tree’s growth is dictated by the primary growth-limiting factor within the stand (Pilcher et al. 1990). Accordingly, by selecting forest stands at sites where tree growth is restricted by a particular limiting factor (e.g., growth at a xeric site will likely be dominated by the availability of moisture), dendrochronologists can sample trees to target specific variables for investigation. By collecting increment cores from multiple trees within a forest stand, the variability in growth response for each individual tree can be averaged out and an aggregate growth-index for the site can be developed.

To ensure the temporal accuracy of the tree-ring chronologies, dendrochronologists have developed crossdating techniques which allow exact calendar dates to be assigned to each ring in the chronology (Yamaguchi 1991; Stokes 1996; Speer 2010). The chronologies can then be compared to environmental data compiled at the same or finer temporal scale (e.g., annual, seasonal, monthly). By incorporating samples from dead or semi-fossilized trees, researchers have produced well-replicated chronologies extending more back more than a millennium. In addition, the global distribution of trees enables dendrochronologists to aggregate multiple site chronologies on a spatially expansive scale (from watershed to Northern Hemisphere) while providing annual or sub-annual measurements.

**Blue Intensity Analysis**

Trees are referred to as multi-proxy archives because it is possible to extract data beyond tree-ring widths. Proxies like stable isotope analysis have been demonstrated to record different environmental signals than the corresponding tree-ring width chronologies (Young et al. 2010).
Alternatively, other techniques, such as density analysis, are valued for the ability to produce a stronger climate signal when compared to tree-ring widths (Wilson et al. 2016). The research that has contributed to the development of Blue Intensity Analysis (BIA) has been largely motivated by an interest in developing a surrogate for Maximum Latewood Density (MXD) measurements. MXD time-series are valued for their ability to produce strong climate reconstructions with low levels of replication (Parker and Henoch 1971; Schweingruber et al. 1988; Wilson et al. 2014). However, the production of MXD measurements is time consuming, requires specialized equipment, and can be expensive (Parker and Henoch 1971; Schweingruber et al. 1978). Recent efforts to derive Northern Hemisphere summer temperatures from dendrochronological materials found MXD (and BIA) data outperformed tree-ring-width measurements and suggested that ring-widths alone may be insufficient for robust, millennium-scale reconstructions (Wilson et al. 2016). As such, there is a need to evaluate the capabilities of BIA to act as a surrogate for MXD chronologies, to make an affordable but robust alternative available to dendrochronologists.

The origins of BIA lie in the image-analysis of tree-rings. Researchers employed digital imagery or video image analysis to derive information suitable for climate reconstructions from the structure and wood anatomy of radial-growth increments (Yanosky and Robinove 1986; Yanosky et al. 1987; Park and Telewski 1993). Yanosky et al. (1987) made the significant discovery that brightness profiles measured across ring-boundaries were similar to x-ray densitometry profiles. Following these initial developments in the image-analysis of tree-cores, researchers began to focus their efforts on the utility of reflected light from tree-core surfaces. Subsequent research between brightness parameters and MXD data found that the strongest cross-correlation relationship was between minimum latewood brightness and the MXD (Sheppard et al. 1996). Additionally, sample discoloration, either by anomalous discoloration or
through storage of phenols and photosynthetic byproducts, was identified as a key source of error which distorted the brightness signal (Sheppard et al. 1996; Pallardy 2010).

Advancements in technology allowed customized camera-microscope setups to be replaced with conventional, flatbed scanners (McCarroll et al. 2002). Comparisons between MXD and red, green, blue, UV, and infrared latewood brightness values found that minimum blue reflectance \( (r = -0.951) \) and average blue reflectance \( (r = -0.953) \) had the strongest correlation \( (p < 0.05) \) with the MXD time series (McCarroll et al. 2002). Campbell et al. (2007) performed the first significant assessment of BIA analysis by comparing the summer temperature reconstructions developed from minimum blue reflectance \( (B_{min}) \) and MXD chronologies for three *Pinus sylvestris* stands in Finland. Blue intensity data were well correlated with the MXD chronologies at the three test sites (mean \( r = -0.84) \). July – August temperatures from the longest-running metrological dataset used in the study were significantly correlated \( (p < 0.05) \) with the blue intensity \( (r = -0.65) \) and MXD \( (r = 0.58) \) measurements.

Following the initial findings which demonstrated BIA’s potential to act as a surrogate for MXD measurements, a number of studies developed improved procedures for producing high-quality blue intensity data. Initial preparation of the samples, either increment cores or lathes, were performed according to standard dendrochronological practices (Stokes 1996; Speer 2010). Samples required sanding to a fine grit (>600) to emphasize ring boundaries in the scanned images (Babst et al. 2009; Campbell et al. 2011). Samples should be refluxed in ethanol for 40 hours to remove the near-surface resins which result in discoloration and skewed blue intensity values (Campbell et al. 2011). Campbell et al. (2011) suggested the calibration of the program WinDendro be performed using a Monaco EZ-color card to allow brightness measurements generated by using different scanners to compared directly and to compensate for
scanner bulb dimming. The presence of ambient light while scanning was found to introduce significant bias in the BIA measurements (Rydval et al. 2014). Isolation of the scanning bed by enclosing it with a box whose interior was coated in a dark, matte finish was sufficient to remove the influence of ambient light (Rydval et al. 2014). Recently, researchers have transformed the blue intensity measurements by inverting them (multiply by -1) to allow direct comparisons with MXD values (e.g. the minimum blue reflectance value becomes the maximum reflectance value) (e.g., Rydval et al. 2014; Wilson et al. 2014).

Subsequent work in BIA has attempted to resolve the issues associated with sample discoloration. Björklund et al. (2013) introduced the parameter ΔBI, developed by subtracting the minimum blue intensity value (BI_{Min}) from the maximum blue intensity value (BI_{Max}) for each ring measurement. Similar to previous adjustments proposed by Sheppard et al. (1996), this reduces the systematic bias resulting from sample discoloration. Additionally, removing the earlywood blue intensity values from the latewood values eliminates the spring growth signal from the summer growth (June, July, and August), more effectively isolating the summer temperature signal (Linderholm et al. 2014). ΔBI possessed a strong correlation with transformed MXD values across a multi-generational, 800-year chronology (Björklund et al. 2014). However, the chronology still suffered from issues related to heterogenous discoloration between different samples. Björklund et al. (2015) proposed a methodology to contrast adjusted BIA data in the absence of MXD data. First, the sample mean for the earlywood blue intensity (EWBI) data is calculated (\overline{EWBI}). Then, the EWBI data and latewood blue intensity (LWBI) data are pooled into a single group P_{BI}. The entire group can be adjusted based upon parameters derived from their study. The pooled data, P_{BI}, are then transformed into P_{BI adjusted} through the following calculation:
(1) $\alpha = 0.048 \times \overline{\text{EWBI}} + 3.0$

(2) $\beta = -12.6 \times \overline{\text{EWBI}} + 838$

(3) $P_{\text{BI adjusted}} = \alpha \times P_{\text{BI}} + \beta$

The pooled values are then separated back into two groups, $\text{EWBI}_{\text{Adj}}$ and $\text{LWBI}_{\text{Adj}}$ and transformed into the parameter $\Delta \text{BI}_{\text{Adj}}$ through the following transformation:

(4) $\Delta \text{BI}_{\text{Adj}} = \text{LWBI}_{\text{Adj}} - \text{EWBI}_{\text{Adj}}$

For the development of the parameter $\Delta \text{BI}_{\text{Adj}}$ to be successful, the scanning protocol described in Björklund et al. (2014) should be followed.

A number of studies using BIA have focused on evaluating the proxy’s performance to reconstruct summer (June, July, and August) temperatures and its ability to act as a surrogate for MXD. A 1200-year multi-proxy reconstruction of summer temperatures from Northern Europe to the Kola Peninsula, Russia, incorporated blue intensity time series alongside ring-width and MXD chronologies (McCarroll et al. 2013). The chronology was correlated ($r = 0.81$, $P<0.05$) with summer temperatures and quantified how volcanic eruptions impacted pre-industrial summer temperatures in the far north of Europe. Linderholm et al. (2014) incorporated three $\Delta \text{BI}$ timeseries alongside seven $\Delta \text{MXD}$ timeseries and performed a regional reconstruction of Fennoscandia summer temperatures spanning 900-years. The adjusted values were found to capture both short-term and long-term variability, suggesting that long-term studies using BIA will need to incorporate adjustments to capture centennial variability. This indicates that these adjustments to BIA data may have resolved earlier problems noted in Wilson et al. (2014), in which BIA time series failed to capture low-frequency (centennial) variability. Recent efforts to produce a millenium-scale reconstructions of Northern Hemisphere summer temperature
incorporated BIA chronologies and indicated that they produced a more robusted temperature reconstruction than tree-ring widths (Wilson et al. 2016).

Conclusion

In the following chapter, we will utilize tree-ring-derived chronologies to assess which environmental variables dominate the growth of two dominant tree species in the Northern Forest. Two metrics, tree-ring width and blue intensity, will be used in the analysis. Blue intensity is a novel technique whose prior applications has predominantly focused on a single species (scots pine; *Pinus sylvestris*) and has been used to reconstruct a single variable (maximum summer temperature) (e.g. McCarroll et al. 2013; Björklund et al. 2015; Wilson et al. 2016). In order to assess the utility of this technique in a broader context, it is necessary to test it on different tree species and in different forest ecosystems. Two species that have not yet been explored using BIA, eastern hemlock and red spruce, will be used in this study. Our study will help determine whether the investment of time and resources in obtaining BIA data from these chronologies is worthwhile in identifying a stronger or alternative climate signal. Based on previous studies of other tree species (e.g., Rydval et al. 2014; Wilson et al. 2014), we anticipate that the blue intensity chronologies will allow for the identification of a stronger relationship with a growth-limiting factor over tree-ring chronologies in each of the two stands.
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CHAPTER 2: NEW DENDROCHRONOLOGICAL APPROACHES TO IDENTIFYING CLIMATE DRIVERS IN NORTHERN CONIFERS

Abstract

Quantifying the influence of climate on tree health and productivity in the Northern Forest of New England is necessary for understanding how trees have responded to environmental conditions in the past and may respond to changing conditions in the future. Tree-ring width (TRW) and Blue Intensity Analysis (BIA) chronologies were developed for a low-elevation eastern hemlock (*Tsuga canadensis*) stand and a low-elevation red spruce (*Picea rubens*) stand in the Green Mountains, Vermont, USA. This study represents the first attempt to use BIA with eastern hemlock and red spruce trees within the Northeastern United States for dendroclimatological analysis. Correlation and response function analysis relating the chronologies to multiple temperature and precipitation datasets, a moisture index, and other novel climate variables were used to explore the dominant climate drivers within each forest stand over the past 115 years. Further analysis using mixed models found that climate drivers related to moisture variability were capable of explaining 35% of the variance for eastern hemlock TRW ($R^2 = 0.34$) and BIA ($R^2 = 0.35$) chronologies. Similar variability in red spruce TRW chronologies was captured by previous summer temperature signal ($R^2 = 0.33$). The red spruce BIA model captured only 6% ($R^2 = 0.068$) of the variance and was dominated by a weak spring temperature signal. Our study demonstrates that while climate can predict approximately a third of the annual growth trend in three of the four chronologies, almost 2/3rds of the total annual growth signal could not be quantified with climate drivers. The unexplained variability could potentially be the result of stand dynamics and endogenous disturbances, atmospheric pollution (e.g. CO$_2$ fertilization), topography, and stochastic variability (e.g. noise). Further stand level analysis is needed to identify and quantify the role of environmental and site specific variables in addition to climate. BIA was found to perform less well than TRW chronologies, possessing notably lower levels of interseries correlations. This may be attributable to heterogeneous variability in the lignin content across our samples or other issues arising for inadequate sample depth.
Introduction

Dendrochronology, the study of tree rings, is ideally suited for the analysis of climate’s impact upon forest growth. The ability to produce annually resolved records of forest growth over long time periods enables researchers to quantify how, why, and when climate change has altered forest growth regimes. Additionally, the proxy records offered by tree-ring-based chronologies can help to determine how the significance of climate drivers has evolved over time in response to global climate changes.

Dendroclimatic studies of Northern Forest tree species are limited. Previous studies in the eastern United States have utilized tree-ring chronologies to identify how drought stressors can produce synchronous disturbances within deciduous forests (Martin-Benito and Pederson 2015). Broad, multi-species analyses produced a multi-century reconstruction of soil moisture availability for the New York City watershed (Pederson et al. 2013). In Vermont, red spruce chronologies (Picea rubens) have been used to investigate the impacts of acid deposition and winter injury events (Kosiba et al. 2013; Engel et al. 2016). However, few studies have explicitly sought to quantify the influence of climate drivers in the Northern Forest and none have considered BIA as a potential metric of yearly productivity.

The analysis of reflected blue light, measured within the latewood portion of a tree ring, is a newly developed technique which can potentially yield a stronger climate signal than tree-ring widths. The development of blue intensity analysis (BIA) has been motivated by the need to create a more affordable proxy to maximum latewood density (MXD) measurements – the “go-to” tree-ring-based measurement for developing strong temperature reconstructions. However, the specialized equipment and costs associated with producing MXD data have prevented the technique’s proliferation and has limited the exploration of MXD data. A recent reconstruction
of Northern Hemisphere summer temperatures based upon tree-ring data found that MXD (and BIA) chronologies produced a more robust millennial reconstruction of temperature than traditional tree-ring width chronologies (Wilson et al. 2016). A number of studies have found blue intensity data to be well correlated with MXD data (Campbell et al. 2011; Wilson et al. 2014). BIA is more affordable than density analysis and can be developed with commercially available scanning equipment (Campbell et al. 2007; Campbell et al. 2011). However, BIA analysis has been limited in its application. Principally, it has been used to reconstruct single variable, high-latitude, summer temperatures, and has predominantly utilized a single species, scots pine (*Pinus sylvestris*) (e.g. McCarroll et al. 2013; Björklund et al. 2014; Linderholm et al. 2014; Wilson et al. 2014). It is, therefore, necessary to investigate how and whether BIA can be used on different species and in mid-latitude forests.

In this study, the primary goal was to identify the principal climate drivers of growth for two temperate conifer species, eastern hemlock (*Tsuga canadensis*) and red spruce (*Picea rubens*) found in the Northern Forest using dendrochronological techniques. To this end, annually-resolved, long-duration tree-ring width and blue intensity chronologies were developed for two sites in the Green Mountains, Vermont, USA. While tree-ring width chronologies exist for eastern hemlock and red spruce, blue intensity chronologies have not been previously developed for these species. Following development of the chronologies, the temporal stability of the climate signal(s) over the 20th and 21st century for each species was quantified to explore the potential change in climate-chronology relationships. Novel climate datasets will be explored alongside traditional monthly precipitation and temperature data to more thoroughly investigate the relationship between climate and tree growth. This information will help
determine whether producing BIA data is worthwhile for subsequent investigations of climate drivers within Northern Forests.

**Methods**

***Site Information***

Two forests stands were sampled for tree-ring analysis (Fig. 1). The Abbey Pond site (ABP: 44.032088°N, 73.082600°W; 300 m a.s.l.), located in East Middlebury, Vermont, is comprised of large grove of dominant eastern hemlock (*Tsuga canadensis*) and white pine (*Pinus strobus*) trees. The forest is characterized by low-levels of understory growth with sub-dominant sugar maple (*Acer saccharum*), yellow birch (*Betula alleghaniensis*) and American beech (*Fagus grandifolia*). A stream was noted to be running throughout the hemlock stand.

The Cape National Research Area (NRA) site (Cape: 43.815380°N-72.988375°W; 670 m a.s.l.), situated in Green Mountain National Forest, Vermont, is a steep (40°), spruce-dominated (*Picea rubens*) stand with co-dominant sugar maple, along with paper birch (*Betula papyrifera*) and sugar maple in the middle canopy.

***Dendrochronology***

Increment cores were taken from 20 trees considered to be dominant within the forest canopy at each site. The increment cores were retrieved at breast height (1.3m), parallel to the contour of the slope to avoid compressional growth on opposing sides of the stem (Speer 2010). Samples were processed according to standard dendrochronology procedures (Stokes and Smiley 1996; Speer 2010) and measured on Velmex sliding stage unit (accuracy of 0.001mm) using the software Measure J2X. Crossdating was manually performed using list method (Yamaguchi
and then verified statistically using the software COFECHA (Holmes et al. 1986; Grissino-Mayer 2001) (Table 1).

Individual tree-ring width series were standardized in the program ARSTAN. This program produces chronologies from tree-ring measurements by detrending and indexing (standardizing) the series, then applying a robust estimation of the mean value function to remove the effects of endogenous stand disturbances. Detrending involves fitting a curve to the ring-width series, and then dividing each ring-width value by the corresponding curve value to generate growth index metrics. This process allows samples with large differences in growth rates to be combined, and can be used to remove any undesired growth trends or other non-climatic influences on stem radial growth (www.ncdc.noaa.gov/paleo/treeinfo.html; accessed April 2016).

The variance within the chronologies was stabilized using an adaptive power transformation (Cook and Peters 1997; Martin-Benito and Pederson 2015) to produce homoscedastic indices, from which the chronologies were standardized using the linear regression (negative slope) method (Cook 1985). For each site, the individual tree-ring series were averaged into site chronologies using the biweight robust estimation of the mean (Cook 1985). Chronology quality statistics including the Expressed Population Signal (EPS; Wigley et al. 1984), the Subsample Signal Strength (SSS; Wigley et al. 1984), the signal-to-noise-ratio (Fritts, 1976) and the mean between-series correlation (RBAR) were examined to assess the signal strength of the detrended series. The common period of analysis for the chronology quality statistics was 1900-2010. The ARSTAN chronologies which had the strongest correlations across a greater number of the climate variables were selected for further analysis.
The standard (STD) chronology was selected for the Abbey Pond site and the residual (RES) chronology was selected for the Cape site.

**Blue intensity analysis**

Sixteen samples from the Abbey Pond site and 9 samples from the Cape NRA site were analyzed for blue intensity (BIA). The blue intensity data were developed according to the protocol described in Campbell et al. (2011). Prior to measurement, cores were refluxed with ethanol in a Soxhlet extractor for 40 hours to extract resins and minimize sample discoloration. The cores were then measured for blue intensity values using the software package WinDENDRO and a high quality scanner. The increment cores were scanned at 1000 DPI. In WinDENDRO, the reflected blue-light value for the latewood portion of each tree-ring was measured three times to obtain an average value for each latewood segment. Scanner calibration was performed using a Monaco EZ color card. The final year of the chronology, 2010, was omitted from blue intensity chronologies because the samples were collected before the latewood could fully develop. The BIA chronologies were crossdated based on the tree-ring width chronologies (see above) and then standardized with ARSTAN using the same procedure described above for the tree-ring width chronologies.

Unlike previous studies which have utilized BIA to reconstruct climate drivers (e.g. Rydval et al. 2014; Wilson et al. 2014), these blue intensity chronologies were not inverted (see transformation described in Rydval et al. 2014). Previously, this inversion was performed to allow for a direct comparison between blue intensity data and MXD measurements which share an inverse relationship (Rydval et al. 2014). As no MXD chronologies were included in this study, this was not viewed as necessary. Thus, in this study, lower BIA values indicate better
growth. As such, a negative correlation between a climate variable and the BIA data indicates the tree responded positively to increases in the climate variable.

**Climate Data**

Monthly temperature and precipitation values (1895 - 2010) were retrieved from the PRISM Climate Group’s (Oregon State University; [www.prism.oregonstate.edu/](http://www.prism.oregonstate.edu/); accessed April 2016) 800m, gridded AN81m dataset. Variables included monthly minimum temperature ($T_{\text{min}}$, °C), mean temperature ($T_{\text{mean}}$, °C), maximum temperature ($T_{\text{max}}$, °C), and precipitation totals (PPT, mm). Monthly Palmer Drought Severity Index (PDSI) values were selected as an additional metric to assess the influence of moisture variability ([www.ncdc.noaa.gov](http://www.ncdc.noaa.gov); accessed April 2016).

The influence of photosynthetically active radiation (PAR) has not been explored with blue intensity tree-ring data because long-term PAR chronologies are not readily available to researchers. Three proxy variables were selected to capture PAR: total sunshine hours (TSSH; 1946-2008), total percent possible sunshine (TPPS; 1920-2008), and a diametrically-related variable, total percent cloudiness (TPC; 1944 - 1995). Several of these variables have previously been explored in studies which have evaluated stable isotope ratios within tree-rings from high latitude, cool, moist forest species (Gagen et al. 2007; Young et al. 2010). The TSSH, TPPS, and TPC datasets were developed from observational records produced by the Burlington, VT metrological station (44.4683°N, 73.1499°E; elevation 100.3 m). The monthly values for the TSSH, TPPS, and TPC datasets were produced from averaged daily, visual observations. The metrological station is located 55.65 km away from the ABP site and 78.6 km away from the Cape site.
Statistical analyses were performed using the dendrochronology software package DENDROCLIM2002 (hereafter referred to as DendroClim). DendroClim runs correlation and response functions between environmental datasets and tree-ring timeseries (Biondi and Waikul 2004). The correlation function utilizes the coefficients to estimate Pearson’s product moment correlations (Biondi and Waikul 2004). The response function is intended to show the relative effects of each monthly variable by using coefficients from a principal components regression model for identification (Fritts 1976; Biondi and Waikul 2004). The response function coefficients are useful for identifying the stability of the relationship over time. The software utilizes boot-strapped confidence intervals to evaluate the significance of both the correlation and response functions ($p < 0.05$) (Biondi and Waikul 2004).

Single interval analysis (entire period of overlap common to both datasets) was used to assess the relationship between monthly climate variables (see below) and the tree-ring-based chronologies. A 17-month period was explored beginning in May of the previous year to September of the current year. This time frame would allow for potential climate relationships in the early growing season of the previous year through the termination of the present year growing season to be identified. In addition, seasonal periods (e.g., June, July, August) were also investigated. Investigation of relationships between tree-ring based metrics and previous-year climate variables may account for integrative effects across and between growing seasons.

DendroClim is additionally capable of evaluating the correlation and response functions for moving intervals. In environments where tree-ring-based metrics are not governed by a single environmental factor, moving intervals are better suited to showing relationships between tree growth and multiple climate variables (Biondi 1997). The moving variables are additionally
capable of demonstrating how the influence of climatic parameters evolve over long periods of time. This is especially important in the 20th and 21st centuries, during a period of rapid climate change. The moving windows iterate from the most recent year of growth backwards in time, calculating correlation and response function coefficients, until the end of the chronology is reached (i.e. the final year of a moving window for which it was calculated for is equal to the chronology length, less the specified base length) (see: Biondi and Waikul 2004). Thirty-four-year moving windows were selected to assess higher frequency variability changes in the data. Fifty-year moving windows were used to investigate low frequency variability. As DendroClim requires the moving interval to be less than 80% the base length of the chronology, a 41-year window was used to accommodate the shorter length (51 years) of the TPC dataset; all other datasets utilized the 50-year window.

Partial correlation and linear mixed model regression analyses

DendroClim analysis acted as a first pass to identify which climate variables individually correlated with TRW and BIA. Subsequently, partial correlation analysis was performed using the significant (P<0.05) DendroClim variables. Partial correlation analysis considers the variables simultaneously to account for covariance between the climate parameters and isolate the unique contribution of each variable to the TRW and BIA chronology.

The climate variables found to have the strongest unique relationship as determined by the partial correlation analysis, were then used in regression analysis to quantify the overall contribution of climate to productivity. A linear mixed model regression analysis was used to account for the autocorrelation present within the repeated measures of the tree-ring chronologies. Mixed models enabled random variability introduced by the repeated annual
measures of growth to be accounted for, which provide a more conservative and robust estimate of how much of the variability in the tree’s growth can be accounted for by climate drivers.

Results

Chronology Selection

Prior to statistical analysis, it was necessary to determine which method of standardization would optimize the performance of the chronologies. A variety of methods were evaluated based upon recent studies (McCarroll et al. 2013; Wilson et al. 2014; Martin-Benito and Pederson 2015) including 67%n spline, the Friedman Super Smoother, and linear regression (negative or zero slope). The three techniques were assessed for both the tree-ring width and BIA chronologies from both sites (Table 2).

A number of metrics have been developed by dendrochronologists to describe the levels of interseries correlation between samples and quantify the ability of a subset of samples to represent the chronology’s common signal. RBAR ($\bar{r}$) is a metric which indicates the level of correlation between all series in the chronology (Cook et al. 1990). The Signal-to-Noise Ratio (SNR) describes the strength of the common signal among series within the chronology (Wigley et al. 1984). Subsample Signal Strength (SSS) describes the ability of a subset of samples to model the signal of the overall chronology (Cook et al. 1990). Expressed Population Signal (EPS) describes, given a particular sample, the amount of the common variability is retained in the chronology (Cook et al. 1990).

For the ABP tree-ring width chronology, linear regression detrending produced the best standardizations ($\bar{r} = 0.443; \text{SNR} = 13.529$). Linear regression standardization also produced the greatest SSS value ($\text{SSS} = 0.858; \# \text{of trees} = 5$) and a comparable EPS value based on the lowest
number of trees ($EPS = 0.849; \# \text{ of trees} = 7$). Standardization of the ABP blue intensity chronology was also maximized using linear regression ($\bar{r} = 0.210; SNR = 3.993; SSS = 0.851, \# \text{ number of trees} = 8; EPS = 0.800, \# \text{ number of trees} = 15$).

The linear regression standardization produced the greatest interseries correlation and SNR values for the Cape TRW ($\bar{r} = 0.423; SNR = 11.749$) and BI chronologies ($\bar{r} = 0.155; SNR = 1.101$). It was decided that maintaining the best possible interseries correlations and optimizing the strength of the climate signal would be given priority over concerns regarding changes in chronology strength as sample depth declined (e.g. $SSS$ and $EPS$). Accordingly, linear regression standardization was chosen as the standardization technique for both the Cape TRW and BIA chronologies.

Through an initial data exploration using correlation and response function analysis (described below), the performance of the STD, RES and ARS chronologies was evaluated and compared for both sites. It was decided that the STD chronology would be used for the ABP TRW and BI chronologies and the RES chronology would be used for the Cape TRW and BIA chronologies.

**Chronology Characteristics**

The ABP TRW chronology (1829-2010) was composed of 19 series (Figure 2a). The BIA chronology (1801-2009) was comprised of 16 series (Figure 2b). The final chronology statistics have been summarized in Table 3. The RBAR and SNR for the TRW chronology ($\bar{r} = 0.443; SNR = 13.529$) was greater than the BI chronology ($\bar{r} = 0.234; SNR = 4.504$) indicating a stronger common signal. For both $SSS$ and $EPS$ values, a threshold of 0.85 is suggested as a baseline to assess the necessary sample depth (i.e., number of trees) for climate reconstruction.
(Wigely et al. 1998). The TRW chronology was able to maintain greater SSS and EPS values as sample depth declined compared to the BIA chronology.

Overall, the summary statistics for the Cape chronologies were weaker than those of the ABP site (Table 3). The TRW chronology was composed of 24 series (Figure 2c). The BIA chronology contained 9 series (Figure 2d). The TRW chronology was characterized by higher RBAR and SNR values ($\bar{r} = 0.423; SNR = 11.749$) than the BIA chronology ($\bar{r} = 0.155; SNR = 1.101$).

Correlation and Response Function Analysis

Given that there is a limited understanding about the climate drivers of *T. canadensis* and *P. rubens* in Vermont, an initial data exploration exercise was carried out to explore which climate variables appear to be the most influential on tree-ring width and BIA values. The strongest predictor for growth in the ABP TRW chronology was summer (June-July-August) precipitation ($r_{\text{correlation}} = 0.47; r_{\text{response}} = 0.407$) (Fig. 4 g). Other significant correlations include: June TPC ($c_{\text{correlation}} = 0.292; r_{\text{response}} = 0.237$), June TSSH ($r_{\text{correlation}} = 0.305; r_{\text{response}} = -0.263$), previous-year July $T_{\text{max}}$ ($r_{\text{correlation}} = -0.229; r_{\text{response}} = -0.187$), July PDSI ($r_{\text{correlation}} = 0.507; r_{\text{response}} = 0.145$), spring PDSI (March-April-May; $r_{\text{correlation}} = 0.442; r_{\text{response}} = 0.196$), summer PDSI ($r_{\text{correlation}} = 0.535; r_{\text{response}} = 0.156$), late-summer PDSI (August-September-October; $r_{\text{correlation}} = 0.479; r_{\text{response}} = 0.117$), and fall PDSI (September-October; $r_{\text{correlation}} = 0.463; r_{\text{response}} = 0.107$) (Fig. 4 a, i, k, m). Summer $T_{\text{max}}$ (JJA) ($r_{\text{correlation}} = -0.194; r_{\text{response}} = -0.432$) was also found to be negatively correlated with TRW and had the greatest response function coefficient of all the climate variables evaluated for ABP.
For the ABP BIA chronology, current year June TPC had the highest correlation coefficient ($r_{\text{correlation}} = -0.372; r_{\text{response}} = -0.347$) (Fig. 4 j). Other significant variables included: June $T_{\text{max}}$ ($r_{\text{correlation}} = 0.346; r_{\text{response}} = 0.200$), summer $T_{\text{max}}$ ($r_{\text{correlation}} = 0.272; r_{\text{response}} = 0.333$), September $T_{\text{min}}$ ($r_{\text{correlation}} = -0.291; r_{\text{response}} = -0.191$), Spring $T_{\text{min}}$ ($r_{\text{correlation}} = -0.286; r_{\text{response}} = -0.448$), and September $T_{\text{mean}}$ ($r_{\text{correlation}} = -1.183; r_{\text{response}} = -0.169$) (Fig. 4 b, d, f).

Analysis of the Cape TRW chronology demonstrated a consistent negative relationship between the temperature during the July and August and TRW. The significant correlations were found for: July $T_{\text{max}}$ ($r_{\text{correlation}} = -0.418; r_{\text{response}} = -0.308$) and August $T_{\text{max}}$ ($r_{\text{correlation}} = -0.349; r_{\text{response}} = -0.235$), July $T_{\text{mean}}$ ($r_{\text{correlation}} = -0.368; r_{\text{response}} = -0.285$) August $T_{\text{mean}}$ ($r_{\text{correlation}} = -0.341; r_{\text{response}} = -0.236$), July $T_{\text{min}}$ ($r_{\text{correlation}} = -0.233; r_{\text{response}} = -0.209$), August ($r_{\text{correlation}} = -0.262; r_{\text{response}} = -0.197$), late-summer $T_{\text{min}}$ ($r_{\text{correlation}} = 0.338; r_{\text{response}} = 0.179$) and fall $T_{\text{min}}$ ($r_{\text{correlation}} = 0.356; r_{\text{response}} = 0.219$), Spring PPT ($r_{\text{correlation}} = -0.209; r_{\text{response}} = -0.251$) PDSI ($r_{\text{correlation}} = 0.192; r_{\text{response}} = 0.160$) (Fig 5. a, c, e, g).

The strongest relationship found between the tested climate variables and the Cape BIA chronology was with spring $T_{\text{min}}$ ($r_{\text{correlation}} = -0.265; r_{\text{response}} = -0.314$) (Fig 5. f). Spring $T_{\text{mean}}$ ($r_{\text{correlation}} = -0.217; r_{\text{response}} = -0.067$) exhibits a similar but weaker relationship (Fig. 5 d).

**Partial correlation analysis**

Partial correlation analysis accounts for covariance among variables in order to quantify which climate variables are most uniquely correlated with the TRW and BIA chronologies. Based on a partial correlation analysis ($p > 1.441$), 7 of the 14 previously identified ABP TRW-climate relationships were selected for inclusion in the linear mixed model regression analysis: June PPT ($r = 0.446$), summer PPT ($r = 0.467$), June PDSI ($r = 0.532$), spring PDSI ($r = 0.444$),
summer PDSI ($r = 0.536$), late-summer PDSI ($r = 0.462$), and fall PDSI ($r = 0.478$). Analysis of the ABP BIA chronology yielded four climate variables for inclusion in the modeling, although with lower partial correlations ($p > 1.281$): June $T_{\text{max}}$ ($r = 0.332$), September $T_{\text{min}}$ ($-0.299$), spring $T_{\text{min}}$ ($r = -0.284$), and June TPC ($r = -0.483$). Partial correlations for Cape TRW-climate relationships identified five variables which were then selected for modeling ($p > 1.341$): July ($r = -0.430$) and pAugust ($r = -0.350$) $T_{\text{max}}$, pAugust $T_{\text{mean}}$ ($r = -0.341$), late-summer ($r = 0.331$) and fall ($r = 0.351$) $T_{\text{min}}$. For the Cape BI chronology, only two climate variables with partial correlations ($p > 1.212$), Spring $T_{\text{mean}}$ ($r = -0.212$) and spring $T_{\text{mean}}$ ($r = 0.262$), were selected for regression analysis.

Mixed Model Analysis

Using mixed model regression analysis, four models with statistically significant ($P < 0.05$) climate variables were developed for each of the four chronologies (Table 4). The mixed model approach allows the random portion of the year-to-year variations in growth to be accounted for in the regression analysis, thereby focusing on which fixed effect (e.g. the climate variables) best explain the annual variance of growth. Additionally, by removing degrees of freedom associated with repeated measures, a more conservative description of annual variance was produced. The model for the ABP BI chronology explained the greatest amount of variance ($R^2 = 0.350$, $\text{adj}R^2=0.324$) based on September $T_{\text{min}}$ and June TPC as predictors. The ABP TRW model explained the second highest amount of variability ($R^2 = 0.340$, $\text{adj}R^2=0.328$) based on Summer PPT and June PDSI. The CAPE TRW and BI model explained 31% ($R^2 = 0.33$, $\text{adj}R^2=0.310$), based on pJuly $T_{\text{max}}$, pAugust $T_{\text{mean}}$, and Fall $T_{\text{min}}$, and 7% ($R^2 = 0.068$, $\text{adj}R^2=0.060$), based on Spring $T_{\text{min}}$, of the variability, respectively.
**DendroClim moving windows**

The climate variables identified in the linear mixed model regression analysis were considered to be the principal drivers of TRW and BIA for each chronology. To understand how the relationship between these climate drivers and tree growth may have evolved over time, shorter (34-year) and longer (50-year) moving windows were used to calculate correlation and response function coefficients (Fig. 6 – 12) and are discussed below.

**Discussion**

**General chronology observations**

The quality of the ABP and Cape TRW chronologies (Fig. 3) are comparable to other Vermont *T. canadensis* and *P. rubens* chronologies found in the International Tree-Ring Databank (NOAA Climate Data Center; [www.noaa.gov/paleo](http://www.noaa.gov/paleo); accessed April 27, 2016). This study’s series intercorrelation and mean sensitivity values were found to be highly comparable to previously developed chronologies (Table 1). Thus, this indicates that the chronology preparation meets regional standards. As the ABP and Cape BIA chronologies are the first ever developed for these species, or for any species in eastern North America, no direct comparison of chronology quality statistics with prior studies can be made. Based on EPS values, the ABP and Cape TRW chronologies are characterized by a strong population-based signal from 1858-2010 and 1848-2009, respectively. During these time periods, as sample depth declines, the chronologies retain an EPS value greater than 0.85, the generally accepted threshold for dendroclimatology studies (Wigley et al. 1984). Thus, the TRW chronologies are acceptable for understanding the effects of climate on the ecology of the species, as well as for climate reconstruction. However, the ABP and Cape BIA chronologies are less robust (EPS < 0.85), as
the time series are characterized by a reduced standwide signal, and thus, they would not be sufficient for reconstructing climate. Future studies are advised to increase the sample depth (i.e., number of trees) and to select sites with a clearer growth limiting factor to increase the suitability of using BIA chronologies for climatic reconstructions. Previous studies with large sample depths and a greater number of samples experienced better performance (Wilson et al. 2014).

Neither of the BIA chronologies developed for this study were found to be significantly correlated (P < 0.05) with their respective TRW chronologies (Fig.3). This result is not surprising as the two metrics represent different aspects of tree growth and are likely influenced by different environmental variables. Tree-ring width is the product of processes (both exogenous and endogenous) that occur in the year prior to and in the current growth year. Blue intensity analysis is a measure of reflected light from the latewood portion of the tree ring which forms from current year (June-September) photosynthates, and thus, its signal should be isolated from the previous year. In previous studies (Linderholm et al. 2014; Wilson et al. 2014), BIA was intended to serve as a proxy for MXD analysis, not tree-ring widths. Depending upon the context of the research, the use of BIA can highlight the target signal by removing the noise introduced by non-growing season variables. This has been demonstrated in prior blue intensity studies which have sought to isolate the summer (June-July-August) temperature signal in alpine and boreal forests (Björklund et al. 2013; Wilson et al. 2014; Björklund et al. 2015).

However, the potential utility of isolating the latewood portion of the growing season using BIA has not been tested in other forest types with different environmental or ecological circumstances. Presently, the implementation of BIA has been almost exclusively limited to the analysis of conifers in high latitude environments where growth is principally regulated by summer temperature. This leaves a number of unresolved questions regarding how well the
technique will perform in a more diverse environment. Environments such as the Northern Forest are influenced by multiple factors and thus frequently lack a single growth limiting factor. As seen in the chronologies assessed in this study, climate only accounts for a third of the annual variability of growth in three of the four chronologies (discussed below). Dendrochronologist wishing to perform landscape-wide analysis in a heterogeneous environment such as the Northern Forest need to quantify how significantly variations in the regional geology (e.g. soil conditions), multiple or temporally instable growth limiting factors, and differences between species can affect BIA measurements. The limitations of TRW analysis have been extensively explored, but the same cannot be said for BIA. This study represents the first study to use BIA on temperate conifers in mid-latitude, low elevation forests and the first study to use BIA in the Northeastern United States. Ideally, this study, alongside subsequent work, will help unravel the aforementioned questions and concerns that have been laid out.

Abbey Pond chronologies and climate drivers

Tree-Ring Width

Current year summer moisture availability is the dominant climate driver of eastern hemlock TRW at the ABP site. Mixed model analysis revealed that summer (JJA) precipitation and June PDSI alone explained 34% of the variance ($R^2 = 0.340$). Eastern hemlock is a temperate conifer species known for its sensitivity to available moisture, likely due to its shallow roots (Burns and Honkala 1990). In fact, eastern hemlock TRW chronologies have been used repeatedly to reconstruct past moisture in the eastern United States (Lyon 1935, 1936; Cook and Jacoby 1977; Cook et al. 2007; Martin-Benito and Pederson 2015). Given this signal, however, a full two-thirds of the annual variability could not be quantified based only on the climate
variables assessed. Stand dynamics may be another factor influencing eastern hemlock growth. When examining the chronology (Fig. 3a), there are several instances of increased growth, most notably from 1878 – 1925, which may be explained by the release of trees from suppression in the understory into the canopy.

Moving window analysis revealed a shift in timing of the summer precipitation signal over the 20th and 21st centuries (Fig. 6). Both the 34-year and 50-year moving windows illustrate a shift from the dominant influence of July precipitation in the early part of the 20th century towards a May/June precipitation signal starting in the mid-1950s. The 50-year moving windows suggest that this trend is reasonably stable over time as the correlation and response function coefficients remain significant over almost the entire period assessed. Recent regional studies indicate a shift towards warmer temperatures and an earlier start to the growing season which may predispose eastern hemlock to moisture stress earlier in the summer (Groffman et al. 2012). The benefit of early season moisture is further emphasized when considering the moving window analysis for the PDSI (Fig. 7), which shows a continuous and stable period of strong, positive correlation coefficients between PDSI and TRW growth from the 1920s to the late 1960s and early 1970s. Prior to and including mid-1960s has been identified as period of lower moisture availability and drought respectively, based on a multi-species tree-ring reconstruction of the PDSI for the New York City (NYC) region (Pederson et al. 2013). PDSI was capable of explaining 66.2% of the variance in the TRW for chronologies assessed in the NYC watershed (Pederson et al. 2013). The 1960s drought was previously identified in a tree-ring width-based reconstruction by Cook and Jacoby (1979) who used eastern hemlock to reconstruct PDSI in the Hudson Valley, New York (also see: Cook and Jacoby 1977). After the mid-1960s, the eastern United States entered a pluvial with above average precipitation (Pederson et al. 2013), but with
occasional periods of aridity. Assessments of PDSI throughout New York have found the index was capable of explaining between 41.9 – 66.2% of the variance in the chronologies (Cook and Jacoby 1977; Pederson et al. 2013).

**Blue Intensity Analysis**

Climate variables at the beginning and end of the growing season appear to be the most influential on eastern hemlock BIA at ABP explaining 35% of the variance ($R^2 = 0.350$), the highest percentage of any model developed in this study. Two variables were ultimately found to be significant predictors of growth including June TPC and September $T_{min}$. Moving window analysis for $T_{min}$ (Fig. 8) shows a strong, stable and negative relationship between September $T_{min}$ and the BI chronology from the 1960s to the 1990s. Accordingly, a negative relationship between September $T_{min}$ and the BI chronology might suggest that with higher minimum temperatures late in the growing season, photosynthesis can continue within the tree, allowing for more lignin to be incorporated into the latewood cells.

Both the 34-year and 41-year correlation and response function coefficients for TPC (Fig. 9) demonstrate a consistent, stable relationship with ABP BIA. Higher cloud cover in the early growing season appears to result in lower BIA values and the increased incorporation of lignin into the latewood cells. Increased cloud cover may have the benefit of reducing the amount of evapotranspiration from needles and soils, thus preserving canopy and soil moisture content. Interestingly, both TPC and PDSI for June were selected by the final model. This indicates that the tree is specifically sensitive to soil moisture availability during that month. Previous BIA studies have inferred that blue reflectance varies in accordance to the lignin content (e.g. Campbell et al. 2007) but, have not thoroughly investigated the relationship
between climate and lignin. Previous studies have demonstrated that climate is capable of influencing the degree of lignification in tracheid (Gindl et al. 2000; Gindl 2001). Gindl et al. (2000) found that lignin content in the secondary cell wall of the terminal latewood cells was significantly correlated with the mean September-October temperatures in a high altitude Norway spruce (*Picea abies* [L.] Karst.) stand. Similarly, Gindl (2001) found a negative correlation between the cellular lignin content and the water stress in a summer precipitation sensitive Austrian pine (*Pinus nigra*) stand. This indicates that there is a relationship between a growth limiting factor (e.g. low temperatures or moisture availability) and lignin content. However, previous temperature reconstructions using BIA have cited Gindl et al. (2000) without further expanding the necessary circumstances which are needed to maintain this relationship (Campbell et al. 2007; Campbell et al. 2011). More specifically, these studies have not provided a reason for the variations in the BIA measurements; it is only assumed that BIA values are associated with lignin content. Gindl et al. (2000), a piece of literature most BIA papers cite, does not conclude that temperature and gross lignin content are inherently related. Additional analysis would be necessary to demonstrate that the relationship observed within this study would apply elsewhere. Other studies have found that the degree of lignification in conifers can vary with elevation, with trees incorporating greater lignin to maintain stem integrity in response to thinner cell walls (Gindl et al. 2001). This finding may indicate that lignin may be capable of responding to other environmental cues beyond climate (Gindl et al. 2001). Further exploration, in a more diverse set of environments, is necessary to be certain that conclusions drawn from future BIA studies are well founded. This is especially necessary if BIA research will be conducted in environments with various growth limiting factors (e.g. the Northern Forest) or where the growth limiting factor accounts for only part of the annual variance in productivity.
Cape NRA chronologies and climate drivers

Tree-Ring Width

The variance in the Cape red spruce TRW chronology was best modeled using previous year summer temperatures ($p$ July $T_{\text{max}}$, $p$ August $T_{\text{mean}}$) and current year fall (September $T_{\text{min}}$) temperatures. The final model developed was able to account for 33% of the variance in the annual growth ($R^2 = 0.33$). Fifty-year moving window analysis revealed that the negative correlation coefficients for $T_{\text{max}}$ $p$July (Fig. 10) and $T_{\text{mean}}$ $p$August (Fig. 11) are stable throughout the chronology. Higher mean and maximum temperatures during these summer months induces stress, potentially through higher evapotranspiration which forces stomata to close to conserve moisture. This, in turn, reduces the photosynthetic rate and ultimately, the amount of carbon that trees can be sequestered. Looking at the moving window analysis for the $T_{\text{min}}$ (Fig. 12), the 50-year windows indicate that the September temperature signal is also relatively stable. A positive correlation between Cape TRW and September $T_{\text{min}}$ indicates that the species benefits from warmer temperatures at the end of the growing season. Red spruce is known for its capacity to photosynthesize outside of the normal growing season, providing temperatures are warm enough.

Ultimately, climate drivers were able to account for 33% of the total variance in annual growth in the Cape TRW chronology. Based on the analysis of the time series from individual tree-cores, it is likely that stand dynamics and other endogenous disturbances contributed to the unresolved variance (not shown). In particular, the effect of winter injury events on red spruce growth has been investigated in numerous studies (DeHayes et al. 1999; Kosiba et al. 2013; Engel et al. 2016). As seen in this study’s TRW chronology (Fig 3 b), the years 1996 and 2003-2007 are marked periods of below average growth and have been attributed to winter injury.
events that were likely precipitated by earlier acid deposition and calcium loss from soils (Kosiba et al. 2013; Engel et al., 2016).

**Blue Intensity Analysis**

The best model for the Cape BIA chronology accounted for only 7% of the total variance, with Spring $T_{\text{min}}$ as the sole significant predictor identified in the mixed analysis (Spring $T_{\text{mean}}$ was also identified in the partial correlations analysis but, was ultimately not found to be a significant in the mixed model regression analysis). It is difficult to interpret this outcome given the current understanding of BIA as it relates to the latewood portion of the tree-ring growth, particularly in light of the poor fit of the model. However, given this relationship, higher Spring $T_{\text{min}}$ temperatures may result in lower BIA values (lower reflectance, greater lignin incorporated into latewood cells). It is hypothesized that an earlier start to the growing season may allow for an overall longer period of photosynthesis and the transport of carbohydrates throughout the tree. The moving window analysis shows a stronger correlation in the earlier part of the 20th century that appears to shift to April in the 1970s (Fig. 13). It is also possible that this correlation is ultimately spurious. Due to problems incorporating several cores into the Cape BIA chronology, the sample depth was reduced. The chronologies’ SNR and RBAR values indicate that the chronology is characterized by a weaker common signal. Ignoring all else, the RMSR (Table 4) indicates that the chronology ultimately has more variation in the residuals than the predictive model is capable of explaining and therefore, the relationship is highly suspect.
Conclusions

In this study, the climate drivers and their influence on the growth of eastern hemlock and red spruce stands in Vermont were successfully identified, particularly for ABP TRW and BIA and Cape TRW chronologies. In combination with the modeling results, DendroClim proved to be an exceedingly valuable tool for assessing the stability of climate relationships over time. However, the model results also indicate that there is still a large percentage of unexplained variability. It is hypothesized that the unexplained variability in the models reflects the influence of complex forest dynamics and other environmental variables which cumulatively impact the annual growth of temperate conifers in the Northern Forest.

This study produced the first BIA chronologies for the United States, and more specifically for eastern hemlock and red spruce, two important temperate conifers in the Northern Forest. The ABP BIA chronology performed as well as the TRW chronology for hemlock and was able to isolate a different climate signal, thereby expanding the utility of the tree-ring-based archive for climate studies. This suggests that it would be worthwhile to pursue BIA in future studies using eastern hemlock. However, it is suggested that red spruce BIA be re-evaluated based on the study results as sample depth issues may have weakened the chronology signal.

Since the development of the current study’s blue intensity chronologies, improved methodologies for BIA have been published. Björklund et al. (2015) and Rydval et al. (2014) have made numerous improvements to the measuring and chronology building procedures which may improve the SNR in future studies and address some of the issues found in our data. This study represents the first attempt to use BIA in an environment not limited by summer temperature, using species which have not yet been previously evaluated. Recent studies (e.g.
Björklund et al. 2014; Björklund et al. 2015) have focused on devising methodologies to improve the signal derived from BIA measurements in the context of relatively homogenous environments, such as Fennoscandia. However, our results highlight that a greater understanding of the processes which drive variation in the BIA chronologies is necessary to allow for the expansion of the technique into less homogenous environments, like the Northern Forests.
References


Paleoclimatology, N., cited 2016: Description of Tree Ring Data Files and Procedures


**FIGURES**

*Figure 1.* A map of New England showing the location of the study sites. Point A denotes the Abbey Pond site. Point B denotes the Cape NRA site.
Figure 2 Timeseries of raw mean (plot-level) measurements (± standard error) for: a) tree-ring ring widths for the Abbey Pond site, b) blue intensity for the Abbey Pond site, c) tree-ring widths for the Cape NRA site, d) blue intensity for the Cape NRA site. The dotted line represents the sample depth over time.
Figure 3. ARSTAN standardized and normalized timeseries (z-scored). The black line represents the tree-ring width (TRW) timeseries and the blue line represents the blue intensity analysis (BIA) timeseries. a) The ARSTAN Standard TRW and BIA timeseries for Abbey Pond b) The ARSTAN Residual TRW and BIA timeseries for the Cape RNA. Pearson’s correlation coefficients were calculated for the TRW and BIA timeseries; the correlations were not significant (p > 0.05).
Tree-Ring Width

\[ T_{max} \]

Blue Intensity

\[ T_{max} \]
Figure 5. Pearson’s product moment correlations (black bars) and response functions (gray bars) coefficients ($p < 0.05$) for the Abbey Pond site. “p” denotes a month in the previous year of growth. Four seasonal periods were evaluated: Spring (MAM; March-April-May), Summer (JJA; June-July-August), Late-Summer (August-September-October), and Fall (September-October). a) Maximum temperature ($T_{\text{max}}$) coefficient(s) using tree-ring widths (TRW), b) $T_{\text{max}}$ coefficient(s) using blue intensity analysis (BIA), c) Mean temperature ($T_{\text{mean}}$) coefficient(s) using TRW, d) $T_{\text{mean}}$ coefficient(s) using BIA, e) Minimum temperature ($T_{\text{min}}$) coefficient(s) using TRW, f) $T_{\text{min}}$ coefficient(s) using BIA, g) Precipitation (PPT) coefficient(s) using TRW, h) PPT coefficient(s) using BIA, i) Total percent cloudiness (TPC) coefficient(s) using TRW, j) TPC coefficient(s) using BIA, k) Total sunshine hours (TSSH) coefficient(s) using TRW, l) TSSH coefficient(s) using BIA, m) Palmer Drought Severity Index (PDSI) coefficient(s) using TRW, n) PDSI coefficient(s) using BIA, o) Total percent possible sunshine (TPPS) coefficient(s) using TRW, p) TPPS coefficient(s) using BIA.
Figure 7. Pearson’s product moment correlations (black bars) and response functions (gray bars) coefficients ($p < 0.05$) for the Cape NRA site. “p” denotes a month in the previous year of growth. Four seasonal periods were evaluated: Spring (MAM; March-April-May), Summer (JJA; June-July-August), Late-Summer (August-September-October), and Fall (September-October). a) Maximum temperature ($T_{\text{max}}$) coefficient(s) using tree-ring widths (TRW), b) $T_{\text{max}}$ coefficient(s) using blue intensity analysis (BIA), c) Mean temperature ($T_{\text{mean}}$) coefficient(s) using TRW, d) $T_{\text{mean}}$ coefficient(s) using BIA, e) Minimum temperature ($T_{\text{min}}$) coefficient(s) using TRW, f) $T_{\text{min}}$ coefficient(s) using BIA, g) Precipitation (PPT) coefficient(s) using TRW, h) PPT coefficient(s) using BIA, i) Total percent cloudiness (TPC) coefficient(s) using TRW, j) TPC coefficient(s) using BIA, k) Total sunshine hours (TSSH) coefficient(s) using TRW, l) TSSH coefficient(s) using BIA, m) Palmer Drought Severity Index (PDSI) coefficient(s) using TRW, n) PDSI coefficient(s) using BIA, o) Total percent possible sunshine (TPPS) coefficient(s) using TRW, p) TPPS coefficient(s) using BIA.
Figure 8. DendroClim2002 moving window analysis using the Abbey Pond tree-ring width chronology and PRISM precipitation data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50 year moving window correlation function coefficients, d) 50-year moving window response function coefficients
Figure 9. DendroClim2002 moving window analysis using the Abbey Pond tree-ring width chronology and Palmer Drought Severity Index data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50 year moving window correlation function coefficients, d) 50-year moving window response function coefficients
Figure 10. DendroClim2002 moving window analysis using the Abbey Pond blue intensity analysis chronology and PRISM $T_{\text{min}}$ data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50 year moving window correlation function coefficients, d) 41-year moving window response function coefficients
Figure 11. DendroClim2002 moving window analysis using the Cape NRA tree-ring width chronology and PRISM T_{mean} data:

- a) 34-year moving window correlation function coefficients,
- b) 34-year moving window response function coefficients,
- c) 50-year moving window correlation function coefficients,
- d) 50-year moving window response function coefficients.

Figure 12. DendroClim2002 moving window analysis using the Abbey Pond blue intensity analysis chronology and total percent cloudiness (TPC):

- a) 34-year moving window correlation function coefficients,
- b) 34-year moving window response function coefficients,
- c) 41-year moving window correlation function coefficients,
- d) 41-year moving window response function coefficients.
Figure 13. DendroClim2002 moving window analysis using the Cape NRA tree-ring width chronology and PRISM $T_{\text{max}}$ data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50-year moving window correlation function coefficients, d) 50-year moving window response function coefficients.
Figure 14. DendroClim2002 moving window analysis using the Cape NRA tree-ring width chronology and PRISM T\textsubscript{mean} data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50 year moving window correlation function coefficients, d) 50-year moving window response function coefficients.
**Figure 15.** DendroClim2002 moving window analysis using the Cape NRA tree-ring width chronology and PRISM T_{\text{min}} data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50 year moving window correlation function coefficients, d) 50-year moving window response function coefficients
Figure 13. DendroClim2002 moving window analysis using the Cape NRA blue intensity analysis chronology and PRISM T$_{\text{min}}$ data: a) 34-year moving window correlation function coefficients, b) 34-year moving window response function coefficients, c) 50 year moving window correlation function coefficients, d) 50-year moving window response function coefficients
### TABLES

**Table 1:** Final chronology quality statistics for the Abbey Pond and Cape NRA sites

<table>
<thead>
<tr>
<th>Site Name</th>
<th>Number of Series Dated</th>
<th>Series Intercorrelation</th>
<th>Mean Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abbey Pond</td>
<td>19</td>
<td>0.614</td>
<td>0.254</td>
</tr>
<tr>
<td>Cape NRA</td>
<td>24</td>
<td>0.565</td>
<td>0.242</td>
</tr>
</tbody>
</table>

**Table 2:** Tree-ring width chronology summary statistics for Abbey Pond (ABP) and the Cape (CAPE) sites. The data were used to evaluate the performance of various standardization techniques

<table>
<thead>
<tr>
<th>Site Name</th>
<th>Method</th>
<th>SC</th>
<th>AC (t=-1)</th>
<th>RBAR</th>
<th>SNR</th>
<th>SSS (No. Samples)</th>
<th>EPS (No. Samples)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABP (TRW)</td>
<td>FSS</td>
<td>0.235</td>
<td>0.239</td>
<td>0.424</td>
<td>12.535</td>
<td>0.849(5)</td>
<td>0.855(8)</td>
</tr>
<tr>
<td>ABP (BIA)</td>
<td>FSS</td>
<td>0.307</td>
<td>0.288</td>
<td>0.203</td>
<td>3.812</td>
<td>0.878(9)</td>
<td>0.792(15)</td>
</tr>
<tr>
<td>ABP (TRW)</td>
<td>67% Spline</td>
<td>0.38</td>
<td>0.387</td>
<td>0.431</td>
<td>12.874</td>
<td>0.853(5)</td>
<td>0.858(8)</td>
</tr>
<tr>
<td>ABP (BIA)</td>
<td>67% Spline</td>
<td>0.443</td>
<td>0.384</td>
<td>0.200</td>
<td>3.740</td>
<td>0.877(9)</td>
<td>0.789(15)</td>
</tr>
<tr>
<td>ABP (TRW)</td>
<td>LRNS</td>
<td>0.606</td>
<td>0.527</td>
<td>0.443</td>
<td>13.529</td>
<td>0.858(5)</td>
<td>0.849(7)</td>
</tr>
<tr>
<td>ABP (BIA)</td>
<td>LRNS</td>
<td>0.734</td>
<td>0.511</td>
<td>0.210</td>
<td>3.993</td>
<td>0.851(8)</td>
<td>0.800(15)</td>
</tr>
<tr>
<td>CAPE (TRW)</td>
<td>FSS</td>
<td>0.177</td>
<td>0.212</td>
<td>0.409</td>
<td>11.06</td>
<td>0.879(6)</td>
<td>0.862(9)</td>
</tr>
<tr>
<td>CAPE (BIA)</td>
<td>FSS</td>
<td>0.090</td>
<td>-0.072</td>
<td>0.078</td>
<td>0.511</td>
<td>0.883(5)</td>
<td>0.338(6)</td>
</tr>
<tr>
<td>CAPE (TRW)</td>
<td>67% Spline</td>
<td>0.437</td>
<td>0.413</td>
<td>0.423</td>
<td>11.745</td>
<td>0.853(5)</td>
<td>0.854(8)</td>
</tr>
<tr>
<td>CAPE (BIA)</td>
<td>67% Spline</td>
<td>0.189</td>
<td>0.113</td>
<td>0.113</td>
<td>0.764</td>
<td>0.898(5)</td>
<td>0.433(6)</td>
</tr>
<tr>
<td>CAPE (TRW)</td>
<td>LRNS</td>
<td>0.836</td>
<td>0.724</td>
<td>0.423</td>
<td>11.749</td>
<td>0.853(6)</td>
<td>0.855(9)</td>
</tr>
<tr>
<td>CAPE (BIA)</td>
<td>LRNS</td>
<td>0.752</td>
<td>0.320</td>
<td>0.155</td>
<td>1.101</td>
<td>0.913(5)</td>
<td>0.524(6)</td>
</tr>
</tbody>
</table>

Site name, tree-ring width (TRW) or blue intensity analysis (BIA); Method: the ARSTAN detrending technique, Freidman Super Smoother (FFS), 67% n Spline, Linear Regression with negative or zero slope (LRNS); Serial Correlation (SC); Autocorrelation (AC) for the previous year; SNR: Signal-to-Noise Ratio; SSS: subsample signal strength (number of samples necessary to achieve SSS > 0.85 in parentheses); EPS: expressed-population signal (the number of samples necessary to achieve EPS > 0.85 in parentheses).
Table 3:  Summary statistics for the Abbey Pond (ABP) and Cape RNA (CAPE) tree-ring width (TRW) and blue intensity analysis (BIA) chronologies.

<table>
<thead>
<tr>
<th>Site Name</th>
<th>No. of samples (Trees)</th>
<th>First Year</th>
<th>Last Year</th>
<th>Total Years</th>
<th>Mean</th>
<th>StdDev</th>
<th>RBAR</th>
<th>SNR</th>
<th>SSS (No. Samples)</th>
<th>EPS (No. Samples)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABP (TRW)</td>
<td>19(19)</td>
<td>1828</td>
<td>2010</td>
<td>183</td>
<td>1.476</td>
<td>0.347</td>
<td>0.443</td>
<td>13.529</td>
<td>0.858(5)</td>
<td>0.864(8)</td>
</tr>
<tr>
<td>ABP (BIA)</td>
<td>16(16)</td>
<td>1801</td>
<td>2009</td>
<td>209</td>
<td>51.70</td>
<td>15.846</td>
<td>0.234</td>
<td>4.504</td>
<td>0.863(6)</td>
<td>0.818(15)</td>
</tr>
<tr>
<td>CAPE (TRW)</td>
<td>24(15)</td>
<td>1811</td>
<td>2010</td>
<td>200</td>
<td>1.313</td>
<td>0.569</td>
<td>0.423</td>
<td>11.749</td>
<td>0.853(5)</td>
<td>0.855(8)</td>
</tr>
<tr>
<td>CAPE (BIA)</td>
<td>9(9)</td>
<td>1815</td>
<td>2009</td>
<td>195</td>
<td>55.943</td>
<td>10.303</td>
<td>0.155</td>
<td>1.101</td>
<td>0.913(5)</td>
<td>0.524(6)</td>
</tr>
</tbody>
</table>

Site name (analysis methodology); No. of samples: number of increment cores in chronology with total trees represented by samples in parentheses; Mean: the mean TRW (mm) or BIA value (8-bit value); StdDev: standard deviation of the raw chronologies; SNR: Signal-to-Noise Ratio; SSS: subsample signal strength with the number of samples necessary to achieve SSS > 0.85 in parentheses; EPS: expressed-population signal with the number of samples necessary to achieve EPS > 0.85 in parentheses.

Table 4:  A summary of the mixed model regression analysis using the Abbey Pond (ABP) and Cape NRA (CAPE) tree-ring width (TRW) and blue intensity analysis (BIA) chronologies

<table>
<thead>
<tr>
<th>Site Name</th>
<th>Rsquare</th>
<th>Rsquare Adjusted</th>
<th>RMSE</th>
<th>MoR</th>
<th>Var1(df)</th>
<th>Var1 sig.</th>
<th>Var2(df)</th>
<th>Var2 sig.</th>
<th>Var3(df)</th>
<th>Var3 sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABP (TRW)</td>
<td>0.340</td>
<td>0.328</td>
<td>0.161</td>
<td>0.987</td>
<td>PPT JJA(1)</td>
<td>0.0023</td>
<td>PDSI Jun</td>
<td>&lt;0.0001</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ABP (BIA)</td>
<td>0.350</td>
<td>0.324</td>
<td>0.122</td>
<td>1.079</td>
<td>Tmin Sep(1)</td>
<td>0.0003</td>
<td>TPC Jun</td>
<td>0.0094</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CAPE (TRW)</td>
<td>0.330</td>
<td>0.312</td>
<td>0.103</td>
<td>1.012</td>
<td>Tmax pJul</td>
<td>&lt;0.0001</td>
<td>Tmean pAug(1)</td>
<td>0.0077</td>
<td>Tmin Fall(1)</td>
<td>0.0002</td>
</tr>
<tr>
<td>CAPE (BIA)</td>
<td>0.068</td>
<td>0.060</td>
<td>0.107</td>
<td>0.993</td>
<td>Tmin Spring(1)</td>
<td>0.0047</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Site name (analysis methodology); Rsquare; Adjusted Rsquare; RMSE: Root mean square error; MoR: Mean of Response; Var1(df): first variable in the model (degrees of freedom); Var1 sig: significance of the first variable; Var2(df): second variable in the model (degrees of freedom); Var2 sig: significance of the second variable; Var3(df): third variable in the model (degrees of freedom); Var3 sig: significance of the third variable
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