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Developing Spectral Metrics as Early Indicators of Water Stress Detection at the Canopy Level

Korik Vargas

University of New Hampshire, Durham

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DEVELOPING SPECTRAL METRICS AS EARLY INDICATORS OF WATER STRESS DETECTION AT THE CANOPY LEVEL

BY

KORIK VARGAS MORENO
BS, University of Los Andes, 2009

THESIS

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Master
in
Natural Resources
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This dissertation has been examined and approved in partial fulfillment of the requirements for
the degree of Master in Natural Resources by:

Thesis Director, Heidi Asbjornsen, Associate Professor of Ecosystem Ecology

Dr. Michael W. Palace, Associate Professor of Environment Science, Remote Sensing, Geospatial Analysis

Dr. Matthew Vadeboncoeur, Research Scientist

On July 31st, 2018

Original approval signatures are on file with the University of New Hampshire Graduate School.
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DEVELOPING SPECTRAL METRICS AS EARLY INDICATORS OF WATER STRESS DETECTION AT THE CANOPY LEVEL

by

Korik Vargas Moreno

University of New Hampshire, September 2018

Drought has become an increasing concern over the last few years in forest ecosystems. Understanding how forests respond to drought is critical to elucidate possible drought consequences for forest ecosystem structure and function. There is growing consensus that future climates will be characterized by extreme droughts and extreme precipitation events that will fall outside the historical range to which species and ecosystems are adapted. The limited information of how Northeastern U.S. forest tree species will respond to moderate to extreme drought events have promoted an increasing need to develop monitoring techniques which help us better understand the implications of future drought events on forest structure. Recent technological advances in remote sensing techniques have opened up new opportunities for forest health monitoring which are a great complement to the ecological and physiological data that have been collected within current monitoring programs. The aim of this project was to monitor the vegetation water content at the canopy level for 4 plots that are part of the DroughtNet project, a manipulative ∼50% throughfall removal experiment in the Northeastern U.S. forest. To obtain spectral information from the canopy level I used two different hyperspectral sensors: 1) the G-
LiHT airborne hyperspectral sensor with a high spatial (1m) and spectral (4nm) resolution, and 2) the ASD FieldSpec Pro spectrometer that records reflected radiation within the 350–2500 nm spectral domain with a spectral resolution of 3 nm. Ten different water-sensitive hyperspectral indices were calculated to analyze differences between treatments looking for the most reliable way to detect water stress signals. The reflectance of the canopy was analyzed over time as well as the behavior of the two dominant species of the forest: White Pine and Red Oak. To estimate periods of time representing a range of water-stress conditions at the Thompson Farm throughfall experiment, soil moisture and soil water potential were also monitored continuously at multiple locations and depths within each plot. Our results suggest that for the weather conditions which occurred in 2017, the spectral comparison between treatments did not indicate that the spectral indices are more sensitive than the physiological measurements commonly used for water content estimations (i.e. gas exchange, sap flow data). Although none of the spectral indices showed early signals of water stress conditions, some of the indices performed well with correlation analyses for the leaf water content and specific leaf area, with the NDII and PRI standing out. This investigation reaffirms the importance of continuing with monitoring studies that can complement the DroughtNet experimental project and will be valuable for an overall evaluation of the experiment in the long term.
INTRODUCTION

Drought has become an increasing concern over the last few years in many different types of forest ecosystems (Clark et al. 2016; Trumbore et al. 2015; Bonan 2008). Since water stress is one of the most common limitations of photosynthesis and plant primary productivity, multiple studies have been directed towards understanding possible drought consequences for forest ecosystem structure and function. Allen et al. (2010) showed that at a regional scale vegetation mortality appear to be increasing and is frequently associated with increased temperatures and droughts. In addition, Anderegg et al. (2013) and Breshears et al. (2011) suggested that these broad-scale tree mortalities fundamentally affect a diverse suite of environmental processes and ecosystem services, including forest community and ecosystems dynamics. Other studies have focused on gaining a better understanding of the underlying physiological mechanisms contributing to drought-induced mortality (McDowell et al. 2013; Rowland et al. 2015). Additional studies have focused on a historic view of the occurrence of drought events across the US. They have warned that these events have been on the rise over the last five decades and there is a high probability that they will continue to increase due to climate change (Clark et al. 2016; Peters et al. 2014; IPCC).

It is widely accepted that changing temperature and precipitation patterns will produce novel combinations of drought frequency, intensity and seasonality that could increase drought conditions (Dai, 2012). Some studies based on climate models have proposed that the climate may become more extreme under greater warming, with an increased frequency of both extreme dry and wet seasons (Swain & Hayhoe 2014), and that due to high temperatures, snow packs will melt earlier, generating drier conditions during the growing season in the future, despite projected
increases in precipitation (Pourmokhtarian et al., 2017). However, it is still unknown how these novel conditions will affect tree species performance, and how this species response will affect the forest structure. The knowledge gap between tree species versus stands is relevant because if we want to recognize drought consequences at the forest structure level due, we must first identify species responses for making predictions for future trajectories and designing effective management approaches in moisture-limited conditions (McDowell et al. 2008). In this context, our limited information of how forest tree species will respond to moderate to extreme droughts events have promoted an increasing need to develop monitoring techniques which help us better understand the implications of future drought events in the forest structure (Allen et al. 2010; DroughtNet).

Northeastern U.S. forests have been considered at high risk as a consequence of drought conditions induced by climate change (Coble et al. 2017; Melillo et al. 2014; Roman et al. 2015; Pourmokhtarian et al. 2017). Despite recent attention to large tree mortality in the west, eastern forests are also vulnerable since the Northern U.S. region has had fewer and less intense droughts (Peters et al., 2014; Pederson et al. 2012). Although the period of 1930–2005 was one of the wettest periods on record throughout most of the eastern USA (Pederson et al. 2015), the same region received 25–75% of normal precipitation during the recent summer 2016 (http://www.drought.gov). Pederson et al. (2012, 2013, 2015) based on dendro-chronology studies have proved the strength and extent of climate responses and how tree growth would be affected during years of low precipitation. We know that there are many species which are vulnerable to drought in the eastern forest, but how this vulnerability at the individual scale translates into future forest composition and structure remains uncertain (Clark et al., 2016; Coble et al. 2017). It is also known that forest ecosystems that are exposed to dry conditions are usually composed of species
with adaptations to dry environments, where the species’ functional traits help to regulate transpiration processes or give an advantage at some point of the reproductive cycle. (Kawecki and Ebert, 2004). However, in the northern forests, where dry conditions are not frequent, and most of the species don’t display functional traits for dry environments, new climate change scenarios could represent a risk for these forest ecosystems.

Over the recent years different monitoring programs and experimental projects have been established at a national and global scales to improve our understanding of how drought could affect terrestrial ecosystems (https://drought-net.colostate.edu/ - DroughtNet), and to improve management practices under predicted changes in climate (Hasanuzzaman et al. 2014). These experiments and monitoring strategies have been accumulating valuable information for several climate variables that allow for a proper evaluation of how the ecosystems and species respond under extreme or typical conditions. For the Northeastern U.S. forests, precipitation manipulation experiments have been established as a part of a network experiment to improve understanding about the impact of climate change and altered rainfall patterns on forest health, productivity, and hydrology (DroughtNet). These experimental plots have generated powerful information to identify differences in species’ physiological adaptations and threshold responses for two of the most common tree species of the New England forests, the white pine and the northern red oak (Coble et al. 2017; McIntire et al. *in prep*).

There is a particular interest in these two species, because in addition of their dominance in the northeastern forests, both species exhibit fundamental differences in their adaptive strategies to drought (Coble et al., 2017). In general, species can vary widely in their use of various strategies to mitigate and tolerate drought stress, and these strategies have been historically divided between isohydric and anisohydric species, as an approach for classifying species’ drought responses
according to their stomatal sensitivity. Red oak is considered a drought tolerant species which maintains photosynthesis and stomatal conductance activity (anisohydric) while white pine is considered less tolerant and reduces the photosynthesis process and doesn’t maintain the stomata open for longer periods (isohydric) (Roman et al. 2015; McDowell et al. 2008). The physiological data that has been recorded from the dominant species from the precipitation manipulation experiments have helped to create a drought tolerance classification as an indicator of a particular species’ capacity to survive moisture stress (Coble et al. 2017), and the information has been organized under standard protocols that allow comparisons with other regions through worldwide networking (Asbjornsen et al. In press).

Recent technological advances in remote sensing techniques have opened up new opportunities for forest health monitoring. Although there is a wide variability of tools, sensors and a continuous technological development in this field (Zarco-Tejada et al. 2003; Berni et al. 2009; Asner et al. 2016; Masek et al., 2015), the utilizing of hyperspectral data has been determinant for an estimation of a variety of plant traits and physiological processes based on foliar optical properties, including concentrations of nutrients, structure and secondary metabolites and plant physiological status (Haboudane et al. 2004; Govender et al 2007; Ollinger 2011; Thenkabail & Lyon 2016; Cotrozzi et al. 2017). Although the accessibility to hyperspectral data for most of the passive sensors is now a minor problem within studies for large spatial and temporal scales, the difficulties remain at individual canopies or fine spatial scales (1 to 10 m), where the available satellites missions don’t allow a proper identification of canopies or some foliar optical properties because of their spatial and spectral resolution (Wulder et al. 2004). At small spatial scales, satellite missions are not flexible, and their spatial resolution limits some terrestrial ecology applications. However, airborne platforms, the use of thermal and hyperspectral sensors attached to UAVs have
allowed a diversification and more flexible platforms for developing and testing data fusion at fine spatial (1 to 10 m) and spectral resolutions (Berni et al. 2009; Kampe et al.; Cook et al. 2013; Asner et al. 2016).

High resolution airborne sensors, like NEON-AOP or NASA - G-LiHT, have been trying to fill these gaps with aircraft platforms that carry remote sensing instrumentation designed to achieve sub-meter to meter scale ground resolution, bridging scales from organisms and individual stands of vegetation to satellite-based remote sensing (Kampe et al. 2010; Cook et al. 2013). G-LiHT combines hyperspectral, LiDAR and thermal sensors to improve global remote sensing of terrestrial ecosystems at fine spatial (~1m) and spectral resolutions (Cook et al. 2013). Furthermore, the addition of LiDAR, thermal IR and imaging spectrometer data extends the range of potential terrestrial ecology applications on hydrology and forest health. Light detection and ranging provides quantitative information on terrain and vegetation cover as well as height and distribution of canopy elements. In addition, imaging spectroscopy provides quantitative information on species composition and biophysical and chemical properties that can be derived from measurements of reflected sunlight in the visible through shortwave infrared wavelengths (Cook et al. 2013). G-LiHT has been successfully mixed with long-term inventory datasets as an attractive approach to mapping forest above-ground biomass at stand and regional scales. The use of the LiDAR and hyperspectral data, obtained with the aircraft plus the use of very detailed and long-term information, have allowed the use of novel models to improve the forest biomass prediction and the estimate growth (Babcock et al. 2016).

Hyperspectral data could also be obtained through the use of hand-held field spectrometers which have been widely used as remote sensing instruments, but these usually must be used close to the target (Milton et al., 2009; Turner et al., 2004; Wang and Jin, 2015). Although these sensors
don’t allow an assessment at a large spatial scale, field spectroscopy serves to upscale processes of interaction between energy and mass from single individuals up to large-scale alignments (Gamon et al. 2006). Being closest to the target, field spectrometers provide the most reliable information about the spectral behavior of all different kinds of surfaces (Schaepman et al. 2009). These devices are designed to detect, measure, and analyze the spectral content of incident electromagnetic radiation and are more flexible in terms of revisit time. Field spectrometers allow a wide evaluation of the electromagnetic spectrum with a high spectral resolution.

Remote sensing provides methods for early detection of plant stress based on changes in the reflection of different regions of the electromagnetic spectrum. The vegetation water content from remotely sensed data is estimated based on the fact that water absorbs radiant energy throughout the near-infrared (NIR, 750–1300 nm) and shortwave infrared (SWIR, 1300–2500 nm) spectral regions. It is known that there are five water absorption features centered at 970, 1200, 1450, 1940, and 2500 nm widely observed from vegetation spectral curves (Tucker 1980). However, for satellite-based sensors, the amount of water vapor present in the atmosphere doesn’t allow an appropriate lecture in all of these wavelengths, reducing the reliability for water stress measurements to the VIS and NIR regions. Therefore, for water stress detection studies, the spectral resolution is an important factor to consider for an appropriate evaluation. The number of bands and how wide they are, would affect the accuracy of the indices calculation and would have an incidence for distinguishing reflectance curves on the vegetation spectrum. However, with the use of high resolution spectral instrumentation, the number of bands obtained by remote sensing is increasing, and the bandwidth is getting narrower (Danson et al. 1992; Berni et al. 2009).

It has been claimed that spectral vegetation indices can provide a useful and accurate estimation tool for water stress analysis and qualitative evaluations of vegetation cover, vigor, and
growth dynamics, among other applications (Ceccato et al. 2001; Thenkabail & Lyon, 2016; Xue and Su, 2017). Vegetation indices are simple and effective algorithms that extract vegetation information using individual light spectra bands or a group of single bands for data analysis. Several studies have demonstrated the relationship between vegetation water content and spectral indices in forest canopies (Tucker, 1980; Serrano et al., 2000; Hunt and Rock 1989, Sims and Gamon 2003; Colombo et al. 2008). Bowyer and Danson 2004, among others, have showed the empirical relationship of leaf reflectance in the near infrared (NIR) and shortwave infrared (SWIR) regions with the equivalent water thickness and fuel moisture content, which are a relative measure of the amount of water. More recently Liu et al (2016), demonstrated that hyperspectral water-sensitive indices have proven to be reliable factors in estimating the canopy water content. 

The most common water-sensitive indices are calculated in the NIR region, but there are also tested water-stress indices in the SWIR region which have been widely used for assessing water stress (Sims and Gamon 2003; Ceccato et al. 2001; Liu et al. 2016). In addition, other indices which are not related with water absorption features have also been proposed as an indicator of the leaf structure (Liu et al. 2014), or because of the correlation with the leaf area index and other canopy structure attributes (Maki et al. 2004). Due to the water absorption in the SWIR region and the use of high resolution spectral instrumentation that allows an evaluation of wider regions of electromagnetic spectrum, it is intriguing how different indices are giving similar or better results. However, a key knowledge gap remains surrounding which indices are more accurate for differentiating drought signals and which wavelengths on the vegetation spectrum have the most reliable information (Sims and Gamon 2003; Zarco-Tejada et al., 2003; Davidson et al., 2006; Smitson et al., 2005; Filella et al., 2009) (Table 1).
The aim of this project is to monitor the vegetation water content at the canopy level over the growing season (Jun – Sep 2017) for four 900 m² plots which are part of the DroughtNet experiment at Thompson Farm (Durham, NH, USA) (McIntire et al. In prep), a manipulative ∼50% throughfall removal experiment in the Northeastern U.S. forest in which plant physiological data have been collected since 2015. To analyze water stress signals at the canopy level, we used two different hyperspectral sensors: 1) the G-LiHT airborne hyperspectral sensor with a spatial resolution of 1m and high spectral resolution, and 2) the ASD FieldSpec Pro spectrometer that records reflected radiation within the 350–2500 nm spectral domain with a spectral resolution of 3 nm. The reflectance data was collected from four different plots, 2 controls and 2 treatments, over time during the growing season (Jun – Sep 2017). My main objective was to analyze how the reflectance of the canopy varies over time, in response to the drought treatment, as well as the behavior of the two dominants species of the forest: White Pine (Pinus strobus L.) and Red Oaks (for the purpose of this study we are lumping Quercus rubra L. and Quercus velutina Lam.). To estimate water content at the forest canopy I used reflectance data in the NIR and SWIR, to calculate multiple spectral indices of vegetation looking for the most reliable spectral bands to detect water stress signals. To estimate periods of time representing a range of water-stress conditions at the Thompson Farm throughfall experiment, soil moisture and soil water potential were also monitored continuously at multiple locations and depths within each plot. These data will be critical to targeting physiological and remote-sensing observations with drought conditions.
METHODS

Study site

The monitored area is located at Thompson Farm, Durham, NH (N 43°06.535', W 70°56.912') here the forest canopy is dominated mainly by red oak (*Quercus rubra*) and white pine (*Pinus strobus*). Other species including red maple (*Acer rubrum*), sugar maple (*Acer saccharum*), American beech (*Fagus grandifolia*), shagbark hickory (*Carya ovata*), and yellow birch (*Betula alleghaniensis*) occur mostly in the understory and mid-canopy positions. In this forest, a throughfall exclusion experiment (TFE) was created to simulate the impacts of a prolonged drought on critical hydrologic services of the northern forest and evaluate the response of dominant species under drought conditions and water stress by regulating their water consumption over time.

The TFE is comprised of two drought treatment plots and two control plots (30x30m each) constructed in fall 2015 and initiated during the summer season of 2016. Each treatment plot has a system of gutters designed to prevent 55% of precipitation input from reaching the soil during the growing season (gutters are in place from late May – late October each year), and is closely paired with a control plot on the same soil unit.

For red oaks and white pines, physiological data have been recorded each growing season since 2015. Whole-tree water use is measured continuously from June-October using heat-ratio sapflow sensors (Burgess et al. 2001) in three trees per species per plot. Foliar samples have been collected 2-3 times per summer season to measure stomatal conductance, photosynthetic rate, water-use efficiency, water potential, specific leaf area, and concentrations of nutrients. These measurements, collected by other project collaborators, will be used to correlate spectral data with water stress conditions.
Figure 1. Crown delineation maps made with the Canopy Height Model using lidar from G-LiHT at Thompson Farm. Each pixel in the image represents 1 m (spatial resolution). Drought and control treatments are identified with sap flow trees for both species. White crowns correspond to the tallest trees, most of them white pines. Black pixels represent vegetation shorter than 20 m. Gray colors symbolized vegetation in between.
Inside each plot, soil moisture and soil temperature have been recorded during the growing season since summer 2016. The data were collected at multiple locations and depths (5, 10, 15 and 30 cm). In 2014, an Eddy covariance tower was constructed at Thompson Farm (within 500 m of the TFE plots) in a forest of similar composition (dominated by white pine and red oak). This canopy tower produces micrometeorological data, including temperature, vapor pressure, radiation and wind, as well as soil moisture. These towers allow a proper estimation of evapotranspiration and the net ecosystem exchange of carbon (Terrestrial Ecosystems Analysis Lab; Burakowski et al., 2018). In addition, a NOAA weather station (Durham 2 SSW) is located at Thompson Farm (within 700 m of all plots) which is collecting temperature, dew point, relative humidity and precipitation among other climate data.

All of these climate and physiological data that are currently monitored at the study area play an important role in targeting remote-sensing observations to periods of time representing a range of water-stress conditions at each study site. The analysis of the precipitation, temperature, soil moisture and evapotranspiration over time at the Thompson Farm, gave elements to determine whether these climate variables were related to drought conditions and their potential influence on reflectance of white pine and red oak and their spectral vegetation indices calculation. For all of the climate variables, I also made a comparison between the datasets from 2017 and 2016 arguing that the 2016 summer season was considered an extreme drought season in New England (http://www.drought.gov).

Vegetation sampling

Leaf samples were collected under sunny and cloud-free conditions between 11:00 and 14:00, from four trees per species per plot, twice a month from June to September 2017. The
samples were collected from sap flow trees and non-sap flow trees, but all of them were tagged from inside the plots. The samples came from branches at the top of the canopy and as much as possible without shade. In total, I collected 182 leaf samples; 83 samples for white pines and 99 samples for red oak. The collection days were chosen following extended rain-free periods. Foliage was collected using a 12-gauge shotgun with 1.25 ounce, 2.75 inch cartridges loaded with #3 steel shot. Samples were stored with moist paper towels in ziplock plastic bags in a cool storage container with fresh ice packs and returned to the EcoHydrology Lab at Morse Hall in Durham, NH for spectral, and structural measurements within 5 hours of collection. Samples were collected from sap-flow trees or from other permanently tagged trees inside the TFE and control plots.

Spectroscopy

Leaf spectra of fresh samples from the upper canopy were obtained using an Analytical Spectral Device (ASD) FieldSpec 4 handheld spectrometer. This spectrometer has a 350-2500 nm spectral range and 1 nm spectral resolution. The measurements were taken in a darkened room, with a Wiko AV/Photo lamp (120V) which can illuminate the leaves with a constant inner light source. To obtain spectra, five measurements were taken for each sample and the average value was used for further analysis. The measurement was made by using a pile of leaves over a dark surface (5 leaves for red oak). The distance from the laser to the piles of leaves was different between species since with the white pine we are usually measuring a smaller area. For white pine samples the distance from the laser to the pile of needles was 15 cm. For red oaks samples, the distance from the pile of leaves to the laser was 20 cm. The calibration of the spectrometer to the spectralon (white of reference) was made every 20 measurements to minimize changes in atmospheric condition.
Specific Leaf Area and Water Content

Once the leaves were measured in the laboratory by the spectrometer, 3 leaves or fascicles were processed to obtain the Specific Leaf Area (SLA), the Gravimetric Water Content (GWC) and the nitrogen concentration (%N). First, samples were weighed “wet” and then using an Epson 10000 XL scanner, all the samples were scanned in full color with high resolution (300 dpi) and with contrast and sharpness to the highest level to calculate the area of the leaves. The area of the leaf and needles was calculated with the scanned images using the program Image J. Later, samples were dried at 70°C for 4 days and reweighed to determine water content. Dried samples were ground using a Wiley mill with a 1-mm mesh screen. Finally, SLA and GWC of the leaves were calculated as follows:

\[
SLA = \frac{\text{area of the fresh leaf (cm)}}{\text{dry weight (g)}}
\]

\[
GWC = \frac{\text{fresh weight - dry weight}}{\text{fresh weight}} \times 100\%
\]

G-LiHT

The Goddard Lidar, Hyperspectral, and Thermal Imager (G-LiHT) is a portable multisensor airborne system developed by NASA Goddard Space Flight Center that simultaneously maps the composition and structure of terrestrial ecosystems (Cook et al., 2013). The G-LiHT sensor has been used by NASA Goddard’s monitoring program in different forests of the U.S. and the forest at Thompson Farm is one of these locations where they have been collecting spectral information since 2016. For the purposes of this study, I used the data that were collected during early June in 2016. G-LiHT images were downloaded online from the web page of the Goddard...
Space Flight Center project (https://gliht.gsfc.nasa.gov/) in May of 2017. There is also another collection campaign from June 2017, but these data have not been processed yet.

G-LiHT data do not allow a reflectance comparison over time because from Thompson Farm there are only data available for early June (2016), so it was not possible to estimate how the reflectance data would vary over the growing season, or how it would change with higher temperatures and low precipitation. However, the quality of the G-LiHT information allows a reflectance analysis as well as some forest structure assessments.

Some of the products obtained with the LiDAR sensor are the Canopy Height Model and the Digital Terrain Model (DTM). Both products have 1 m spatial resolution and are available on the G-LiHT project web page (www.gliht.gsfc.nasa.gov) as Google Earth overlay (KML) and as a raster product (GeoTIFF). The imaging spectrometer has a spectrum range of 418 to 918 nm with 4.5 nm of sampling interval (114 bands). Data products are available as orthorectified raster files (ENVI file format) at a nominal 1 m spatial resolution. Vegetation indices could be computed from this sensor reflectance data as indicators of canopy properties and condition. The thermal camera has 1 m spatial resolution and the images are available as Google Earth overlay (KML) and as a raster product (GeoTIFF) (Cook et al., 2013).

Spectral Vegetation Indices

The use of spectral vegetation indices to evaluate structural and physiological conditions of plants is widely documented (Ollinger 2011; Ceccato 2001; Thenkabail and Lyon 2016). For water stress evaluations there are some water-sensitive hyperspectral indices which have been used in previous studies for their relationship with water leaf content and canopy equivalent water thickness and which are listed in Table 1. These vegetation indices are based on different regions
of the spectrum and have different applications. I compared all spectral indices between treatment, and between species.

Table 1. Summary of reflectance-based indices developed for estimating vegetation water content and their applications. Table adapted from Ollinger (2011)

<table>
<thead>
<tr>
<th>Index</th>
<th>Equation *</th>
<th>Application</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized Difference Water Index (NDWI)</td>
<td>(860-1240) / (860 +1240)</td>
<td>Liquid water content of vegetation canopies</td>
<td>Gao et al. (1996)</td>
</tr>
<tr>
<td>Water Index (WI)</td>
<td>900 / 970</td>
<td>Canopy Water Content</td>
<td>Peñuelas et al. (1997)</td>
</tr>
<tr>
<td>Spectral Ratio Index in the NIR region (NSRI)</td>
<td>890 / 780</td>
<td>Leaf structure deterioration</td>
<td>Liu et al. (2014)</td>
</tr>
<tr>
<td>Normalized Difference Infrared Index (NDII)</td>
<td>(850 – 1650) / (850 + 1650)</td>
<td>Equivalent water thickness - Leaf water content</td>
<td>Hardisky et al. (1983)</td>
</tr>
<tr>
<td>Datt Water Index (DWI)</td>
<td>(816 – 2218) / (816 + 2218)</td>
<td>It’s sensitive to increases in leaf water content</td>
<td>Datt (1999)</td>
</tr>
<tr>
<td>Simple Ratio Water Index (SRWI)</td>
<td>860 / 1240</td>
<td>Sensitivity to vegetation moisture and reflectance at different spectral channel</td>
<td>Zarco-Tejada et al. (2003)</td>
</tr>
<tr>
<td>Simple Ratio (SR)</td>
<td>895 / 675</td>
<td>Correlation with leaf area index</td>
<td>Jordan (1969)</td>
</tr>
<tr>
<td>Moisture Stress Index (MSI)</td>
<td>1600 / 819</td>
<td>Sensitive to leaf water content</td>
<td>Hunt and Rock (1989)</td>
</tr>
<tr>
<td>Photochemical Reflectance Index (PRI)</td>
<td>(531 – 570) / (531 + 570)</td>
<td>Carotenoids; Xanthophyll cycle</td>
<td>Gammon et al. (1997)</td>
</tr>
</tbody>
</table>

*The formula’s values in the column Equation represent the reflectance at each of these wavelengths (nm)

Data Spectral Processing and Analysis

Reflectance spectra from G-LiHT were processed using the platform Google Earth Engine (Gorelick et al 2017). The reflectance data were obtained using the Canopy Height Model and the field plots were located within the aerial imagery using GPS coordinates. The GPS coordinates were collected with a Trimble Geo 7X with a Tornado external Antenna during the springtime before the leaves came out for the plot’s corners and for every white pine and red oak tree inside the plots. Detailed crown delineation maps were created for all the white pine and red oaks labeled inside the plots and reflectance and tree height data were extracted for each one of these trees (Figure 1). To facilitate comparison between treatments and species, only spectral bands from the
NIR region were used in the analysis. The comparisons were made only with the dataset from 2016, since the 2017 data are not yet available (www.gliht.gsfc.nasa.gov).

**Hierarchic Modeling Development**

To analyze the reflectance data obtained with the ASD spectrometer between species and treatments, I calculated 10 different spectral vegetation indices (Table 1) which have been proposed based on their sensitivity to water stress (Ollinger 2011; Liu et al 2016, Ceccato 2001), and I created a matrix for the vegetation indices values over time for each treatment and species.

With this matrix, I generated an ARIMA (autoregressive integrated moving average) model in R version 3.4.1 (R Foundation for Statistical Computing, 2017) to assess the differences between treatments and species and to define a tendency over time. ARIMA models are time series analyses in which past observations of the same variable are collected and analyzed to develop a model describing the underlying relationship (Zhang 2003). In this modeling approach, the future value of a variable is assumed to be a linear function of the past observations and random errors. In other words, the average values of the variable at a previous point (date of collection), are moving forward to the next point to define a value for the variable at this point according to some parameters already established ($\beta_0, \beta_1, \ldots, \beta_n$). The rest of the variation could be explained by other factors such as climate or habitat variables.

To evaluate the differences between treatments and between species I created nested versions of the model within the main one (hierarchic modeling). The main model tries to establish the tendency of the spectral variable over time, but it does not distinguish that there are different treatments and different species in the data. With the second and third model I evaluated if the tendency of the spectral variable differs between treatments or between species over time. The
forth and the most complex model, is an assessment of the tendency of the spectral variable over time indicating that the data contains two different treatments and inside each treatment there are two different species. To rank the models and to find out which one adjusts better to the distribution of my data I calculated the AIC values.

The hierarchic modeling was made possible by creating a subset of the data for the different treatments and for each of the species as well as a new subset of parameters. However, the main analysis was always made based on the same original parameters. It is important to mention that the number of parameters that I can add to the model is limited by the total size of the data set. To calculate the confidence intervals for the best predictions of the model, I calculated a parametric bootstrap. The key idea of the bootstrap is to perform computations (1000 replicates) on the data itself to estimate the variation of point estimates; that is, to estimate confidence intervals computed from the same data. The bootstrap is based on the law of large numbers that means that with enough data the distribution will be a good approximation of the true distribution.

Statistical Analysis

Statistical analysis, graphs and figures were generated in R version 3.4.1 (R Foundation for Statistical Computing, 2017). I used the ggplot2 package (Wickham 2009) to generate the graphs, the corrgram package (Wright 2017) for the correlation analysis and the factoextra package (Kasambra and Mundt 2017) to visualize the p-values from the correlation analysis. A Pearson’s correlation analysis was made to quantify how strong the relationship was between the leaf functional traits measured (SLA and GWC) and the spectral indices calculated (Table 1) during the growing season. The correlation coefficients were calculated as well as the p-values to evaluate which of the high correlations established between variables were significant for both species.
RESULTS

The spectral analysis showed that each species has a distinct reflectance signature (a finding that is not impressive if I consider that the species have different traits), but their reflectance pattern are not responding to the treatments. For both species, the reflectance pattern in the control and drought plots is similar over time, suggesting that the drought conditions simulated in the plots are not distinguishable through analyzing the spectral data obtained for each species (Figure 2, 3, 4).

The hierarchical modeling approach shows that for all the vegetation indices the reflectance between treatments show no major differences for analysis made with both combined and single species (Figure 2, 4). On the other hand, the comparison between species suggests that each species has a distinct reflectance signature that is consistent for all the different vegetation indices as well as constant over time, once the leaves are fully formed in June (Figure 3). The model that best predicted the distribution of the spectra data was the model proposed for different species, based on the AIC values (Table 2), although the species model outperformed the treatment model for some indices and then the treatment outperformed the species model in other cases.

Table 2. AIC values to rank the hierarchy modeling approach. A good model is the one that has minimum AIC among all the other models or the one with the biggest negative value. Four models (no differences between treatments and species, differences between treatments, differences between species, and differences between treatments by each species) are assessed across ten indices. Gray cells indicate the highest negative AIC values.

<table>
<thead>
<tr>
<th></th>
<th>MSI</th>
<th>NSRI</th>
<th>PRI</th>
<th>SR</th>
<th>NDVI</th>
<th>DWI</th>
<th>NDH</th>
<th>WI</th>
<th>NDWI</th>
<th>SRWI</th>
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<td>No differences between treatments nor species</td>
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<td>-688.88</td>
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<td>-438.36</td>
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<td>-422.65</td>
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<td>-164.22</td>
<td>715.26</td>
<td>-141.79</td>
<td>-122.93</td>
<td>-131.27</td>
<td>-173.72</td>
<td>-154.91</td>
<td>-117.56</td>
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</table>
Figure 2. Spectral differences among treatments for each of the vegetation indices over the growing season of 2017. There are no differences in the distribution of the spectral data between treatments for any of the indices over the whole season. Each date represents a day of leaf sample collection.
The comparison between climate variables datasets from 2017 and 2016 were useful to illustrate that drought conditions were more extreme during the 2016 summer season in New England (Figure 5, 9, 10, 11). The soil moisture shows that in 2016 the water content decreases below 10% and the drought plot experienced the lowest moisture condition during August and September (~7%). In 2017, the soil moisture never decrees more than 10% and the drought plot experienced the same soil moisture conditions of the control plot in 2016 (Figure 5). The precipitation data shows that during the growing season in 2017, rain events above 20 mm per day were more common and they are distributed over the whole season, compared with the 2016 season where the rainy events above 20 mm were less common and most of them were concentrated in June and July (Figure 9). The temperature values in 2017 suggests that from June through August the temperature remained constant with some fluctuations between 20 and 25°C, but without significant patterns of decreasing or increasing temperatures. Similar high temperature values were observed in 2016 with the exception that in 2016 high temperatures were concentrated in June and August, but in general above 20°C during the whole growing season (Figure 10).

The soil moisture data from 2017 shows that in June and July there is a continuous decreasing pattern in both of the plots (drought and controls), with lower moisture values in the drought plot that reach 10% of water content in the soil. During August and September, although there is some variation in the soil moisture, the soil moisture content declines at the end of September (Figure 5). The reference evapotranspiration (ETo) (Sanders-DeMott unpublished data) shows a high oscillation from values that go from 1 to 8 mm per day. However, this oscillation is higher and more frequent during June and July where most of the high values rise 7 mm per day.
Figure 3. Spectral differences between species for each of the vegetation indices over the growing season of 2017. The spectral distribution over time suggest differences between species for all of the indices. Each date represents a day of leaf sample collection.
During August and September, the oscillation is less frequent and the highest values per day are between 5 and 6 mm (Figure 11).

ETo suggests that transpiration was higher at the beginning of the 2017 season when the soil water content was higher. Then transpiration decreased the remainder of the growing season, even when soil moisture increases early-august. Although the reduction in transpiration and soil moisture are evident over time, such changes did not affect the reflectance data of the species. At the beginning of August, when the soil moisture was lowest and ETo ranged from 2-6 mm day\(^{-1}\), I did not detect changes in the spectral behavior in any of the vegetation indices evaluated for both species (Figure 3).

The specific leaf area (SLA) and the gravimetric water content (GWC) values are reported in Table 3 and Table 4. The correlations between the spectral vegetation indices and both SLA and GWC were significant when grouped by species (Figure 6, Figure 7). The p-values are posted in Table 5 and Table 6. For red oak, the correlation between spectral indices and the SLA shows a weak relationship (R < 0.24) between some of the spectral indices and the p-values suggests that the correlation with these indices PRI, SR, NDII and NDWI are statistically significant (p-value < 0.05). On the other hand, the correlation analysis with the leaf water content shows that there is not a statistically significant correlation between GWC and some of the indices, although there is some moderate correlation with the indices: NDII (R = 0.44), PRI (R = -0.26) and NSRI (R = 0.18) (Table 5, Figure 6). In the case of the white pine the correlations between the spectral indices and the SLA are higher than the red oak (-0.18 < R < -0.54) and remains weak for the GWC (-0.01 < R < -0.21). For the leaf water content, the correlation is significant for some of the indices (NDWI, NDII, MSI and PRI). For the SLA, all the correlations are negative with highest one being the
Figure 4. This graph exemplifies the spectral differences between species but also illustrates that there are not spectral differences within each species’ spectral distribution by treatment. Red lines illustrate the ARIMA lines for red oak and black lines the ARIMA lines for white pine. Straight lines are from the control and intermittent lines represent the drought plots.
Water Index (R = -0.54). The p-values suggest a significant correlation with these indices: NDII, SRWI, SR, DWI, WI (Figure 7, Table 6).

The analysis between control and drought plots based on G-LiHT spectral data did not show significant differences between treatments (p > 0.05) (Figure 8, 12). The comparative analysis made with the reflectance data obtained from the canopy height model showed that both white pine and red oak have similar reflectance in the control and drought plots. There is not an effect of the treatment on the reflectance for both species. However, there is a clear difference between species. Both species are significantly different from each other and have a unique reflectance signature.

G-LiHT data are also very useful to expose different features of the forest structure. From the canopy height model, it is possible to extract information about forest species composition, location of each species on the plot and at the species level; tree height and crown size (Cook, et al. 2013; Figure 1). The G-LiHT data showed that on average white pine trees are taller than red oak (28.74 m & 25.51 m). Specifically, it is possible to measure how tall trees with sapflow sensors are relative to neighboring trees, and to evaluate the average height between treatments to validate if comparisons between treatments have been made under similar circumstances (Figure 13, 14, 15).
Figure 5. Soil Moisture data registered from Thompson Farm at the plot level by each treatment. For both years the soil moisture is always lower in the Drought plots through the growing season. 2016 was definitely dryer than 2017; in 2017 the water content was not lower than 0.1mm as occurred in 2016, and the control plot in 2016 had similar water content to the drought plot in 2017.
The DTM showed that Control 1 and Drought 1 are located at the same elevation with similar conditions. The terrain in Control 1 is more homogeneous (20 – 21 m) while Drought 1 has more slope variation (19.5 – 23 m), specifically on the northeast side of the plot (Figure 16). On the other hand, between Control 2 and Drought 2, there are a few meters of elevation in difference (C2: 21-24m, D2: 25 – 27m). The terrain in Control 2 is flatter except at the south west corner. Drought 2 is located two meters higher but in a homogeneous terrain. Information of this kind would be valuable to determine which plots are likely to have drier or wetter soil or to develop a model to analyze how much sunlight the species can get or to determine which species are under shade compared to the others (Figure 16).

Figure 6. Correlation analysis between the spectral indices and the red oak specific leaf area (SLA) and the leaf water content (GWC). The dot plots (bottom left) represent the direction of the correlation between variables. The pie graphs (upper right) illustrate the strength and direction of the relationships shown with the dot plots. Full pie graphs represent high correlation between variables and the colors symbolize if the correlation is positive (blue) or negative (red).
Figure 7. Correlation analysis between the spectral indices and the white pine specific leaf area (SLA) and the leaf water content (GWC). The dot plots (bottom left) represent the direction of the correlation between variables. The pie graphs (upper right) illustrate the strength and direction of the relationships shown with the dot plots. Full pie graphs represent high correlation between variables and the colors symbolize if the correlation is positive (blue) or negative (red).

DISCUSSION

In this study I evaluated the sensitivity of spectral metrics for water stress detection in white pine and red oak within two different treatments as a part of the DroughtNet throughfall removal experiment. To recognize drought conditions and associate them with remote-sensing observations, soil moisture and climate variables were monitored at the site level. My results indicate that for the weather conditions that occurred in the summer of 2017, and which do not represent stressful conditions compared with previous years, there was no significant difference in spectral indices between the treatment and control plots. Although sap flow and gas exchange data indicated reduced water use at the end of the season in the drought plots relative to control plots
or relative to early season water use (EcoHydrology Lab unpublished data), spectral data did not detect differences between the treatment and control plots, which suggests that the spectral indices are not more sensitive than the physiological measurements commonly used for water content estimations. I also evaluated whether the reflectance indices developed for plant water content assessment were able to illustrate the distinctive strategies that each species has to mitigate drought stress (their stomatal conductance activity respond in different ways to water availability in the environment). Although there are spectral differences between the species, I couldn’t conclude that those differences conform to the susceptibilities that anisohydric and isohydric species have to drought conditions.

The spectral differences that I found between red oak and white pine are perhaps related to the distinctive features such as the leaf structure and leaf chemistry, instead of representing differences that follow water stress performance. The analyses of soil moisture, temperature, precipitation and evapotranspiration (Figure 5, 9, 10, 11) show that the fluctuations observed in these variables are not correlated with the spectral pattern observed over time for either species (Figure 4). Conversely, the spectral pattern for both species remains fairly constant during the growing season with few fluctuations, suggesting that the spectra are not responding to fluxes of the dry or wet conditions, and probably they are obeying traits or structures that are constant in the plants over time. Thus, the isohydric and anisohydric strategies don’t suggest a singular spectral behavior based on the weather conditions experienced during the growing season of 2017.

One factor that could persuade the finding of differences between treatments for both species would be related to the threshold that white pine and red oak may have when they start suffering water limitation conditions and they are forced to down-regulate their stomatal conductance. There are known changes in soil water status that can affect stomata regulation,
however, sometimes when the soil water status declines for several days or more it is not enough to arise a change in the water potential that induces the liberation of the plant hormone abscisic acid (ABA) from the roots (Buckley 2005). Sap flow data from the plots showed that both white pine and red oak started to regulate down their stomata in 2015 and 2016 when the soil water concentration (VWC) went below 10% (VWC) (Figure 17) (McIntire et al. In prep.). Conversely, during the growing season in 2017 soil moisture data never came down below 10% and the VWC values of the drought plot are similar to the VWC values from the control plot in 2016 (Figure 5, 17).

These non-stressful conditions in 2017 suggest two possible scenarios. 1) Both species didn’t experience water limitations during 2017 in any of the treatments and for that reason, I couldn’t identify spectral differences between the control and drought plots, because the species were never forced to regulate their stomata, and because of this I didn’t find changes in the reflectance data for the species in the drought plots. 2) If at some point I was expecting that vegetation indices would be more sensitive than sap flow measurements for identifying early signals of stress between species and between treatments, our results suggest that spectral metrics are not very sensitive when plants are not beyond their threshold for water limitation. Although I analyzed a variety of water-sensitive hyperspectral indices, located in different regions of the spectrum and sensitive to different plant structures and plant processes, my results suggested that for any of the vegetation indices I was not able to distinguish early signals of water stress conditions.
Figure 8. Spectral differences between species and between treatments from G-LiHT data. The reflectance was calculated in the NIR region. The box plot on the top shows the differences between treatments for each species. Differences between treatments are not statistically significant for both species. The box plot on the bottom illustrates the differences between species for the control and drought plots, with the bigger differences being between species at the control plot.

Several studies have evaluated the relationship between vegetation indices and plant water content (Peñuelas et al., 1993, 1997; Zarco-Tejada et al., 2003; Ceccato et al., 2001; Liu et al., 2016), but few studies have tried to relate physiological variables and ground-based measurements with spectral indices to elucidate the sensitivity of these spectral metrics for early water stress signals (Marino et al., 2014; Tsonev et al., 2014; Manzanares et al., 2017). It is widely accepted that water absorption bands appear in the NIR and SWIR regions (Tucker 1980; Ceccato et al., 2001; Liu et al., 2016), but some studies have found that the most sensitive bands are in the 900 - 1500 section (Sims & Gammon 2003; Zarco-Tejada et al., 2003), and others have shown that water absorption bands from the 1500 - 2500 are more reliable (Hunt and Rock 1989; Davidson et al.,
In addition, other studies focused on tracking variations in photosynthetic activity have demonstrated that the Photochemical Index, located in the VIS region with a reflectance signal at 531nm, also offers very reliable information for water stress detection (Peñuelas et al., 1994; Thenot et al., 2002; Filella et al., 2009), because this index is measuring the state of the xanthophyll cycle which is related to the active metabolism of the leaf.

For the NIR-based spectral indices, the ability of the water index (WI) to evaluate physiological status and water content is documented in several studies exploiting leaf, ground, and airborne measurements (Sim & Gammon 2003; Peñuelas et al., 1994), although some studies have shown that it is sensitive to the structural effects of the canopy (Serrano et al. 2000; Colombo et al. 2011). Sims and Gammon (2003) tried to determine the water content at the canopy level (equivalent water thickness) using a spectrometer and they found that the optimal wavebands were centered in three regions, 950 – 970, 1150 – 1260 and 1520 – 1540 nm. Though they only evaluated the water index (WI) and the normalized difference water index (NDWI), within the regions which they considered sensitive, the simple ratio water index (SRWI) could be also included. Numerous studies have demonstrated the ability of the NDWI to estimate leaf and canopy equivalent water thickness (Serrano et al., 2000; Sims and Gamon 2003; Colombo et al., 2008), the fuel moisture at the leaf and ground level (Zhang et al., 2010) and satellite data (Gao, 1996; Deninson et al., 2005). NDWI is also insensitive to foliar dry matter biochemical compounds like lignin or cellulose (Thenkabail & Lyon 2016). The 860 and 1240 nm wavelength, which compose the NDWI as well as the SRWI, are located in the high reflectance plateau where the contribution of vegetation scattering to reflectance is similar. Our results showed that the correlation for the NIR-based spectral indices to the leaf water content were not very strong for
any of the indices. In the case of the red oak, there was no significant correlation, and with the white pine the NDWI and MSI had a weak correlation.

The SWIR region is recognized for having a high presence of intermediate and weak absorption bands (1520-1540, 1650, 2130-2250) that can penetrate the canopy and sense a larger portion of the total water content. Because of this, these spectral regions are most suitable for optical remote sensing of vegetation water content at landscape level (Thenkabail & Lyon 2016). Although the moisture stress index (MSI) and the normalized difference infrared index (NDII) were specifically designed for satellite application, Hunt and Rock (1989) and Hunt (1991) showed that the MSI calculated at the leaf level also has a good performance calculating the equivalent water thickness.

The NDII has been studied by numerous authors (Yilmaz et al., 2008) to estimate vegetation water content or the equivalent water thickness, and some studies have demonstrated that the NDII allows successful tracking of seasonal variability of equivalent water thickness at the canopy in forest ecosystems (Maki et al., 2004; Yilmaz et al., 2008). NDII was precisely the index that exhibited more sensitivity at the beginning of the season, when greater fluctuations were observed in some of the climate variables that I analyzed, such as the soil moisture and reference evapotranspiration over time (Figure 3). However, I can’t attribute the sensitivity expressed for the NDII to the variation in the soil moisture and the ETo, at least not only to these variables. As I mentioned in the results, at the beginning of August when I observed the lowest values of soil moisture and intermediate values in ETo (Figure 11), the reflectance of the species didn’t explicitly display any change corresponding to those conditions. There is no reason to believe that the species were responding to the fluctuations at the beginning of the season, but not in August when the conditions were more extreme. In addition, although I was expecting more variation in the
reflectance of the white pine, which is considered drought sensitive, the reflectance of the red oak expressed more sensitivity with the NDII index.

Indirect effects of water content have also been found in the green spectrum where it is possible to capture physiological responses. The photochemical reflectance index (PRI) expresses the relative down-regulation of photosynthesis induced primarily by high light intensities via the xanthophyll pigment cycle, but it also is affected by secondary factors such as drought (Gamon et al., 1997). With PRI, short term responses to high light conditions are very sensitive and the photosynthetic down-regulation is indicated by the most positive value observed. Although the PRI signal is relatively weak compared to spectral indices in the NIR and SWIR it has been successfully observed remotely in forest studies (Thenot et al., 2002; Filella et al., 2009; Thenkabail & Lyon 2016). Although Thenot et al (2002) found that under control conditions (low to moderate stress intensity) PRI was considered a reliable water stress index, in this study I was not able to discriminate between two treatments and I didn’t identify early signals of stress. However, PRI had an acceptance performance for both species. In both cases, PRI exhibited a moderate correlation with the specific leaf area and the leaf water content unique to each species, even though in some cases those correlations were not significant.

Although I didn’t find early signals of water stress conditions with any of the vegetation indices reviewed, analyzing the correlation between spectral vegetation indices for both species and the specific leaf area (SLA) and the gravimetric water content (GWC), there are some moderate correlations that indicate a good performance for water stress detection for some indices. In the case of the red oak, only the PRI and the NDII had a moderate or high correlation with both SLA and GWC (Figure 6, Table 5). For the white pine, most of the indices showed a decent sensitivity to water content analysis, but only NDII had a moderate correlation with the SLA and
GWC, even though the NDWI, SRWI and WI had a high and significant correlation with the SLA (Figure 7, Table 6). These results indicate the sensitivity of SWIR reflectance to variation in the water content, and the sensitivity of the NDII to successful tracking of seasonal variability of leaf water content in forest ecosystems. However, these results don’t suggest that the SWIR region as the only sensitive region for water stress analysis if I consider that PRI and other indices like WI and NDWI from the NIR region also had a good performance (Figure 6, 7).

CONCLUSIONS

In total, I evaluated 10 indices along the VIS, NIR and SWIR regions, all of them recognized for their sensitivity for vegetation water content assessments and which are sensitive to different leaf structures and physiological leaf processes (Serrano et al., 2000; Ceccato et al., 2002; Liu et al., 2016; Ollinger 2011). Although none of the spectral indices showed early signals of water stress conditions, some of the indices performed well with correlation analyses for the species leaf water content and specific leaf area, with the NDII and PRI standing out. These results don’t suggest that there is a more reliable region of the spectrum for water content assessment. On the contrary, this ground-based spectral assessment shows that a wider evaluation of the spectrum will increase the chances of finding vegetation indices that perform well with plant water content over time. However, not all of the sensors and remote sensing techniques allow for an evaluation of wider regions of the spectrum. In this sense, it was positive to show that spectral indices like PRI, which wavebands are very easy to obtain with sensors like G-LiHT or satellite missions like LANDSAT or MODIS, were able to show a high sensitivity for vegetation water content evaluations.
This study reaffirms the importance of continuing with monitoring that can complement the water stress assessment in ground and the experimental projects (DroughtNet). Although this study did not show spectral differences between treatments and I was not able to identify early stress signals, these kinds of results will be valuable for an overall evaluation of the experiment in the long term. Experiments of this type, may take years to make evident the consequences of the intervention. We know that there are identifiable soil moisture thresholds for tree mortality beyond which phases of rapid change can be expected. That means that once the threshold is reached and tree mortality occurs, the following changes will come fast (Meir et al. 2015). For this reason, it is valuable to continue the monitoring to elucidate at some point early signals of stress or merely to have elements of analysis that would be able to show gradual changes over time.

**LITERATURE CITED**


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Table 3. Specific Leaf Area (SLA) values calculated for white pine and red oak. The calculations were made for each date of collection over time, and they are separated by species and treatment.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Species</th>
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<th>13-Sep</th>
<th>27-Sep</th>
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Table 4. Leaf Gravimetric Water Content (GWC) values calculated for white pine and red oak. The calculations were made for each date of collection over time, and they are separated by treatment and species.

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Table 5. Correlation coefficients (R) and p-values calculated for the correlation analysis between the spectral indices and the Red Oak specific leaf area (SLA) and leaf water content (GWC). On the right side and above the diagonal of the indices, there are the p-values, which indicate if the relationships between variables are significant. All the dark gray cells represent the significant relationships. The correlation coefficients are on the left side below the diagonal of the vegetation indices acronyms. All the gray cells represent the coefficients values which correspond to significant relationships. These coefficients determine the strength and direction of the relationships between variables.

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MSI: Moisture Stress Index; NSRI: Spectral Ratio Index in the NIR region; PRI: Photochemical Reflectance Index; SR: Simple Ratio; NDVI: Normalized Difference Vegetation Index; DWI: Watt Water Index; NDII: Normalized Difference Infrared Index; WI: Water Index; NDWI: Normalized Difference Water Index; SRWI: Simple Ratio Water Index

Table 6. Correlation coefficients and p-values calculated for the correlation analysis between the spectral indices and the White Pine specific leaf area (SLA) and leaf water content (GWC). On the right side and above the diagonal of the indices, there are the p-values, which indicate if the relationships between variables are significant. All the dark gray cells represent the significant relationships. The correlation coefficients are on the left side below the diagonal of the vegetation indices acronyms. All the gray cells represent the coefficients values which correspond to significant relationships. These coefficients determine the strength and direction of the relationships between variables.

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MSI: Moisture Stress Index; NSRI: Spectral Ratio Index in the NIR region; PRI: Photochemical Reflectance Index; SR: Simple Ratio; NDVI: Normalized Difference Vegetation Index; DWI: Watt Water Index; NDII: Normalized Difference Infrared Index; WI: Water Index; NDWI: Normalized Difference Water Index; SRWI: Simple Ratio Water Index
Figure 9. Precipitation data during the growing season for 2016 and 2017. The graph only shows rain events greater than 5 mm/day and they are separated by month and the days are indicated. The frequency of these events was more common in 2017 as well as the intensity. During the same period of time in 2016, there were registered less rain episodes and only three of them were greater than 20 mm/day.
Figure 10. Temperature data during the growing season for 2016 and 2017 at Thompson Farm, from NOAA dataset. Higher temperatures are similar in both years but in 2017 higher temperatures started earlier in the season.
Figure 11. Reference Evapotranspiration calculated from data took from the Eddy covariance tower at Thompson Farm, from June to September 2017 (Sanders-DeMott unpublished data). There is a higher variation of evapotranspiration from June to July than from August to September.
Figure 12. Spectral differences between species and between treatments from G-LiHT data. The graph on the top shows the differences between species for each treatment. The X axis represents the spectral band from G-LiHT data and the Y axis the reflectance. Differences between species at the control plot are greater than the differences in the drought. The graph on the bottom shows the differences between treatments for each species, but they are not statistically significant in both cases.
Figure 13. Average plot tree height pooling species in each plot. C1: Control 1, C2: Control 2, T1: Drought 1, T2: Drought 2.

Figure 14. Tree height average by species and by sap flow and non-sap flow trees.
Figure 15. Average plot tree by each species. C1: Control 1, C2: Control 2, T1: Drought 1, T2: Drought 2.
Figure 16. Digital terrestrial model for all each treatment. Control 1 and Drought 1 are located at similar elevations. Control 2 and Drought 2 are located within a few meters of differences between them. Green colors represent lower elevations (10 – 18 m), orange and red intermediate elevations (19 – 22 m) and blue colors higher areas (23 – 28 m).
Figure 17. Soil Moisture data registered from Thompson Farm at the plot level by each treatment since 2015. Blue boxes indicate drought plots and purple boxes are control plots (McIntire et al. In prep.).