

ASSESSING FUNCTIONAL DIVERSITY OF A  
MANAGED FOREST-SAVANNA LANDSCAPE USING  
REMOTE SENSING TECHNIQUES

By

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Abstract: Global biodiversity loss and changing disturbance patterns are having significant effects on the composition, function, and productivity of biological communities. Functional diversity, a multifaceted trait-based component of biodiversity, is emerging as an effective metric of community function, resilience, and response to environmental change. Remote sensing techniques can be used to measure the biochemical, physiological, and morphological traits of plants and assess functional diversity across a landscape. In this study, I demonstrated the use of multispectral imagery and light detection and ranging (LiDAR) to determine relationships between physiological and morphological functional diversity metrics - functional richness, functional evenness, and functional divergence - and forest management implemented at Pushmataha Forest Habitat Research Demonstration Area (FHRA). Indices of vegetation biochemistry, physiology, and morphology were affected by forest management, including combinations of prescribed fire, selective thinning, and pine timber harvest, while the effects of management on functional diversity metrics estimated from remote sensing were less defined. Morphological functional evenness and divergence differed between treatments, and fire return interval was determined to play a key role in vegetation community morphology and functional diversity. By expanding the methodology to assess metrics of functional diversity across the larger forest-savanna landscape of Pushmataha Wildlife Management Area, I examined the scale dependency of functional diversity metrics and demonstrated the potential for using multispectral imagery from satellite platforms to fill gaps in global functional diversity knowledge.

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## CHAPTER I

### INTRODUCTION

Disturbance is an influential and widespread phenomenon affecting the composition, dynamics, and function of vegetation communities across the globe (Attiwill 1994; Franklin et al. 2002; Thom and Seidl 2016). In forest and savanna ecosystems, fire, tree-fall, insects, wind, weather events, and other disturbances operate at various sizes, frequencies, and intensities forming disturbance regimes that are characteristic to these systems. Historically, these disturbance regimes have occurred naturally, determined by a number of endogenous and exogenous factors (Attiwill 1994). However, anthropogenic disturbances, suppression of disturbances, and modifications to the landscape are causing disruptions to the intensity and frequency of natural disturbance regimes (Thom and Seidl 2016), often having consequences for the composition and function of vegetation communities.

Land managers are more frequently implementing adaptive management, building upon foundational knowledge of the natural disturbance regime of an area, to maintain forest biodiversity and increase community function and ecosystem services provided. The successful management of a forest system can become very complex when managers account for, or try to replicate, the system's natural disturbance regimes (Thom and Seidl 2016). Despite this, many researchers argue that forestry practices and management need

to more closely mimic natural disturbance patterns in order to manage heterogeneous, multi-functional landscapes for biodiversity, ecosystem services, and ecosystem function (Attiwill 1994; Bengtsson et al. 2000; Palik et al. 2002).

Functional diversity serves as a link between vegetation diversity and ecosystem functioning (Díaz and Cabido 2001) and is a measure of the variation in organismal traits that determine the niches in a community and influence overall ecosystem functioning (Tilman 2001). Metrics of species diversity, such as richness and evenness, have frequently been used as primary measures of biodiversity; however recent works of literature suggest that functional diversity has emerged equally as a component of biodiversity and a valuable measure of ecosystem productivity and resilience to disturbance (Petchey et al. 2004; Cadotte et al. 2011). Measuring the functional diversity of a community relies on the measurement of species' functional traits within it. In plant communities, functional traits are associated with a plant's ability to acquire, utilize, and conserve resources and influence the establishment, survival, and fitness of species (Reich et al. 2003).

Traditional field data collection methods have been used to collect data on vegetation functional traits of forest communities to assess functional diversity at small scales. Limitations arise at larger scales due to the time, effort, and costs required to collect detailed functional trait data. Recently, remote sensing techniques have been used to supplement field data collection methods to reduce costs and efficiently collect data at finer spatial and temporal resolutions for functional diversity studies.

Remote sensing techniques can be used to collect data over larger spatial extents and can offer cost-effective methods to monitor biodiversity in a variety of landscapes (Cavender-Bares et al. 2017; Jetz et al. 2016). Both passive and active remote sensing techniques of data collection have allowed scientists to measure functional traits of vegetation, including traits associated with plant biochemistry, physiology, and morphology, such as leaf chlorophyll content and foliage height diversity (Schneider et al. 2017). Utilizing remote sensing methodology, researchers can continue to fill gaps in knowledge of ecosystem functional diversity at a global scale (Jetz et al. 2016).

While numerous studies have demonstrated the potential for using remote sensing methods to assess functional diversity of vegetation communities across a landscape (Jetz et al. 2016; Asner et al. 2017; Schneider et al. 2017), the relationships between functional diversity, management strategies, landscape heterogeneity, and resilience are not fully understood. The objective of this thesis research is to utilize environmental remote sensing techniques to examine the effects of forest management on functional diversity of vegetation. In this thesis, I present methodology utilizing two types of remotely sensed data, specifically multispectral imagery and light detection and ranging (LiDAR), to assess and map physiological and morphological functional diversity across a managed forest-savanna landscape in southeastern Oklahoma. Utilizing multispectral imagery and LiDAR point clouds, I calculate vegetation indices and morphological traits to assess three different metrics of functional diversity - functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv). The results of this study provide insight on relationships between functional diversity and forest management practices such as prescribed fire, selective hardwood thinning, and timber harvest. The

methodology I utilize in the study serves as a basis for future research on the functional diversity and resilience of managed, heterogeneous landscapes across the globe.

## CHAPTER II

### REVIEW OF LITERATURE

Natural disturbance regimes are known to be important drivers of forest ecosystem dynamics (Franklin et al. 2002; Kuuluvainen and Aakala 2011; Thom and Seidl 2016). Disturbance within forest communities and ecosystems is fundamental to the species composition, resilience, and overall function of that system (Bengtsson et al. 2000). Across the globe, many disturbance regimes have been affected by climate change and anthropogenic modifications to the landscape (Thom and Seidl 2016). This intensification likely has implications for ecosystem diversity, resilience, and function, many of which are not fully understood. The role of specialized management is essential to maintaining stable ecosystems and communities for both wildlife and humans. With this thesis research, I explore the role of management strategy in the functional diversity of a forest-savanna landscape using remote sensing techniques. I discuss natural and anthropogenic disturbance within forests and the implementation of management strategies to replicate it. In addition, I demonstrate the use of remotely sensed data to measure functional traits and diversity to assess the impacts of disturbance and management on forests. Understanding the role of management and monitoring of vegetation condition is essential in sustaining overall ecosystem biodiversity.

## 2.1 Role of Disturbance in Forest Systems

Disturbance has been an important concept discussed in ecological literature and has played a role in various ecological theories, such as patch dynamics (White and Pickett 1985; Kane et al. 2011). Disturbance has been examined in a number of different ecosystems (Graham et al. 2009; Jorgenson et al. 2010), at various levels of organization (Spagnuolo et al. 2009; Hotes et al. 2010), and as an impact on numerous organisms (Binh et al. 2007; Dornelas 2010; Bicknell and Peres 2010). Despite its pervasiveness in the literature, the term is often broad and ill-defined in many studies (Dornelas et al. 2010). Disturbance is, however, characterized as a localized, temporary event or events, defined by its occurrence in a given space at a specific time (Dornelas 2010). Ecological phenomena such as fire, disease, storms, floods, and land-clearing are disturbances that are well-known to the public. Under many circumstances, authors consider these disturbances to be a negative shift in demographic rates, defined as “events that cause mortality, displacement or damage individuals” (Sousa 1984) or “events that kill or cause loss of biomass” (Huston 1994). Despite this negative connotation in some of the literature, disturbance can be viewed as any shift in demographics, as disturbance can also release resources previously stored within living organisms and increase habitat heterogeneity of a landscape (White and Pickett 1985). For the purpose of this review, I use the inclusive definition from the foundational piece by White and Pickett (1985) for disturbance – “a discrete event that has a significant effect on community composition, structure, or function” to account for shifts in community demographics that can occur in a vegetation community such as a forest.

Natural disturbance is a crucial driver of ecosystem structure and function in forests (Franklin et al. 2002; Thom and Seidl 2016). While many different types of disturbances occur in forest systems, including storms, wind, fire, insects, and disease, in this literature review I will be focusing on two disturbances: fire and tree-fall. Fire and tree-fall in forest communities are important disturbances that can have an effect on species composition, diversity, biomass, and overall ecosystem function (Attiwill 1994; Bengtsson et al. 2000; Thom and Seidl 2016). Extensive research and reviews of the literature demonstrate the role of these disturbances in forest dynamics and the spatial and temporal patterns in forested landscapes (Rykiel 1985; Oliver and Larson 1990; Attiwill 1994; Seidl et al. 2011).

The history of fires in forested systems is well established, especially in North America pre-European settlement (Attiwill 1994). However, the role of fire in specific systems and conditions needs to be examined further. Fire is an exceptionally dynamic process with extensive variation in time and space; its effects can vary significantly based on the fire's size, intensity, frequency, and time of year, among other conditions (Ryan 2002; Franklin et al. 2003). A fire's spread and intensity are largely dependent on the climate (temperature, moisture, etc.) and the quantity and quality of fuel (Attiwill 1994). Fire frequency can have impacts on regeneration strategies, while fire intensity and severity have consequences for plant survival, forest morphology, and regeneration (Ryan 2002).

In addition to fire, tree-fall is another influential disturbance with consequences for forest community morphology and species composition (Attiwill 1994). Tree-fall is strongly associated with gap dynamics, the process by which gaps in a forest canopy are

created and then filled (Brokaw and Busing 2000). The rate of tree-fall and the size of the gap from a single or multiple tree-falls changes light penetration through the canopy, allowing for greater variation in species and growth rate of individuals that colonize those spaces (Martínez-Ramos et al. 1988; Poulson and Platt 1989).

Many studies indicate that disturbances such as tree-fall and fire can have serious implications on a forest's natural dynamics (Attiwill 1994; Runkle 1985; Poulson and Platt 1989). Understanding how natural disturbance regimes and forest dynamics relate to anthropogenic disturbance and management practices is key to preserving biodiversity and overall ecosystem function in forested landscapes worldwide (Attiwill 1994; Nilsson and Ericson, 1997).

## **2.2 Forest Management**

Organisms have adapted to the disturbance regimes that are characteristic of the forest type they inhabit (Bengtsson et al. 2000). However, with human-induced disturbance or suppression of disturbance, the intensity and frequency of these events are being altered (Thom and Seidl 2016). Anthropogenic modifications to disturbance patterns can cause drastic changes in these systems, and as a result, issues arise in developing successful management strategies for the area. Knowledge of disturbance in maintaining diversity is vital to the management of any forest system.

Forests provide a variety of ecosystem services to humans such as timber production, protection against erosion, carbon storage, nutrient cycling, and air purification (Bengtsson et al. 2000; Palik et al. 2002). Management practices that are



implemented typically fall along a gradient of tradeoffs between maximizing biodiversity and the total ecosystem services that a forest can sustainably provide to humans (Palik et al. 2002). Consequently, the management of these systems becomes complex and successful forest management requires a robust understanding of natural disturbance regimes and how they drive ecosystem dynamics (Thom and Seidl 2016).

Many researchers argue that forestry practices and management need to more closely mimic natural disturbance patterns (Attiwill 1994; Bengtsson et al. 2000; Palik et al. 2002). In many systems where fire was historically a major disturbance, managers are encouraged to use prescribed burning to restore more natural conditions (Bergeron et al. 2002; Thom and Seidl 2016). However, managers must implement the correct intensity and frequency of fire or the results could be counterproductive. Selective thinning has been suggested to replace clear-cutting to maintain a sustainable timber harvest while partially mimicking a tree-fall disturbance in a natural system (Palik et al. 2002). While selective thinning creates gaps in the forest canopy, allowing increased light penetration, colonization of new species, and regeneration of individuals, it lacks the benefits of decomposing wood on the forest floor (Palik et al. 2002). Managing for timber production will inevitably cause some loss of natural dynamics, but many consider this tradeoff justifiable. Bengtsson et al. (2000) suggests that it will always be necessary to manage forests for both production and biodiversity. Monitoring how implemented management strategies affect forest communities and their diversity is vital to understanding their success.

### **2.3 Functional Diversity**

Biodiversity, or simply diversity, includes measures of both number and composition of species, phenotypes, genotypes, and other units of the landscape (Díaz and Cabido 2001). However, many people frequently associate diversity solely with species richness and overlook other measures such as functional diversity. Formally defined by Tilman (2001), functional diversity is the range in values of species traits that influence the operation and functioning of an ecosystem. Functional diversity, therefore, is understood as the differences in these traits amongst the species within a community. Due to its implications on ecosystem stability, productivity, and dynamics, functional diversity may be a more preferred method than traditional measures of species richness and composition (Díaz and Cabido 2001; Petchey and Gaston 2002; Roscher et al. 2013; McGill et al. 2006).

Measuring the functional diversity of a community relies on the measurement of the functional traits of the species that comprise it. Cadotte et al. (2011) describe a functional trait as a measurable feature of an individual that has implications on the individual's biological fitness. These traits are representative of the species' niches and functions, suggesting that functional diversity represents the diversity of niches in a community or ecosystem (Petchey et al. 2004; Cadotte et al. 2011). In plant communities, functional traits influence the establishment, survival, and fitness of species and encompass a variety of chemical, physiological, and morphological characteristics of species (Reich et al. 2003). These traits are often associated with the ability of a plant to acquire, use, and conserve different resources (Reich et al. 2003; Jetz et al. 2016). While many studies examine a small number of traits specifically chosen to fit the needs of the

research project (Cingolani et al. 2005; Lohbeck et al. 2012; Roscher et al. 2013), Cornelissen et al. (2003) offer a much more complete list of plant functional traits, dividing them into whole-plant, leaf, stem, belowground, and regenerative categories.

Often, the most direct functional traits are difficult to measure, requiring experimental studies or the quantification of attributes over extended periods of time. These traits are overtly termed “hard traits” by Weiher et al. (1999) because of their difficulty to measure, especially for the collective flora of a region. As a result, a number of other functional traits that are relatively easier to measure have become proxies for those hard traits. For example, relative growth rate of a plant is a hard functional trait, and specific leaf area (SLA) can be a proxy for this hard trait. SLA determines the ratio of leaf area to leaf dry mass, is associated with whole plant growth, and is much easier to quantify than its counterpart (Weiher et al. 1999; Liu et al. 2017).

To quantify the variation in functional trait data and assess functional diversity, researchers have employed a variety of statistical measures and indices. A number of studies utilize the idea of a multidimensional functional trait space for calculating metrics of functional diversity (Mouillot et al. 2013; Schneider et al. 2017). In this approach, traits correspond to axes, with values (i.e. pixels, points, or species) plotted in multivariate trait space. Researchers then use one or more metrics to measure the distribution of points within that functional space. Three commonly calculated metrics of functional diversity are functional richness, functional evenness, and functional divergence. Functional richness is a measure of the area or volume of functional space that is occupied (Villegger et al. 2008). Functional evenness, analogous to species evenness, quantifies the regularity of the point distribution within the functional space

occupied based on the minimum spanning tree among species in trait space (Villegger et al. 2008). Functional divergence is based on the divergence of abundance from the center of gravity of the occupied functional trait space (Villegger et al. 2008).

## **2.4 Forest Monitoring via Remote Sensing Techniques**

Collecting data on physiological and morphological traits of a forest community is important to assess the results of various implemented management systems.

Historically, researchers utilized field techniques and methods to measure the health and condition of forest stands. Timber cruising, one of the most traditional ways to collect data on vegetation morphology, gathers field measurements such as height, volume, total biomass, and density. Using a collection of simple tools such as a measuring tape, tree caliper, clinometer, prism, and angle gauge, foresters can collect data for a sample of random plots or quadrats. These methods provide stand-level estimates, and the field presence and time required for timber cruising can provide difficulties in collecting sufficient amounts of data. Many researchers look to the developing field of remote sensing for techniques that allow for more widespread monitoring of environmental change and vegetation health (Kerr and Ostrovsky 2003).

Utilizing remote sensing techniques, plant biologists, ecologists, and natural resource managers alike can measure the morphology, phenology, physiology, and health of vegetation for broader spatial extents that is not feasible with field methods (Kerr and Ostrovsky 2003; Ustin and Gamon 2010). Advancements in sensor technology have allowed for finer spatial, spectral, radiometric, and temporal resolutions of data collected.

With the ability to collect data over large areas, remote sensing has furthered our understanding of biodiversity on a more global scale (Jetz et al. 2016).

Both passive and active remote sensing techniques are methods that can effectively gather information on vegetation health and biodiversity. Passive remote sensing uses sensors that measure radiation that is naturally available, with the most common source of radiation being the sun. On the other hand, active remote sensing methods utilize sensors that provide their own source of energy sent in a pulse or wave and then measure the reflected radiation (Turner et al. 2003). I will discuss a few passive and active sensing methods and tools, focusing on multispectral imagery and light detection and ranging, which researchers use to study vegetation and remotely monitor the success of management.

#### *2.4.1 Optical Remote Sensing*

Optical remote sensing, techniques that target visible, infrared, and short-wave energy that are reflected (Turner et al. 2003), has served as one of the primary methods of monitoring the health of vegetation communities, predicting species distribution and richness, and detecting landscape-level changes (Rouse et al. 1973; Gould 2000; Achard et al. 2002; Kerr and Ostrovsky 2003; Glenn et al. 2008). Sensors, often mounted on satellite and airborne platforms, measure surface reflectance in different regions of the electromagnetic spectrum (Ustin and Gamon 2010). Hyperspectral sensors measure reflected light in fine spectral intervals, while multispectral sensors measure reflectance in fewer, broader spectral bands. Both types of sensors are used for measuring a number

of ecological variables, many of which are related to plant functional traits and health. Studies have used hyperspectral imagery to map differences in foliar chemistry (Asner et al. 2015), determine forest species composition (Martin et al. 1998), and assess equivalent water thickness (Schneider et al. 2017), amongst many other applications. Multispectral imagery is often more easily accessible than hyperspectral imagery and has been used similarly in various studies to determine plant community composition (Townsend and Walsh 2001), classify forest ecosystems (Johansen et al. 2007), and map stages of tree mortality (Meddens et al. 2011).

The reflectance from specific bands and wavelengths of the imagery collected provides valuable information for vegetation monitoring. More specifically, combinations and calculations of bands from multispectral imagery provide a number of vegetation indices (VIs) that measure vegetation health and can monitor post-disturbance or management conditions. Researchers can use VIs to locate areas of disturbance and regeneration within forests and detect changes in leaf physiology, chlorophyll and nutrient content, and water uptake relatively easily (Glenn et al. 2008; Hunt et al. 2013). A few studies have also found correlations between remotely sensed VIs and fire severity estimates (Turner et al. 1994; Conard et al. 2002; Chafer et al. 2004). The simplicity of VIs and their applicability to assessing vegetation health have allowed them to become widely used as successful proxies for functional traits.

#### *2.4.2 Light Detection and Ranging*

While the physiological data gained from passive aerial and satellite platforms are beneficial, the structural information that can be collected about the canopy and understory is limited (Alonzo et al. 2018). The morphology and composition of a forest, while difficult to assess and quantify, can provide additional understanding of system responses to various disturbances and guide the implementation of management strategies (Alonzo et al. 2018). Light detection and ranging (LiDAR) is being utilized to meet this demand for structural information and quantify the morphology of forests (Reutebuch et al. 2005; Alonzo et al. 2018).

Unlike the passive remote sensing techniques discussed above, LiDAR is an active technique that utilizes a sensor to emit a laser pulse (Lim et al. 2003). Knowing the speed of light and the elapsed time from laser emission to reception, the sensor can measure ranges (i.e. distance) to objects and surfaces. While one of its most familiar uses is to create high-accuracy digital elevation models (DEMs), LiDAR has a significant number of applications including modelling floods (McArdle et al. 1999), mapping glaciers and ice-sheets (Krabill et al. 1995), studying bird biodiversity and populations (Davenport et al. 2000), and studying vegetation and forest morphology (Lim et al. 2003). The ability of LiDAR to penetrate through the upper canopy to the understory and ground makes it one of the most powerful tools for scientists studying the morphology of forest species.

LiDAR systems are categorized into two main types based on their horizontal and vertical sampling: full waveform systems and discrete return systems (Lim et al. 2003).

Full waveform LiDAR systems sense and record all of the emitted energy that returns to the sensor. This type of LiDAR captures the complete vertical distribution of a forest, but is expensive to collect, can be sensitive to backscatter, and is data intensive (Means 1999). On the other hand, discrete return LiDAR measures a specific number of returns of the emitted energy pulses to gain limited detail on vegetation morphology (Nelson et al. 1984; Lim et al. 2003). The majority of commercial LiDAR systems capture between two and five returns, with a higher number of returns providing more structural detail (Lim et al. 2003). While discrete return LiDAR does not capture the entirety of vertical structure, it is the most common type of LiDAR collected, is often freely available, and can provide enough detail for numerous forestry applications. As a result, it is often sufficient for many forestry applications and thus is commonly used.

LiDAR data can provide information on a number of vegetation and forest metrics, with one of the most common being canopy height. Using discrete return LiDAR data, a canopy height model can be calculated by subtracting the first returns by the corresponding ground points. Throughout the literature, studies have shown that canopy height can serve as a robust predictor of other forest morphological parameters such as volume and total aboveground biomass (Lefsky et al. 2001; Lim et al. 2003). Other metrics, such as Leaf Area Index (LAI) and Plant Area Index (PAI), which estimate the total one-sided area of leaf, or plant, tissue per unit of ground surface area, are calculated using LiDAR (Kwak et al. 2010). Jensen et al. (2008) successfully estimated LAI using discrete return LiDAR data for coniferous stands in the northern Rocky Mountains. In addition, Clawges et al. (2008) measured Foliage Height Diversity (FHD) and Total Vegetation Volume (TVV) from LiDAR data. All of these metrics derived from discrete



return LiDAR provide substantial information on forest morphology that is not accurately obtained with optical remote sensing alone. These LiDAR-derived metrics, in addition to vegetation indices, have allowed researchers and managers easier methods to monitor forest health after disturbance. Utilizing remote sensing methods, researchers can answer questions relating to the effects of management and disturbance on the functional diversity of a forest-savanna landscape.

## CHAPTER III

### EXAMINING THE EFFECTS OF FOREST MANAGEMENT ON PHYSIOLOGICAL AND MORPHOLOGICAL FUNCTIONAL DIVERSITY USING REMOTE SENSING TECHNIQUES

#### **3.1 Introduction**

Natural disturbances play a critical role in the development, composition, dynamics, and function of forest ecosystems across the globe (Attiwill 1994; Franklin et al. 2002; Thom and Seidl 2016). Disturbances such as fire, wind, and insects, form disturbance regimes characteristic to a given forest type. The organisms inhabiting a forest system, both plants and animals, are assumed to adapt to those natural regimes (Bengtsson et al. 2000). However, global climate change and other anthropogenic disturbances, suppression of disturbances, and modifications to the landscape are causing disruptions to the intensity and frequency of these natural disturbances (Dale et al. 2001; Thom and Seidl 2016). In forest communities, the fitness of individual plants is often affected, leading to changes in biodiversity and community composition (Thom and Seidl 2016). As disturbance patterns and regimes continue to change, land managers more frequently implement adaptive management plans to maintain forest biodiversity, and often increase community function and ecosystem

services provided (Attiwill 1994; Bengtsson et al. 2000; Palik et al. 2002; Messier et al. 2019).

Species diversity, measured using species richness and evenness, along with phylogenetic diversity, have historically been used as primary measures of biodiversity (Durán et al. 2019). More recently, functional diversity has been recognized as an important component of biodiversity that is related to ecosystem function (Díaz and Cabido 2001; Petchey and Gaston 2002; Vileger et al. 2008). Functional diversity, a measure of the variation in organismal traits within a community, has emerged as a metric of biodiversity and a valuable measure of ecosystem productivity and resilience to disturbance (Tilman 2001; Petchey et al. 2004; Cadotte et al. 2011).

Measuring the functional diversity of a vegetation community requires the collection of functional trait data for species that occupy it, and researchers have largely focused on using field techniques and global datasets to gather trait data (Durán et al. 2019). Fieldwork presents numerous challenges, including labor-intensive data collection often over rough or thickly-vegetated terrain, substantial time requirements, and high costs. Increasing numbers of researchers are realizing the practicality and efficiency of using remote sensing to collect functional trait data and enhance field data collection methods for studying various ecological systems. Remote sensing can improve the spatial and temporal resolution of studies and offer cost-effective methods to monitor functional diversity in a variety of landscapes (Cavender-Bares et al. 2017; Jetz et al. 2016). Utilizing a combination of passive and active remote sensing methods of data collection has allowed scientists to measure characteristics of plant morphology, biochemistry, physiology, and phenology (Ustin and Gamon 2010). Plant reflectance spectra serve as

effective indicators of canopy biochemistry and physiology, including water, pigment, and nutrient content (Ustin and Gamon 2010, Cavender-Bares et al. 2017), while terrestrial and airborne Light Detection and Ranging (LiDAR) offer powerful methods to measure various dimensions of vegetation morphology (Bergen et al. 2009).

Geospatial technologies show utility for the assessment of functional diversity of forests (Schneider et al. 2017) and promising applications for studying the fundamental connections between functional diversity, disturbance, and forest management. The objective of this study is to use environmental remote sensing to investigate the effects of various forest management practices on functional diversity in an experimental pine-oak forest-savanna in southeastern Oklahoma. Specifically, I used multispectral imagery and LiDAR point clouds to assess indices of plant physiology and morphological functional traits for the Pushmataha Forest Habitat Research Demonstration Area (FHRA) and calculate three complementary metrics of functional diversity - functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv; Mason et al. 2005). By making comparisons of functional traits and diversity between treatments within the FHRA, this study provides insight on relationships between functional traits, diversity, and contemporary forest management practices in the forest-grassland ecotone.

## 3.2 Materials and Methods

### 3.2.1 Study Area

The study took place in southeastern Oklahoma, USA, at Pushmataha Forest Habitat Research Demonstration Area (FHRA) located within the Pushmataha Wildlife Management Area (PWMA) near Clayton, Oklahoma (Figure 3.1). The area is characterized by mixed pine/oak forest and savanna, with shallow, rocky soils, and semi-humid climate (Masters and Waymire 2012). FHRA is a 52 ha land management experiment established in 1982 by the Oklahoma Department of Wildlife Conservation with the purpose of studying the response of herbaceous and woody vegetation to various management regimes (Feltrin et al. 2016; Masters et al. 2006). FHRA has a randomized experimental design with various treatments administered to units approximately 0.8-1.6 ha in size. (Feltrin et al. 2016; Figure 3.2). For the purposes of this study, I used 23 of these units that represent 8 different treatments (Table 3.1); each treatment had three replicate units, with the exception of HT3, which had only two.

Treatments within the experimental forest consist of combinations of pine timber harvest (T), selective thinning of hardwoods (H), and prescribed fire (Table 3.1), and were originally applied to a homogeneous closed-canopy forest with dominant overstory species being *Pinus echinata* (shortleaf pine), *Quercas stellata* (post oak), and *Carya tomentosa* (mockernut hickory) (Masters et al. 1993). For all treatments with timber harvest, *P. echinata* with diameter at breast height (dbh) greater than 11.4 cm was harvested and thinning was completed on selected hardwoods using single-stem injection of 2,4-Dichlorophenoxyacetic acid in 1984 (Feltrin et al. 2016). Prescribed burns were

completed during the dormant season on variable return intervals, 1-4 years and no fire, from 1985 to the present. As a result of these treatments, units now range from savannas to closed canopy forest in various stages of development and structure.

### *3.2.2 Data Acquisition*

For the remotely sensed data, I acquired imagery collected via satellite-based multispectral sensor as well as aurally-acquired LiDAR point clouds. The multispectral imagery dataset was acquired from the MultiSpectral Instrument (MSI) sensor aboard the Sentinel 2 satellite on July 31, 2016. I obtained a single tile (100 km x 100 km) that encompassed the entirety of the study area from the European Space Agency's (ESA) Sentinel-2 Pre Operations Hub (ESA 2020). Sentinel-2 imagery consists of 13 bands between 432-2,290 nm with spatial resolutions of 10, 20, and 60 m. I utilized the ESA's free software, SNAP, with the Sen2Cor plugin to obtain Bottom of Atmosphere reflectance by correcting for atmospheric conditions within the original Sentinel Level 1C product. The super-resolution plugin to SNAP (Brodu 2017) was then applied to the imagery to sharpen the spatial resolution of all bands to 10m using details from the high-resolution bands, while preserving reflectance values. A subset of the 100 x 100 km tile covering the FHRA was used for the analysis of functional diversity.

Discrete-return LiDAR data was obtained to measure various aspects of the vegetation morphological. The Oklahoma FEMA QL2 LiDAR Project previously collected discrete-return LiDAR for the study area in January and February 2016. An Optech ALTM Galaxy T1000 sensor mounted on an aircraft collected points at a

maximum frequency of 550 kHz and up to 8 returns per pulse during leaf-off conditions (USGS 2017). Pre-processing was completed by USGS staff and included creating point clouds from the laser point data using Leica CloudPro software and using TerraScan and TerraModeler software programs to classify returns and clean up point cloud data (USGS 2017). The final processed point cloud data for the study area had a point density of 7.1 points/m<sup>2</sup>.

### *3.2.3 Functional Traits*

Data were collected on morphological, biochemical, and physiological traits for the entirety of the FHRA at a spatial grain of 10 meters. Without the collection of remotely sensed data from multiple dates, I was not able to measure plant phenological traits in this study. I used three vegetation indices as proxies for biochemical and physiological traits (Table 3.2), including Enhanced Vegetation Index (EVI; Huete et al. 2002), Chlorophyll Vegetation Index (CVI; Vincini et al. 2008), and Normalized Difference Water Index (NDWI; Gao 1996), while morphological traits included canopy height (CH), Foliage Height Diversity (FHD), and Total Vegetation Density (TVD). In the selection of these traits, I considered vegetation traits used in other functional diversity studies (Maeshiro et al. 2013, Schneider et al. 2017, Lelli et al. 2019), emphasizing traits that are associated with plant growth, acquisition of resources, and overall health. While a number of traits were suitable, the spectral resolution of the available remotely sensed datasets limited the analysis to indices of plant physiological condition.

To obtain data on the physiology and biochemistry of plant communities in the study area, I used vegetation indices, EVI, CVI, and NDWI, calculated from the Sentinel-2 imagery. EVI measures photosynthetic activity and vegetation condition and is more responsive to variations in canopy structure when compared to traditional Normalized Difference Vegetation Index (Huete et al. 2002; Table 3.2). Studies have found strong correlations between EVI and processes associated with photosynthesis, such as primary productivity and net carbon fixation (Glenn et al. 2008). CVI is an index with specific sensitivity towards leaf chlorophyll content (Vincini et al. 2008; Table 3.2), while NDWI uses the shortwave and near infrared bands to calculate vegetation water content (Jackson et al. 2004; Table 3.2).

From the discrete return LiDAR point clouds, I calculated ecologically relevant morphological functional traits, including CH, FHD, and TVD. I used the BCAL Lidar Tools extension in ENVI (BCAL Lidar Tools) to calculate these selected traits. CH was obtained by subtracting the digital terrain model (DTM) of the study area from the digital surface model (DSM), producing a raster with the maximum height of vegetation from ground level within each pixel. FHD is a measure of the variation of canopy layers and overall canopy complexity (Schneider et al. 2017). The calculation of FHD for each pixel involved applying the Shannon-Wiener Index (MacArthur and MacArthur 1961) for the proportion of LiDAR returns in various foliage height categories ( $H' = -\sum p_i \ln p_i$ , where  $p_i$  is the proportion of horizontal vegetation in the  $i$ th height layer). A bin height of 5 m was chosen to create foliage height categories of 0-5, 5-10, 10-15, 15-20, and 20+ m. The height was selected to divide the vegetation by understory, mid-story, upper-story and canopy (Clawges et al. 2008). TVD is determined by the percent ratio of vegetation point



returns to ground returns for each pixel, providing an estimation of total vegetation cover for the study area.

#### *3.2.4 Functional Diversity Analysis*

Using trait data, I calculated morphological and physiological functional diversity for management units within the FHRA through three different metrics: functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv; Table 3.3). FRic, FEve, and FDiv are the most commonly used metrics of functional diversity and measure aspects of the distribution of species in trait space directly (Mason et al. 2005). FRic is a measure of the total occupied functional space of a community (Villegger et al. 2008). In this study, FRic values represent the total occupied functional space for each of the FHRA units standardized by the total functional space for all units. FEve measures the regularity of the distribution of species within multidimensional functional space (Mouillot et al. 2013), while FDiv measures the extent to which the most extreme species trait values represent the total abundance within a community (Mouillot et al. 2013). For this analysis of functional diversity, each individual FHRA unit was considered a community, while pixels served as ‘species’ with six different functional trait measurements. With a spatial resolution of 10m, trait values for each pixel are representative of all individuals and species found within that space.

I calculated the three metrics of physiological and morphological functional diversity for each unit in the FHRA using the dbFD function from the FD package (Laliberté et al. 2014) in R Statistical Software (R Core Team 2018). All traits were

standardized to mean 0 and unit variance. I performed a Principal Coordinates Analysis (PCoA) on the functional trait matrix, from which the resulting PCoA axes were used as new traits for the calculation of the three functional diversity indices (Laliberté et al. 2014).

### *3.2.5 Statistical Analyses*

The statistical analyses were completed at the treatment level to determine how forest management practices affect functional traits and diversity. I used a Multiple Response Permutation Procedure (MRPP) to test for differences between treatments in multivariate trait space. MRPP calculates a distance matrix and compares within-group distances to between-group distances (McCune and Grace 2002). The analysis also determines an effect size independent of sample size ( $A$ ) that describes within-group homogeneity compared to expected homogeneity due to chance. Values of  $A$  range from 0-1, with 1 indicating identical items within a group and 0 indicating heterogeneity within groups equal to random expectation (McCune and Grace 2002). I conducted two separate MRPP analyses to determine differences in vegetation physiology and morphology between treatments. In addition, the means of the six functional traits, EVI, CVI, NDWI, CH, FHD, and TVD, were calculated for each FHRA unit, and Kruskal-Wallis analyses of variance were performed to determine which functional traits were affected by management.

I conducted Kruskal-Wallis one-way analyses of variance to determine if there were significant differences in functional diversity by treatment. Each of the three

functional diversity metrics, FRic, FEve, and FDiv, for both morphological and physiological diversity, were tested to assess any differences. Post-hoc tests included pairwise comparisons. With small sample sizes of replicates for each treatment, the use of a non-parametric test was appropriate.

### **3.3 Results**

#### *3.3.1 Functional Traits*

Treatments differed in multivariate vegetation morphology and physiology at FHRA based on the MRPP analysis (morphology:  $A = 0.273$ ,  $p < 0.001$ ; physiology:  $A = 0.0786$ ,  $p < 0.001$ ). Examining vegetation community morphology, treatments with high fire frequency were associated with more open, simplified canopies and show low values for CH, FHD, and TVD in morphological trait space (Figure 3.3). Treatments with low frequency fire show taller, more complex canopies with higher values for CH, FHD, and TVD (Figure 3.3). In terms of community physiology and biochemistry, individual treatments showed a higher variation in vegetation indices, EVI, CVI, and NDWI, in physiological trait space (Figure 3.4). Pixels in physiological functional space display more dispersion and less within-treatment clustering, representative of a low  $A$  value (Figure 3.4;  $A = 0.0786$ ).

Differences in individual functional traits were detected between treatments using Kruskal-Wallis tests. Treatments varied most in vegetation morphology, with all three structural traits differing by the treatment applied (CH,  $\chi^2 = 18.536$ ,  $df = 7$ ,  $p$  value =

0.01; FHD,  $\chi^2 = 18.435$ ,  $df = 7$ ,  $p$  value = 0.01; TVD,  $\chi^2 = 19.319$ ,  $df = 7$ ,  $p$  value = 0.007; Figure 3.5). CH ranged from  $9.08 \pm 1.33$  meters (HT1) to  $19.81 \pm 0.29$  meters (RRB). Highest mean CH was detected in RRB and CONT units with low frequency fire and no fire, respectively, while the lowest averages were detected in units with fire every year, HNT1 and HT1 (Figure 3.5). FHD ranged from  $0.59 \pm 0.11$  (HT1) to  $1.23 \pm 0.02$  (CONT) and showed similar patterns between treatments as CH (Figure 3.5). The CONT and RRB treatment had the highest mean FHD, while units with high frequency fire (HNT1 and HT1) had the lowest mean. Mean TVD values ranged from  $53.08 \pm 17.16$  (HT1) to  $216.11 \pm 6.13$  (HT). Similar trends in TVD appear between treatments, with the highest mean values in HT, RRB, and CONT treatments and lowest mean values in HT1 and HNT1 (Figure 3.5).

Indices of vegetation physiology, as measured by EVI, CVI, and NDWI, saw less variation than morphology between treatments. I detected differences in NDWI ( $\chi^2 = 16.496$ ,  $df = 7$ ,  $p$  value = 0.021), while EVI and CVI were not significantly different between treatments (EVI,  $\chi^2 = 7.638$ ,  $df = 7$ ,  $p$  value = 0.366; CVI,  $\chi^2 = 10.130$ ,  $df = 7$ ,  $p$  value = 0.181; Figure 3.5). Distinct trends in vegetation indices were also less apparent than in morphological traits. The control treatment had the highest mean values for all three indices (EVI =  $0.50 \pm 0.01$ , CVI =  $3.87 \pm 0.13$ , NDWI =  $0.33 \pm 0.01$ ; Figure 3.5). Means for EVI showed little variation, ranging from  $0.46 \pm 0.01$  (HT3) to  $0.50 \pm 0.01$  (CONT), while means for CVI and NDWI ranged from  $3.46 \pm 0.10$  (HT1) to  $3.87 \pm 0.13$  (CONT) and  $0.20 \pm 0.04$  (HT2) to  $0.33 \pm 0.01$  (CONT), respectively (Figure 3.5).

Figure 3.6 represents a visualization of differences in morphological and physiological traits across the study area. Within the morphological trait map, yellow-green areas are characterized by high canopy height and vertical diversity, with the brightest pixels also indicating high vegetation density as well. Units with low canopy height and vertical diversity are represented by blue-green areas, while units with a pink hue indicate higher canopy height with little vertical diversity (Figure 3.6). In the map of vegetation indices, larger, purple patches of pixels depict high NDWI and EVI and low CVI. Patches of pink indicate high EVI with moderate NDWI, while green indicates high CVI values. Brightest pixels again represent high values for CVI, EVI, and NDWI.

### *3.3.2 Morphological Functional Diversity*

For the calculation of morphological diversity indices, functional traits were reduced to two principal axes, which accounted for 97% of the variation in morphological data. Axis 1 was negatively correlated with canopy height, vertical diversity, and density (CH,  $r_{\tau} = -0.82$ ; FHD,  $r_{\tau} = -0.76$ ; TVD,  $r_{\tau} = -0.713$ ). Axis 2 was weakly correlated with canopy vertical diversity ( $r_{\tau} = 0.18$ ) and density ( $r_{\tau} = -0.30$ ; Figure 3.3).

I detected no differences in morphological FRic by FHRA treatment ( $\chi^2 = 1.554$ ,  $df = 7$ ,  $p$  value = 0.980). Average morphological FRic ranged from  $0.211 \pm 0.037$  (HNT1) to  $0.327 \pm 0.232$  (HT3). Trends in FRic do not appear to be present based on fire frequency, pine timber harvest, or hardwood thinning.

Morphological FEve was affected by treatment ( $\chi^2 = 15.656$ ,  $df = 7$ ,  $p = 0.028$ ). Treatment HT1 had the lowest mean FEve value of all treatments ( $0.652 \pm 0.059$ ), while the control treatment had the highest mean FEve value ( $0.804 \pm 0.004$ ; Figure 3.7). Post-hoc tests confirm that treatments with high fire frequency, HT1 and HNT1, had significantly lower FEve values than the control and RRB treatments, with no fire and a 4-year fire return interval, respectively (See Appendix; Table A.1). However, the HT treatment with no fire had a significantly lower FEve than the CONT and RRB treatments (See Appendix A; Table A.1), indicating other factors affecting FEve in addition to fire such as thinning and pine harvest.

Morphological FDiv differed among management units with respect to forest management (test statistic = 15.696,  $df = 7$ ,  $p$  value = 0.028). Morphological FDiv values ranged from  $0.620 \pm 0.031$  (HNT1) to  $0.719 \pm 0.018$  (RRB; Figure 3.7). FDiv values were greater in the CONT, RRB, and HT4 treatments compared to the HNT1 treatment (See Appendix; Table A.2). In addition, the CONT and RRB treatments were significantly higher in morphological FDiv compared to the HT1 and HT2 treatments (See Appendix; Table A.2).

### *3.3.3 Physiological Functional Diversity*

In the calculation of physiological diversity indices, functional traits were reduced to two principal axes, which accounted for 86% of the variation in physiological data. Physiological indices EVI and NDWI were negatively correlated with Axis 1 (EVI,  $r_\tau = -$

0.69; NDWI,  $r_\tau = -0.70$ ), while Axis 2 had a strong, positive correlation with CVI ( $r_\tau = 0.94$ ; Figure 3.4).

I detected no differences between management units with respect to treatment for any of the three physiological functional diversity indices (FRic,  $\chi^2 = 3.641$ ,  $df = 7$ ,  $p$  value = 0.820; FEve,  $\chi^2 = 6.670$ ,  $df = 7$ ,  $p$  value = 0.464; FDiv,  $\chi^2 = 10.754$ ,  $df = 7$ ,  $p$  value = 0.150; Figure 3.7). Physiological FRic values ranged from  $0.309 \pm 0.078$  (HT4) to  $0.410 \pm 0.076$  (HNT1), with no significant differences between treatments. FEve values ranged from  $0.774 \pm 0.018$  (HNT1) to  $0.819 \pm 0.021$  (HT3), while FDiv ranged from  $0.691 \pm 0.013$  (HT3) to  $0.752 \pm 0.025$  (HT; Figure 3.7).

## **3.4 Discussion**

### *3.4.1 Functional Traits and Diversity Metrics*

The results of this study demonstrated that management regime has an impact on functional traits obtained from remote sensing in forest communities at FHRA, whereas the effects on metrics of functional diversity are more varied. Analysis of multivariate space demonstrated differences in vegetation morphology and physiology by treatment, and management practices affected the canopy height (CH), vertical diversity (FHD), density (TVD), and water content (NDWI) of plots. While differences in multivariate vegetation physiology were statistically significant, the relatively low A value and dispersion of within-group pixels in trait space indicate that differences in vegetation physiology across FHRA measured using EVI, CVI, and NDWI, are not likely to be

ecologically significant. The higher value of A for multivariate analysis of vegetation morphology suggests an ecologically significant and stronger response in plant community morphology to various silvicultural practices and disturbances within FHRA compared to physiology.

Fire frequency appeared to have the biggest impact on average trait and index values for treatments and played a critical role in vegetation community morphology. Lower mean CH, FHD, and TVD, were associated with frequent prescribed burning. Units with a fire return interval of 1 year had the lowest CH, FHD, and TVD, while the control treatment had the highest canopy height and vertical diversity. Various life-history traits such as regeneration time, ability to resprout, seed production and dispersal, and time to reach maturation, impact species response to fire (Noble and Slatyer 1980). In high-frequency fire units, fire acts as a constraint on community assembly to allow species with quick postfire regeneration, and species resistant or tolerant to fire, successful establishment and persistence (Peterson and Reich 2001; Pausas and Verdú 2008). With less frequent fire or no fire, forest succession occurs as woody vegetation, with decreased resistance to fire, greater canopy height, and density, establish and grow. Peterson and Reich (2001) found similar results in stand structure when examining the effects of fire frequency in oak savannas, observing differences in species composition, lower seedling densities, reduction in overstory density, and higher mortality rates with increasing fire frequency. Likewise, in the FHRA, units with high fire frequency treatments implemented had low canopy density and are predominately occupied by grass species such as *Andropogon gerardii* (big bluestem), *Schizachyrium scoparium* (little bluestem), *Panicum spp.*, *Carex spp.*, and *Scleria spp.* (Masters et al. 1993). The lower



canopy height, vertical diversity, and cover associated with these species and open savannas were successfully detected using the discrete-return LiDAR.

My results indicate that forest management had an effect on the morphology of plant communities, but less impact on overall function, as seen by the differences in functional traits and minimal variability in metrics of functional diversity. Within multivariate functional trait space, no treatment occupied a significantly larger or smaller area, despite significant differences in location between treatments (Figure 3.3 and Figure 3.4), as indicated by the MRPP analysis. Overall, morphological and physiological FRic values were low across all treatments, with pixels plotted in limited areas or clusters within trait space when compared to total occupied community trait space. Reduced morphological functional trait space has been associated with fire frequency (Pausas and Verdú 2008). Frequent fire has the ability to act as a habitat filter on vegetation communities, allowing species with certain life history or functional traits to occupy a given habitat, leaving a community's morphospace restricted to encompass these select species (Pausas and Verdú 2008).

High average morphological FEve was associated with low frequency fire, suggesting a more even distribution of biomass in niche space for units with no fire or fire every 4 years and a more equal utilization of resources available in those communities compared to units with high frequency fire (Mason et al. 2005). Units undisturbed or minimally disturbed by fire are comprised of forest communities with a higher vertical distribution of vegetation with greater vertical diversity between understory, mid-story, and overstory species that is absent in frequently burned units. In FHRA units with low FEve, gaps in niche space may allow for introduced species to

establish, fill unoccupied niches, and potentially encroach on niches of native species (Mason et al. 2005). Similarly, I detected differences in morphological FDiv between treatments, with differences appearing to be related to fire return interval. Throughout the FHRA, units with low frequency fire had higher morphological FDiv than units with fire every 1-2 years, indicating higher niche differentiation and low resource competition in those units (Mason et al. 2005).

The effect of fire interval and intensity on the structure and stand composition of various vegetation communities has been widely studied, but the role fire plays in species' functional traits and communities' functional diversity is not thoroughly understood across systems. In this study, fire return interval seems to be the most influential disturbance on morphological functional diversity indices across treatments, with lower average structural functional traits and diversity associated with high fire frequency. In addition to fire, many treatments at FHRA included pine timber harvest and selective hardwood thinning completed in the initial years of the experiment. Due to low replicate numbers and interaction effects between other implemented management regimes, I was not able to explicitly test the effects of pine timber harvest or selective hardwood thinning on metrics of functional diversity. Patterns in functional diversity metrics in response to the presence or absence of these regimes are difficult to distinguish, and previous research shows disagreement in the effects of various disturbance and silvicultural regimes on functional diversity indices. Significant differences in community-weighted means of functional traits and functional diversity indices in response to high intensity disturbance regimes have been documented in oak forest and riparian systems (Lavorel et al. 2008; Vandewalle et al. 2010). In contrast,

Carreño-Rocabado et al. (2012) found no significant differences in functional diversity indices on a disturbance gradient ranging from undisturbed, control treatments to intense silvicultural practices and logging. More research is needed to understand the complexity and influence various disturbances and management practices have on the functional diversity of pine-oak forests.

Changes in functional diversity have been shown to affect a community's overall function, productivity, and resilience (Tilman 2001, Durán et al. 2019). At FHRA, I found management regimes with moderate levels of disturbance had some of the highest functional diversity values, indicating that vegetation communities managed with disturbance, such as fire, and silviculture practices like pine harvest and selective thinning, applied at intermediate levels have the potential to maximize functional diversity and services provided by that community. Biswas and Mallik (2010) report similar results for plant communities in a temperate riparian system, finding peak functional diversity at moderate intensity of anthropogenic disturbance. In addition, implementing multiple management practices can increase the functional richness of that community. When pixels from any combination of two treatments at FHRA are used for the calculation of functional diversity, FRic is greater than either of those treatments alone (Table 3.4 and 3.5). In some cases, FEve and FDiv increase as well, creating landscapes with a higher diversity of functional traits and a more even distribution of biomass in the community. Applying this at the landscape scale, implementing a diverse mosaic of management regimes across the system has the potential to form more heterogeneous landscapes with increased functional diversity, productivity, and resilience to disturbance. Managers can utilize this information to create multi-functional

landscapes that are more resilient to unpredictable and extreme disturbance, offer services such as timber production, nutrient cycling, and game species habitat, and maintain biodiversity for conservation (Puettmann et al. 2015; Murray et al. 2017; Messier et al. 2019).

### *3.4.2 Remote Sensing Methodology*

Utilizing remote sensing to study functional traits and functional diversity is a relatively new methodology that has been applied to a limited number of systems (Schneider et al. 2017, Durán et al. 2019). Here, I demonstrate the use of openly available remotely sensed data to study functional diversity of a pine-oak forest-savanna community. Applying remote sensing techniques to measure functional traits across the vegetation communities of FHRA, I was able to assess functional diversity without identifying species and using mean trait values and species abundances. The use of remote sensing to measure functional traits inherently includes inter- and intra-specific variability (Schneider et al. 2017) and provides an ideal methodology for studying the effects of management regimes on functional diversity.

When determining the remotely sensed data to obtain for a study of functional diversity, tradeoffs arise between cost of data collection, availability, and the level of detail in spectral and spatial resolution. For this study, I used multispectral satellite imagery and discrete-return LiDAR to gather information on functional traits. These methods offer considerably lower costs, higher availability, and moderate resolution when compared to other types of passive and active remote sensing.

With numerous satellite-borne sensors capturing imagery daily and open-access to that collected data, multispectral imagery is often readily available for public use at moderate spatial resolutions. The wide spectral bands of multispectral imagery can be used effectively to monitor aspects of vegetation health. Broadband vegetation indices, such as the three I use in this study, make use of multispectral imagery with coarser spectral resolutions and relatively easy band math. However, they represent proxies for functional traits and the generalization of spectral wavelengths may lack sufficient resolution needed to detect differences in biochemical properties and nutrient content of the canopy and individual trees and leaves (Jetz et al. 2016). Failure to detect differences in physiological functional diversity indices between treatments could be a result of limited spectral resolution in the multispectral imagery and the functional traits calculated. While I was able to detect some differences in vegetation physiology, hyperspectral imagery would improve the ability to capture spectral detail (Jetz et al. 2016). Current spaceborne hyperspectral imagers such as JAXA's Hyperspectral Imager Suite (HISUI; Iwasaki et al. 2011) and German DLR Earth Sensing Imaging Spectrometer (DESI; Krutz et al. 2018), along with future missions, such as NASA's Surface Biology and Geology (Schneider et al. 2019), will improve the accessibility of hyperspectral imagery with moderate spatial resolution for more direct measures of physiological and biochemical traits of plant communities.

Previous studies have demonstrated how LiDAR may be used to accurately measure 3D structure of various vegetation communities and its promise for studying functional traits across the landscape (Vierling et al. 2008, Davies and Asner 2014). Discrete-return LiDAR point clouds are often easier to obtain and less computationally

demanding than full-waveform LiDAR, but structural detail is often compromised for availability. The effects are seen especially in gathering data on understory species, where detail can be lost. As a result, limitations can emerge when measuring morphological functional traits and diversity in some systems. Despite this, I was able to use discrete-return LiDAR with 4-5 returns to capture differences in morphological traits and functional diversity at FHRA. Methodology used by Schneider et al. (2017) utilized full-waveform LiDAR and was successfully adapted for this study to use discrete-return LiDAR and results from the study coincide with the findings presented here.

Remote sensing applications and the availability of high quality remotely sensed data are continually increasing (Lausch et al. 2016). The methodology provided in this study establishes a base for future research to expand upon and can be adapted to utilize data of improved spectral and spatial resolutions. The advancement of remote sensing technologies will allow for a more complete understanding of the physiological and morphological functional diversity of various vegetation communities.

### 3.5 Tables and Figures

**Table 3.1 Management Regimes of Pushmataha FHRA.** Eight management regimes at Pushmataha Forest Habitat Research Demonstration Area used in this study. Treatments are listed by name, with indication of whether pine timber harvest and selective hardwood thinning were completed, fire return interval, and number of replicate units.

<b>Treatment</b>	<b>Harvest Pine</b>	<b>Thin Hardwoods</b>	<b>Fire Return Interval</b>	<b>Number of Replicate Plots</b>
CONTROL	No	No	No fire	3
HT	Yes	Yes	No fire	3
RRB	No	No	4	3
HT4	Yes	Yes	4	3
HT3	Yes	Yes	3	2
HT2	Yes	Yes	2	3
HT1	Yes	Yes	1	3
HNT1	Yes	No	1	3

**Table 3.2 Vegetation Indices.** Vegetation indices used as proxies for physiological functional diversity.

<b>Index Name</b>	<b>Abbreviation</b>	<b>Equation</b>	<b>Reference</b>
Enhanced Vegetation Index	EVI	$2.5(R_{NIR} - R_R)/(R_{NIR} + 6*R_R - 7.5*R_B + 1)$	Huete et al. 2002
Chlorophyll Vegetation Index	CVI	$R_{NIR}*R_R/(R_G^2)$	Vincini et al. 2008
Normalized Difference Water Index	NDWI	$(R_{NIR} - R_{SWIR})/(R_{NIR} + R_{SWIR})$	Jackson et al. 2004

**Table 3.3 Functional Diversity Metrics.** Functional diversity metrics used to quantify various aspects of functional diversity for each management plot at Pushmataha Forest Habitat Research Demonstration Area. Abbreviations and descriptions for each index from Vileger et al. 2008.

<b>Functional Diversity Index Name</b>	<b>Abbreviation</b>	<b>Description</b>
Functional Richness	FRic	Measures the total occupied functional space
Functional Divergence	FDiv	Measures the divergence of abundance in functional space
Functional Evenness	FEve	Quantifies regularity of point distribution within the occupied functional space



**Table 3.4 Physiological Functional Richness for Management Regime Combinations**

**at Pushmataha FHRA.** Physiological functional richness (FRic) for all possible two-

treatment combinations of treatments at Pushmataha Forest Habitat Research

Demonstration Area (FHRA). Treatment names are indicative of management practices

implemented, including selective hardwood thinning (H), pine timber harvest (T), and

fire return interval (1-4), with CONT and RRB representing the control and rough

reduction treatment with 4-year fire return interval, respectively. All pixels within

management units where either treatment in the pair were implemented were compiled

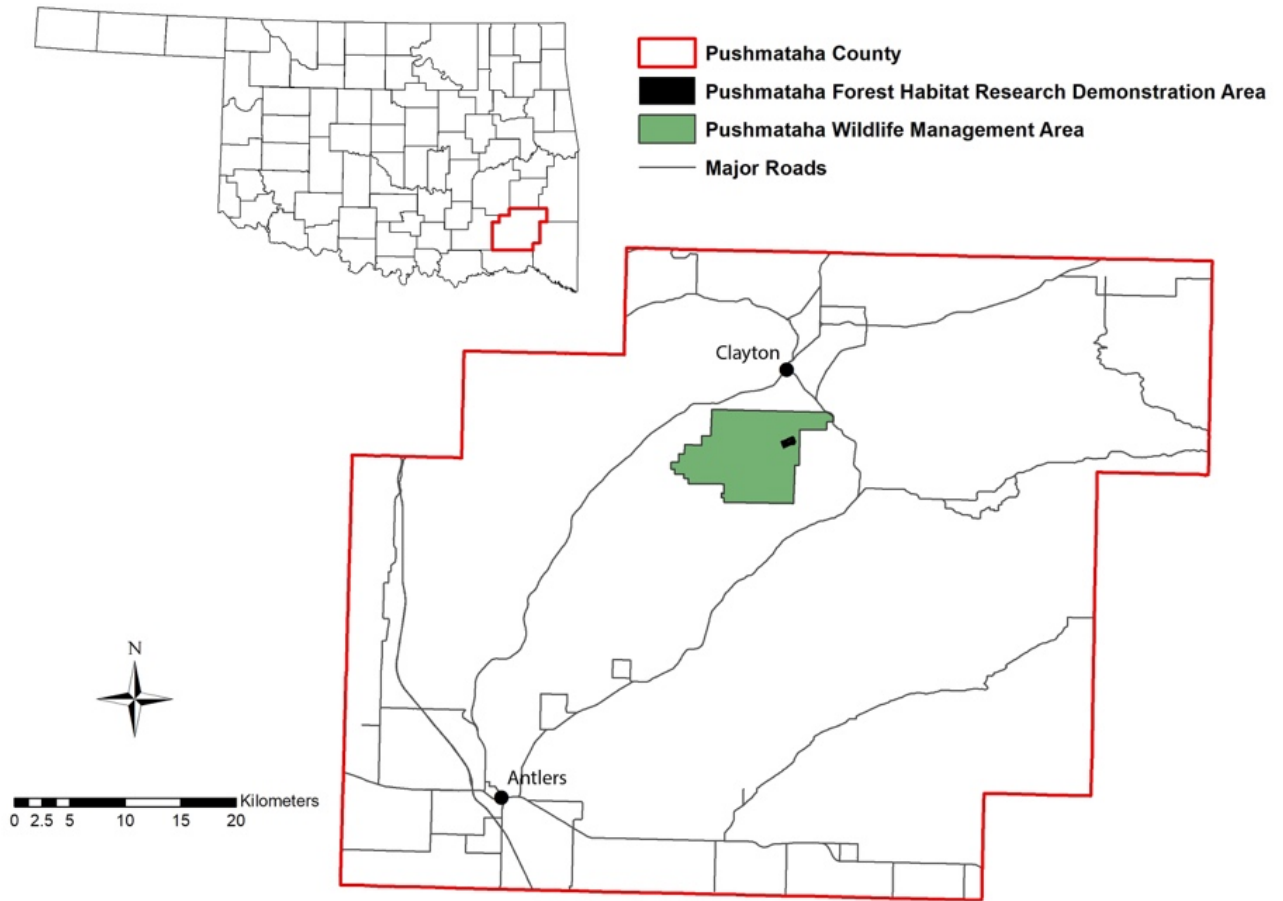
and used in the calculation of physiological FRic.

	CONT	HNT1	HT	HT1	HT2	HT3	HT4	RRB
CONT	0.525857	0.810611	0.725662	0.835513	0.695162	0.635072	0.622672	0.658532
HNT1		0.67322	0.730082	0.780749	0.85989	0.691338	0.706799	0.773681
HT			0.56411	0.73205	0.756732	0.591069	0.607111	0.69869
HT1				0.639083	0.860793	0.684401	0.655629	0.770748
HT2					0.597512	0.722503	0.670644	0.745888
HT3						0.41156	0.515244	0.592403
HT4							0.434496	0.588981
RRB								0.536217

**Table 3.5 Morphological Functional Richness for Management Regime**

**Combinations at Pushmataha FHRA.** Morphological functional richness (FRic) for all possible two-treatment combinations of treatments at Pushmataha Forest Habitat Research Demonstration Area (FHRA). Treatment names are indicative of management practices implemented, including selective hardwood thinning (H), pine timber harvest (T), and fire return interval (1-4), with CONT and RRB representing the control and rough reduction treatment with 4-year fire return interval, respectively. All pixels within management units where either treatment in the pair were implemented were compiled and used in the calculation of morphological FEve.

	CONT	HNT1	HT	HT1	HT2	HT3	HT4	RRB
CONT	0.323119	0.474985	0.683344	0.487912	0.474306	0.54104	0.45023	0.415251
HNT1		0.281488	0.810438	0.401822	0.36348	0.500611	0.362011	0.608533
HT			0.536967	0.849724	0.825471	0.873683	0.790615	0.753669
HT1				0.381591	0.407084	0.511384	0.403843	0.613096
HT2					0.341242	0.518928	0.350227	0.607436
HT3						0.491177	0.500735	0.65688
HT4							0.301393	0.57318
RRB								0.400061

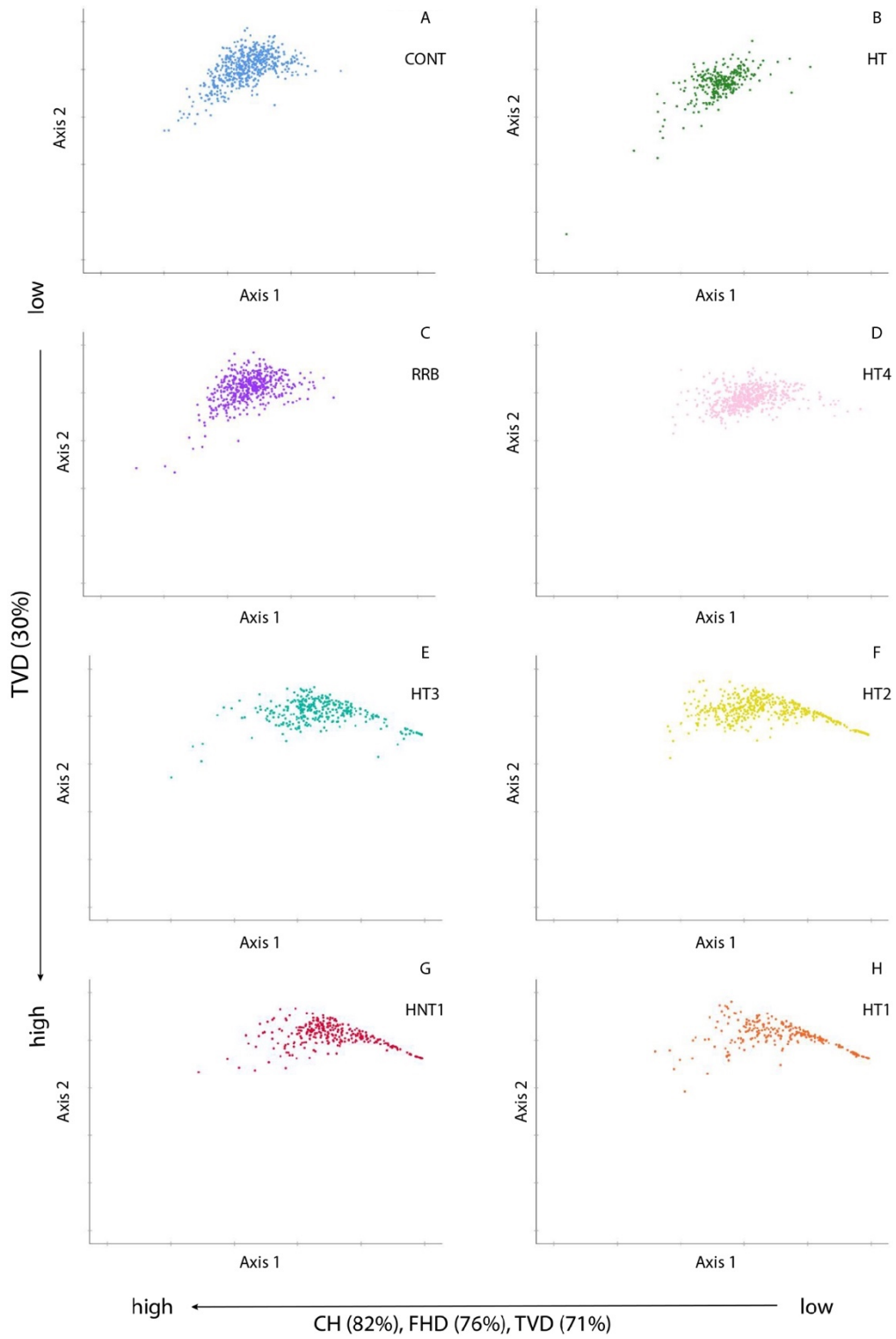


**Figure 3.1 Map of Study Area in Southeastern Oklahoma.** Pushmataha Forest Habitat Research Demonstration Area (FHRA) within the Pushmataha Wildlife Management Area. The approximately 130-acre site is located outside of Clayton, Oklahoma in Pushmataha County and is characterized by mixed pine-oak forest and savanna.



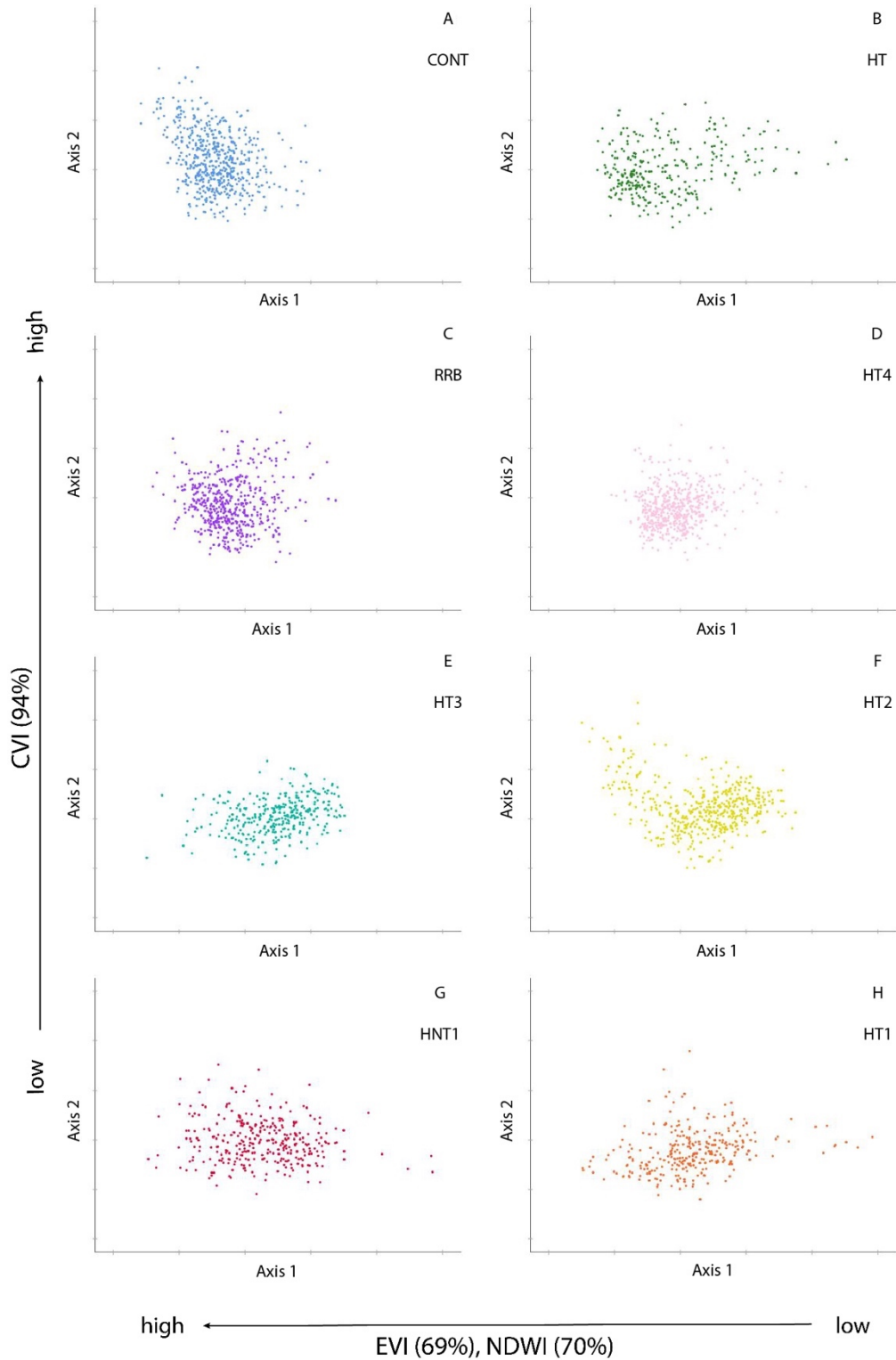
**Figure 3.2 Map of Pushmataha FHRA.** Pushmataha Forest Habitat Research

Demonstration Area (FHRA) with plot boundaries and treatments delineated. Treatment names are indicative of management practices implemented, including selective hardwood thinning (H), pine timber harvest (T), and fire return interval (1-4), with CONT and RRB representing the control and rough reduction treatment with 4-year fire return interval, respectively. Plot size ranges from 0.8 to 1.6 ha in size and are composed of savanna and pine-oak forest of different structure and age class.



**Figure 3.3 Morphological Functional Trait Space.** Morphological functional trait

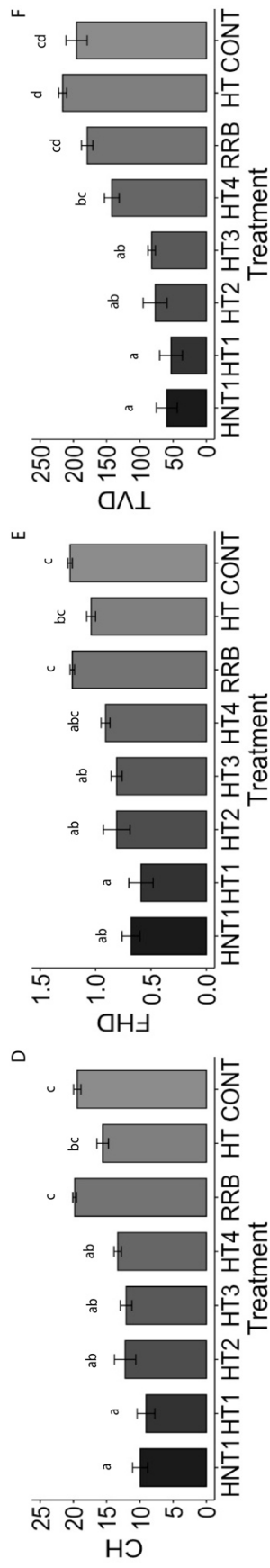
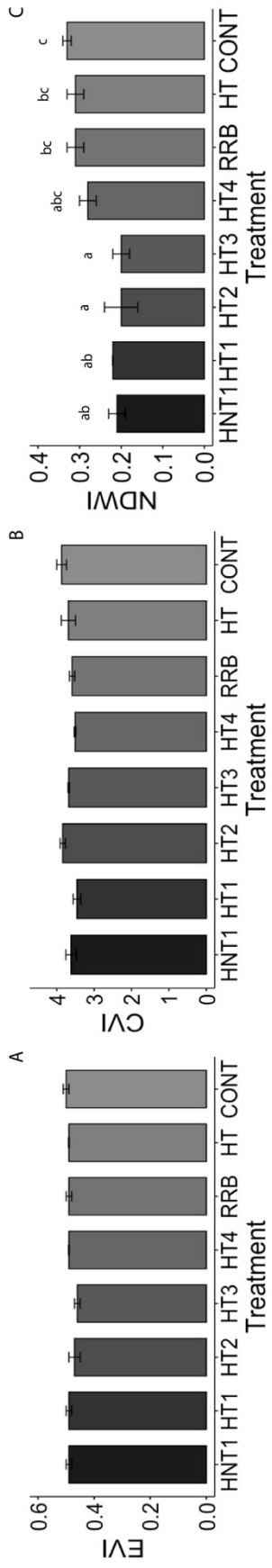
space for treatments (CONT, HT, RRB, HT4, HT3, HT2, HNT1, HT1) at Pushmataha Forest Habitat Research Demonstration Area. Treatment names are indicative of management practices implemented, including selective hardwood thinning (H), pine timber harvest (T), and fire return interval (1-4), with CONT and RRB representing the control and rough reduction treatment with 4-year fire return interval, respectively. The first and second axes from the Principal Coordinates Analysis (PCoA) represent the x and y axes, respectively, with pixels plotted in functional space. Pixel color is assigned based on treatment implemented. Significant Kendall's tau correlation values between traits and PCoA axes are displayed for the x and y axes.



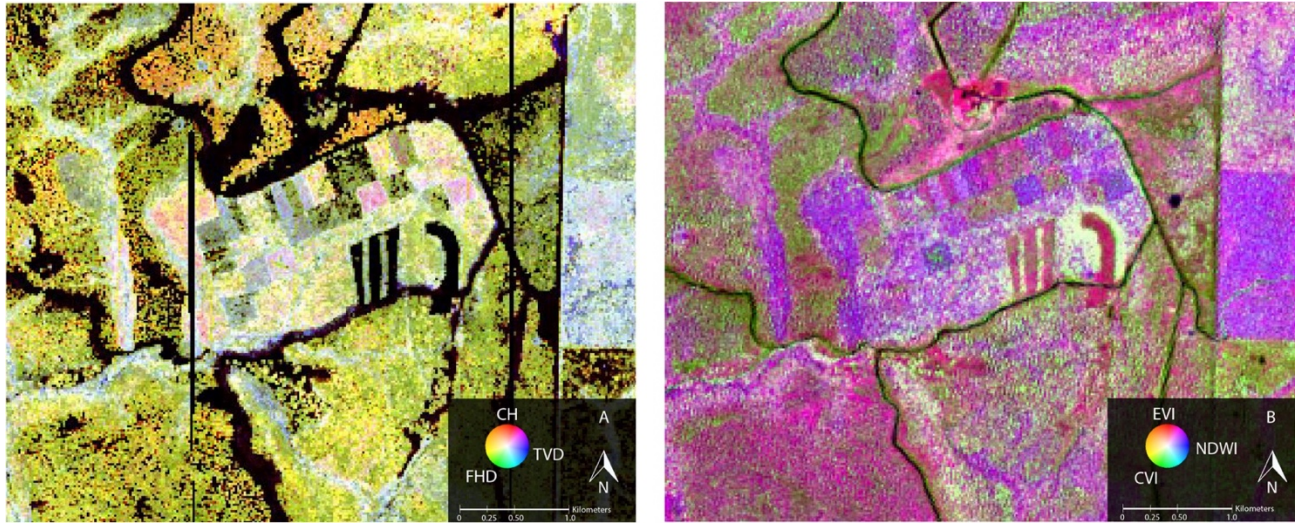
**Figure 3.4 Physiological Functional Trait Space.** Physiological functional trait space for treatments (CONT, HT, RRB, HT4, HT3, HT2, HNT1, HT1) at Pushmataha Forest

Habitat Research Demonstration Area. Treatment names are indicative of management practices implemented, including selective hardwood thinning (H), pine timber harvest (T), and fire return interval (1-4), with CONT and RRB representing the control and rough reduction treatment with 4-year fire return interval, respectively. The first and second axes from the Principal Coordinates Analysis (PCoA) represent the x and y axes, respectively, with pixels plotted in functional space. Pixel color is assigned based on treatment implemented. Significant Kendall's tau correlation values between traits and PCoA axes are displayed for the x and y axes.



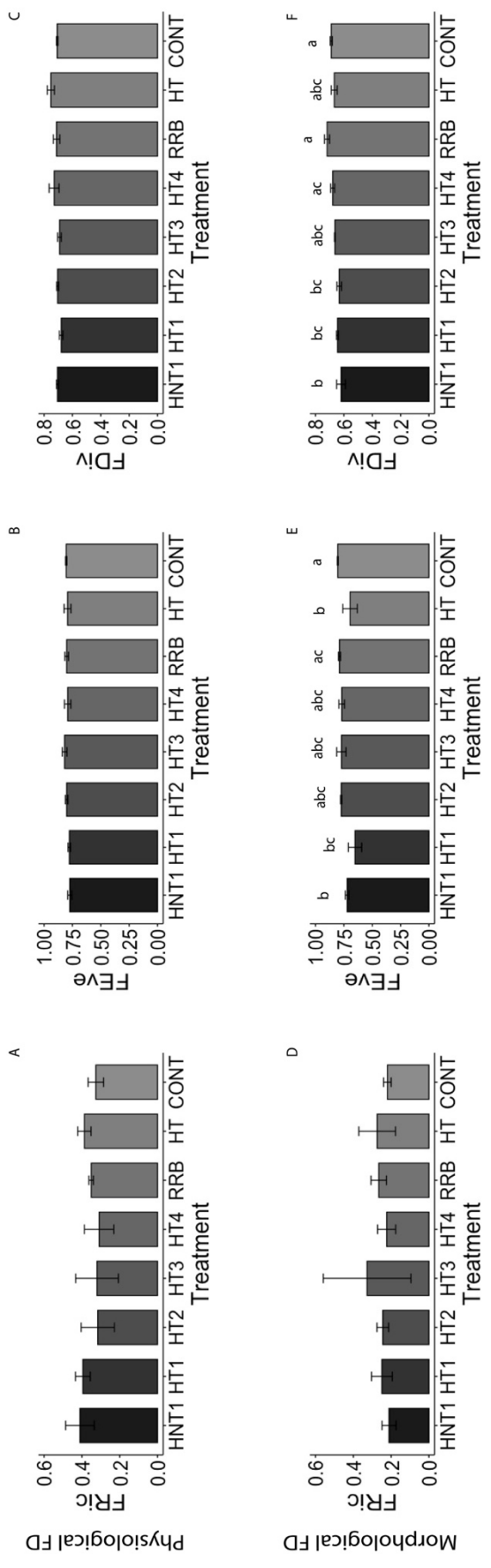


**Figure 3.5 Bar Graphs of Functional Traits and Vegetation Indices.** Bar graphs displaying average Enhanced Vegetation Index (EVI), Chlorophyll Vegetation Index (CVI), Normalized Difference Water Index (NDWI), Canopy Height (CH), Foliage Height Diversity (FHD), and Total Vegetation Density (TVD) by treatment at Pushmataha Forest Habitat Research Demonstration Area (FHRA). Treatment names are indicative of management practices implemented, including selective hardwood thinning (H), pine timber harvest (T), and fire return interval (1-4), with CONT and RRB representing the control and rough reduction treatment with 4-year fire return interval, respectively. An analysis of variance and Tukey's HSD post-hoc test were completed, and groupings are indicated with letters a-d, often corresponding with fire return interval.



**Figure 3.6 False Color Composites of Functional Traits and Vegetation Indices.**

RGB color composites of physiological indices and morphological functional traits across the Pushmataha Forest Habitat Research Demonstration Area. Physiological indices are plotted (left panel) as Enhanced Vegetation Index (EVI, red), Chlorophyll Vegetation Index (CVI, green), and Normalized Difference Water Index (NDWI, blue). Morphological traits are plotted as canopy height (CH, red), Foliage Height Diversity (FHD, green), and Total Vegetation Density (TVD, blue).



**Figure 3.7 Bar Graphs of Functional Diversity Metrics.** Metrics of functional diversity - functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv) - were calculated from morphological and physiological functional traits for 23 units within the Pushmataha Forest Habitat Research Demonstration Area. FRic, FEve, and FDiv values were averaged by treatment applied (CONT, HNT1, HT, HT1, HT2, HT3, HT4, RRB) and are reported with standard error. Panels A-C display metrics of physiological functional diversity, and panels D-F show metrics of morphological functional diversity. Treatment names are indicative of management practices implemented, including selective hardwood thinning (H), pine timber harvest (T), and fire return interval (1-4), with CONT and RRB representing the control and rough reduction treatment with 4-year fire return interval, respectively. Results of the Kruskal Wallis analysis of variance and post-hoc test show significant differences between treatments for morphological functional evenness and divergence, and treatment groupings are indicated using letters a-c.

## CHAPTER IV

### MAPPING PHYSIOLOGICAL FUNCTIONAL DIVERSITY OF VEGETATION USING SENTINEL-2 IMAGERY

#### **4.1 Introduction**

The modification of landscapes due to anthropogenic development, altered nutrient and water cycles, habitat fragmentation, changing disturbance regimes, and unstable weather patterns and climate are having significant effects on biological communities across the globe. Understanding and mitigating biodiversity loss and its effects on ecosystem function is a key challenge in ecology (Schneider et al. 2017; Durán et al. 2019). While much scientific research has focused on examining the effects of species biodiversity loss, there is increasing agreement within ecological research that utilizing trait-based approaches to examine biodiversity loss in terms of ecosystem function is critical to maintaining ecosystem health and productivity (Petchey and Gaston 2002; Díaz et al. 2004; Villegger et al. 2008). As a multifaceted, trait-based component of biodiversity, functional diversity reflects the variation in species' functional characteristics associated with their ecological niche, and its metrics therefore offer improved methods of quantifying biodiversity in relation to ecosystem function (Tilman 2001). Measuring functional traits for species in a given community, rather than

abundance alone, has been shown to provide a more complete understanding of ecosystem productivity and stability (Díaz et al. 2007; Cadotte et al. 2011; Durán et al. 2019). Complementary metrics of functional diversity such as functional richness, functional evenness, and functional divergence quantify the value, range, and abundance of organismal traits in a given community, in addition to providing valuable information on resilience, competition, and resource utilization (Tilman 2001; Mason et al. 2005; Vileger et al. 2008).

Despite increased efforts to use functional trait approaches to study biodiversity of vegetation communities at local scales, there remain large gaps in high-resolution data on functional diversity of vegetation communities at the landscape and global scales (Tittensor et al. 2014; Jetz et al. 2016). Collecting data on functional traits across large scales requires substantial time, effort, and funds when completed with traditional fieldwork. The application of remote sensing techniques to collect functional trait data has the potential to alleviate some of these costs, while providing nondestructive methods for gathering data at various spatial scales across large environmental gradients (Durán et al. 2019; Schneider et al. 2017).

Advancements in satellite remote sensing technologies and increased access to remotely sensed datasets are beginning to fill gaps in continuous, global functional diversity data. Passive remote sensors are capable of measuring vegetation reflectance spectra to assess physiological, biochemical, and phenological traits of vegetation (Ustin and Gamon 2010; Cavender-Bares et al. 2017). Imaging spectroscopy captures light reflectance in a continuous spectrum, allowing data collection of foliar and canopy properties and has been used to study vegetation physiology in various landscapes (Asner

et al. 2017; Schneider et al. 2017; Moreno-Martínez et al. 2018). Similarly, broadband multispectral imagery, with coarser spectral resolution, shows potential for use in collection of biochemical and physiological functional trait data and expanding global coverage of biodiversity data.

The aim of my study was to demonstrate the potential for using multispectral satellite remote sensing to calculate functional traits and map metrics of physiological functional diversity continuously at the landscape scale. To do this, I selected a study area in southeastern Oklahoma, the Pushmataha Wildlife Management Area (PWMA), characterized by a pine-oak forest and savanna landscape and an elevation and soil gradient. Utilizing multispectral imagery, I calculated indices of plant physiology and biochemistry across the PWMA to map three metrics of functional diversity - functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv; Mason et al. 2005). The methodology used in this study provides a basis for future utilization of broadband imagery to assess functional diversity at the landscape scale and monitor biodiversity loss and changes in ecosystem function, stability, and resilience across Earth's ecosystems.

## **4.2 Materials and Methods**

### *4.2.1 Study Area*

The study was conducted in southeastern Oklahoma, USA, at Pushmataha Wildlife Management Area (PWMA) near Clayton, Oklahoma (Figure 4.1). PWMA is an approximately 7,690 ha area comprised of mixed pine/oak forest and savanna. Located in



the Kiamichi Mountains, the landscape is characterized by sloping land, with shallow, rocky soils, and a semi-humid climate (Feltrin et al. 2016; Masters and Waymire 2012). The vegetation communities within PWMA are largely dominated with the overstory species *Pinus echinata* (shortleaf pine), *Quercas stellata* (post oak), *Quercas marilandica* (blackjack oak), and *Carya tomentosa* (mockernut hickory) (Masters et al. 1993; Feltrin et al. 2016). Understory species consist of both woody and herbaceous plants including *Vaccinium arboreum* (sparkleberry), *Toxicodendron radicans* (poison ivy), *Smilax spp.* (greenbriers), *Andropogon gerardii* (big bluestem), *Schizachyrium scoparium* (little bluestem), *Panicum spp.*, *Carex spp.*, and *Scleria spp.*, amongst others.

Vegetation management practices have played an integral part in the conservation and management goals of PWMA since its beginnings in the 1940s. Throughout the PWMA, various vegetation management strategies have been implemented by the Oklahoma Department of Wildlife Conservation, including selective thinning of hardwoods, pine timber harvest, and controlled burning (Masters et al. 1993). Management implemented within the PWMA focus on establishing a mixed shortleaf pine-oak woodland and savanna, with thinning to 60 square feet/acre basal area and prescribed fire every 1-2 years (Shortleaf Pine Initiative, 2019). Within the boundaries of the PWMA, the Pushmataha Forest Habitat Research Demonstration Area (FHRA) was established in 1982 with the purpose of studying the response of herbaceous and woody vegetation to various timber harvest and prescribed fire regimes (Masters et al. 2006). FHRA is an approximately 52 ha experimental forest consisting of 28 units, 0.8-1.6 ha in size, with various management regimes applied in a randomized fashion. Treatments are combinations of selective hardwood thinning, pine timber harvest, and prescribed fire at

various fire return intervals. As a result of these management practices, the vegetation communities at the FHRA and across the entirety of the PWMA range from savanna to closed canopy forest in various stages of development and structure.

#### *4.2.2 Data Acquisition*

Multispectral imagery for the study area was captured by the MultiSpectral Instrument (MSI) sensor aboard the Sentinel 2 satellite on July 31, 2016. I downloaded a single tile (100 km x 100 km), consisting of 13 bands between 432-2,290 nm with spatial resolutions of 10, 20, and 60 m, from the European Space Agency's (ESA) Sentinel 2 Pre Operations Hub (ESA 2020). I corrected the original Sentinel Level 1C product for atmospheric conditions using the ESA's software, SNAP, with the Sen2Cor plugin to obtain Bottom of Atmosphere reflectance. Spatial resolution of all bands was improved to 10m using details from the high-resolution bands, while preserving reflectance values (Super-resolution Plugin; Brodu 2017). A section of this tile was used for the analysis that encompassed an approximate 6,500 ha area and covered a significant portion of the PWMA (Figure 4.1).

#### *4.2.3 Functional Traits*

Vegetation indices were used as proxies for biochemical and physiological traits of plant communities and were calculated across the study area at a spatial grain of 10 m. I calculated Enhanced Vegetation Index (EVI; Huete et al. 2002), Chlorophyll Vegetation

Index (CVI; Vincini et al. 2008), and Normalized Difference Water Index (NDWI; Gao 1996), from the Sentinel-2 imagery. EVI is a measure of photosynthetic activity and vegetation condition responsive to variations in canopy structure (Huete et al. 2002; Table 4.1) and is correlated with primary productivity and net carbon fixation (Glenn et al. 2008). CVI is an index with specific sensitivity towards leaf chlorophyll content (Vincini et al. 2008; Table 4.1), while the NDWI is a measure of vegetation water content (Jackson et al. 2004; Table 4.1).

In the selection of vegetation indices, I emphasized indices that are associated with plant growth, acquisition of resources, and overall health, and considered vegetation traits used in other functional diversity studies (Maeshiro et al. 2013, Schneider et al. 2017, Lelli et al. 2019). Ultimately, the spectral resolution of the available remotely sensed datasets limited the analysis to indices of plant physiological condition.

#### *4.2.4 Functional Diversity Analysis*

Utilizing the data from vegetation indices, I calculated functional diversity across PWMA using three different metrics: functional richness (FRic), functional evenness (FEve), and functional divergence (FDiv). FRic, FEve, and FDiv measure aspects of the distribution of species in trait space directly and are the most commonly used indices in functional diversity studies (Mason et al. 2005). FRic is a measure of the total occupied functional space of a community (Villegger et al. 2008), while FEve measures the regularity of the distribution of species within multidimensional functional space (Mouillot 2013). FDiv measures the extent to which the most extreme species trait values represent the total abundance within a community (Mouillot 2013).

Given the large extent of PWMA and a moderate spatial resolution of 10m, I included over 600,000 pixels in my analysis of functional diversity. Moving window analyses were used to calculate functional diversity across the landscape with varying neighborhood sizes in R Statistical Software (FD package; Laliberté et al. 2014; R Core Team 2018). To determine the effects of spatial extent on functional diversity, neighborhood size increased from 3x3 pixels (900 m<sup>2</sup>) to 11x11 pixels (12,100 m<sup>2</sup>; Figure 4.2). All pixels within a designated neighborhood window were considered a community in the calculation of functional diversity indices. Individual pixels served as ‘species’, with three different functional trait measurements. With a spatial resolution of 10m, the vegetation index values for each pixel are representative of all individuals and species found within that space.

## **4.3 Results**

### *4.3.1 Functional Traits*

Vegetation indices calculated using remotely sensed data showed variation across the landscape, indicating differences in vegetation physiology and biochemistry at PWMA. The mean EVI value across the study area was  $0.479 \pm 0.0791$  (mean  $\pm$  standard deviation), while the mean CVI and NDWI values were  $3.591 \pm 0.502$  and  $0.195 \pm 0.109$ , respectively (Figure 4.3).

Across the landscape of PWMA, a false color composite map revealed substantial differences in vegetation index values in large patches dispersed across the landscape (Figure 4.4). Purple patches of pixels depicted high NDWI and EVI and low CVI.

Patches of pink indicated high EVI with moderate NDWI, while green indicated high CVI values and lower EVI and NDWI values. Brightest pixels represented high values for all vegetation indices, and dark pixels indicated low values for all three indices. The darkest pixels often corresponded with dirt roads found throughout the wildlife area, where vegetation was not present.

#### *4.3.2 Functional Diversity*

Functional diversity metrics, FRic, FEve, and FDiv, assessed using remotely sensed vegetation indices varied across the landscape of PWMA (Figure 4.5). FRic values represented total occupied functional space not standardized by total community richness and are low across the entirety of the study area. At the smallest window size of 900 m<sup>2</sup>, FRic values ranged from  $1.27 \times 10^{-7}$  to 0.00465, and ranged from  $2.75 \times 10^{-5}$  to 0.0176 at the largest window size of 12,100 m<sup>2</sup>. FEve and FDiv also showed considerable variation by pixels across the landscape, each with a wide range in values assessed. FEve values ranged from 0.316 to 0.980 at the smallest window size of 900 m<sup>2</sup> and 0.585 to 0.880 with a neighborhood of 12,100m<sup>2</sup>, while FDiv ranged from 0.509 to 0.957 and 0.584 to 0.866 at 900 m<sup>2</sup> and 12,100 m<sup>2</sup> neighborhood sizes, respectively.

The spatial extent of analysis, modified by neighborhood size, had an effect on all functional diversity metrics (Figure 4.5), although the relationship between functional diversity and extent differed between FRic, FEve, and FDiv. In general, mean FRic showed a positive relationship with spatial extent of analysis, with the highest values of FRic calculated at the largest window size (Figure 4.6). In addition, areas of high FRic at

smaller spatial extents increased in size to include more pixels with moderate to high FRic values at larger extents (Figure 4.5). Responses in mean FEve and FDiv to increasing spatial extent of analysis are minimal (Figure 4.7 and Figure 4.8). As window size increased, mean FEve and FDiv remained consistent (Figure 4.7 and Figure 4.8). However, when FEve and FDiv were mapped across the landscape, areas of high FEve and FDiv showed an increase in value and in number of pixels, while areas of low FEve and FDiv decreased in value and size.

#### **4.4 Discussion**

In this study, I utilized multispectral imagery to calculate and map indices of vegetation physiology and biochemistry and metrics of functional diversity at the landscape level. Vegetation indices, EVI, CVI, and NDWI, showed considerable variation across PWMA. Metrics of functional diversity, FRic, FEve, and FDiv, assessed using these vegetation indices, also varied across the landscape. Areas of highest functional richness included the FHRA, edge habitat throughout the PWMA, and areas next to roads. The FHRA covers a 52-ha area, where a number of management regimes are implemented, and forest and savanna vegetation communities are in various stages of development. The higher heterogeneity of canopy and species composition of the plots could account for increased functional richness. It is worthwhile to note that the high FRic values in some areas are likely affected by the differences in image texture and sudden changes in reflectance values for soil and roads included in the study area. Avoidance of non-vegetated pixels in remote sensing vegetation traits presents challenges

but is likely needed to minimize spectral variation that is not directly due to functional trait variation (Dahlin 2016)

Taking advantage of the continuous nature of remotely sensed vegetation data, I calculated functional diversity metrics using various neighborhood sizes. Results show that mean FRic was affected by the spatial extent of analysis, whereas mean FEve and FDiv show few differences with increasing spatial extent. However, the mean values for functional diversity metrics are the mathematical averages of all pixels covering the landscape and may not be representative of all spatial extent dependency relationships of the functional diversity, which likely vary throughout the PWMA. In mapping the metrics of functional diversity calculated from various window sizes (Figure 4.5), rather than looking at the overall mean functional diversity values for the entire study area, relationships and patterns in functional diversity metrics can be seen with increasing size of spatial extent. Areas of high functional diversity tend to increase in size and functional diversity metric value, while areas of low functional diversity also become more pronounced and show decreased metric values (Figure 4.5). Schneider et al. (2017) used similar methodology to map FRic, FEve, and FDiv with different scales across their study area in a temperate mixed forest site in Switzerland. They report congruent findings in the response of functional diversity metrics at increasing scales mapped across the landscape. In addition to mapping functional diversity metrics, spatial dependency was examined for various sub-regions of the study area using a single-pixel approach (Schneider et al. 2017) and offers potential methodology for continued research on spatial relationships of functional diversity at the PWMA.

While I illustrate some differences in continuous functional diversity data associated with increasing window size of analysis, scale dependency of functional diversity metrics at PWMA is not completely understood. The relationship between functional diversity, specifically functional richness, and area is thought to be related to the species-area relationship, a fundamental concept in spatial ecology (Preston 1960) relating the size of the ecosystem or sample area and the number of species found there. The species-area relationship has been used as a tool to determine optimal sample sizes and predict patterns in biodiversity and species extinction (Connor and McCoy 1979; Gerstner et al. 2014). Smith et al. (2013) extend this relationship to functional traits with the functional diversity-area relationship, and Dalman (2016) uses spectral diversity data from remote sensing to examine area relationships, biodiversity, and provide insight on community assembly processes. Continued analysis of remotely sensed functional traits and diversity at increasing scales is needed to better understand the functional diversity-area relationships of the three metrics of physiological functional diversity at various locations throughout PWMA. In addition, future analysis in the area could explore differences in functional diversity related to disturbance, forest management implemented, and environmental gradients that play an important role in the assembly and composition of vegetation communities in the area.

Utilizing remote sensing techniques in the study of functional diversity of landscapes provides a number of advantages. The continuity of remote sensing traits allows for a pixel-based approach, rather than a species- or individual-based one, and accounts for intraspecific variability that is often overlooked in functional diversity studies that utilize taxonomic data (Schneider et al. 2017). Remote sensing offers



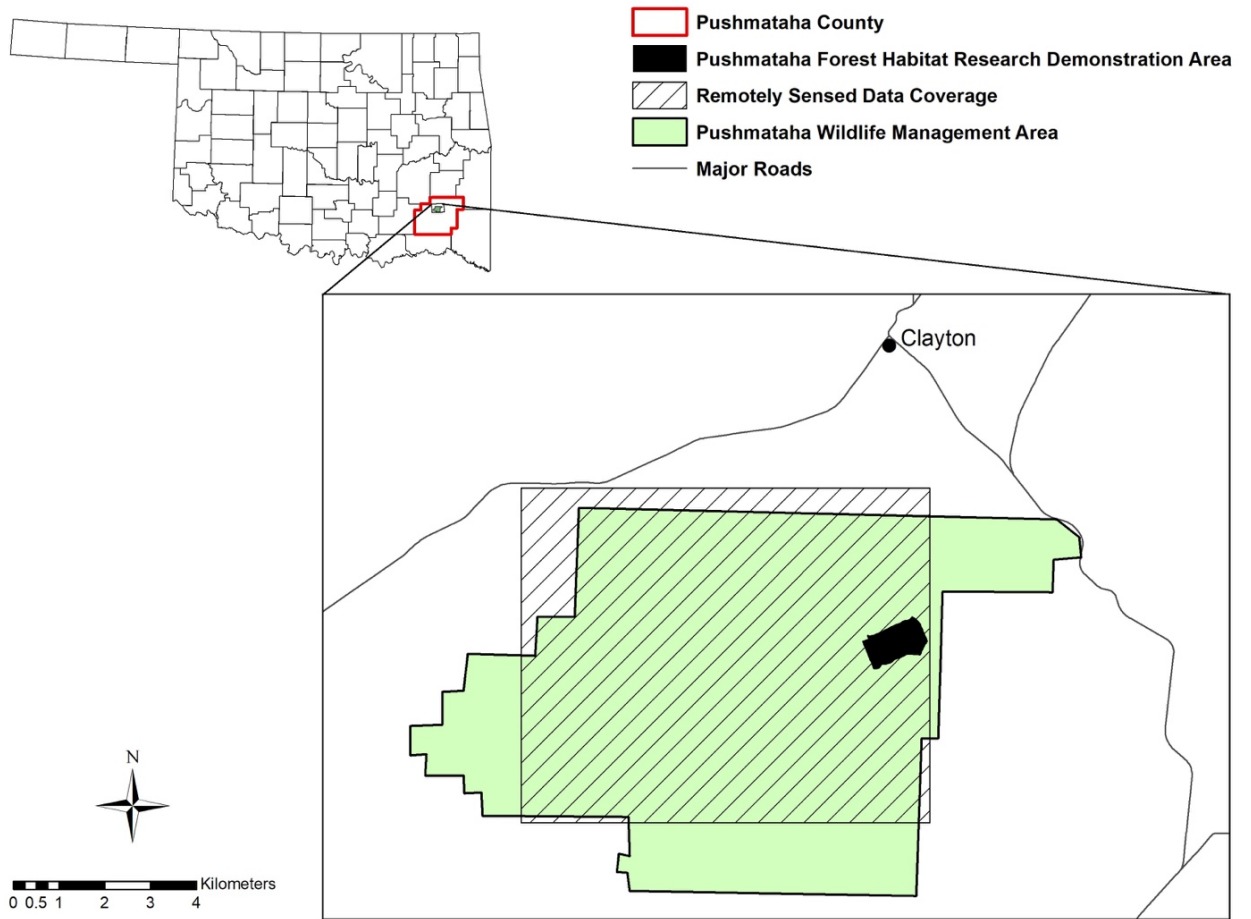
methodology to collect functional trait data over entire landscapes, which would be infeasible with field methods. However, limitations arise when collecting, storing, and analyzing large amounts of remotely sensed data for increasingly larger spatial extents. The computational power and processing time required for analysis of large quantities of functional trait data present challenges to using these methods. In my study, I found increasing the window size used in analyses greatly increased the processing time required. Developments in remotely sensed data processing and raster analysis will allow for continued progress in studying functional diversity across entire landscapes.

Ecological research emphasizes the importance of understanding and developing metrics to predict how biological communities will respond to various environmental changes (Jetz et al. 2016). Innovative tools and methodology are needed to increase the availability of functional diversity data to fill in gaps of our understanding of biodiversity and ecosystem function at a global scale. In this study, I establish a methodology utilizing widely accessible satellite multispectral imagery to assess characteristics of vegetation physiology and functional diversity. Initial success in applying these techniques to a large area shows promise for its utilization to study variation in functional diversity of other ecosystems and regions as well. The methodology presented here offers a suitable tool for land managers and researchers to effectively measure metrics of functional diversity and monitor the impacts of changing disturbance or management regimes across entire landscapes. As global biodiversity continues to change, this tool can be used to provide insight into the ecosystem function, productivity, and resilience of heterogeneous landscapes.

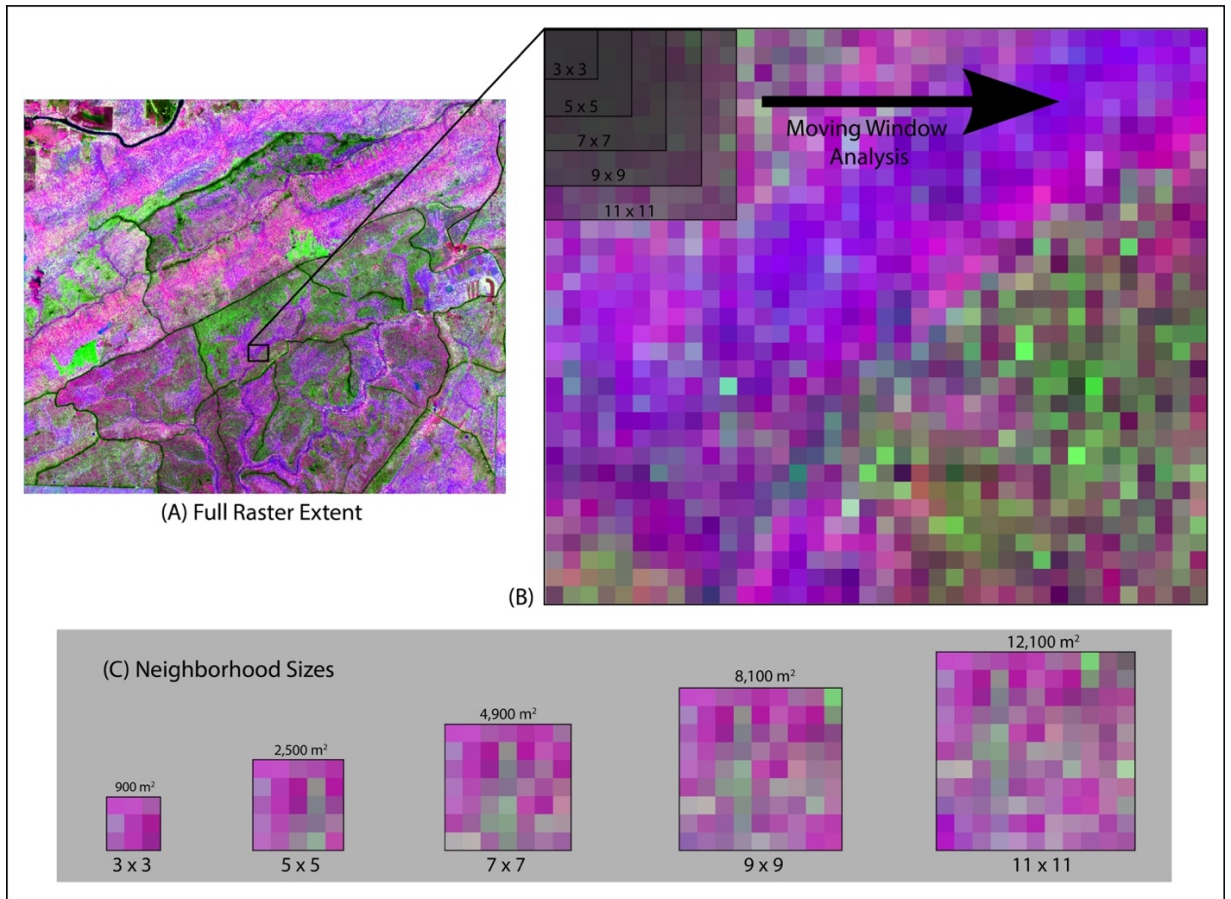
## 4.5 Tables and Figures

**Table 4.1 Vegetation Indices.** Vegetation indices used as proxies for physiological functional traits.

<b>Index Name</b>	<b>Abbreviation</b>	<b>Equation</b>	<b>Reference</b>
Enhanced Vegetation Index	EVI	$2.5(R_{NIR} - R_R)/(R_{NIR} + 6*R_R - 7.5*R_B + 1)$	Huete et al. 2002
Chlorophyll Vegetation Index	CVI	$R_{NIR}*R_R/(R_G^2)$	Vincini et al. 2008
Normalized Difference Water Index	NDWI	$(R_{NIR} - R_{SWIR})/(R_{NIR} + R_{SWIR})$	Jackson et al. 2004

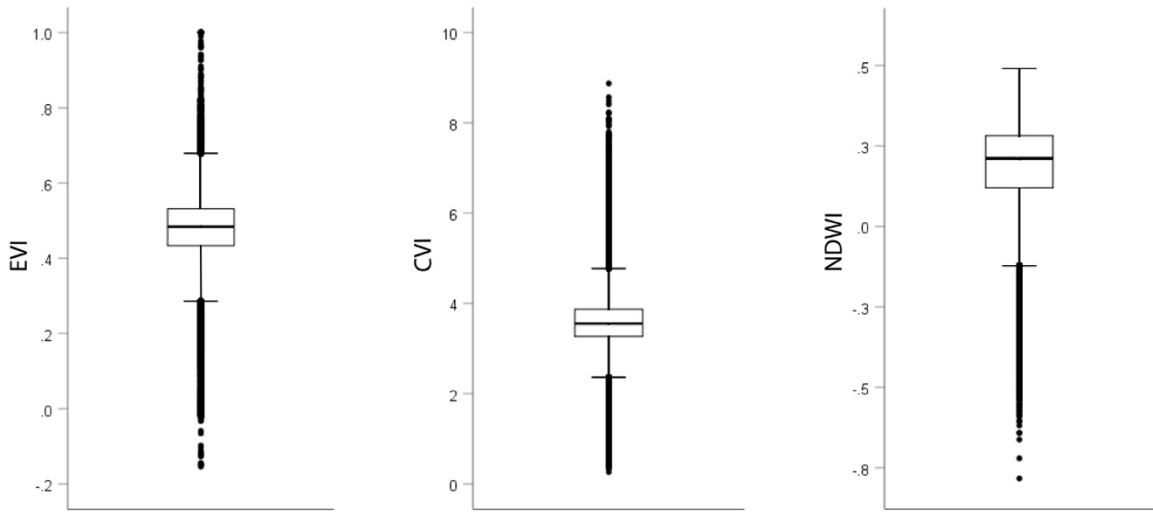


**Figure 4.1 Map of Study Area at Pushmataha Wildlife Management Area.** The study area of Pushmataha Wildlife Management Area (PWMA) and Pushmataha Forest Habitat Research Demonstration Area (FHRA) located outside of Clayton, Oklahoma in Pushmataha County. The extent of remotely sensed data coverage used in the study is indicated and includes approximately 6,500 ha.

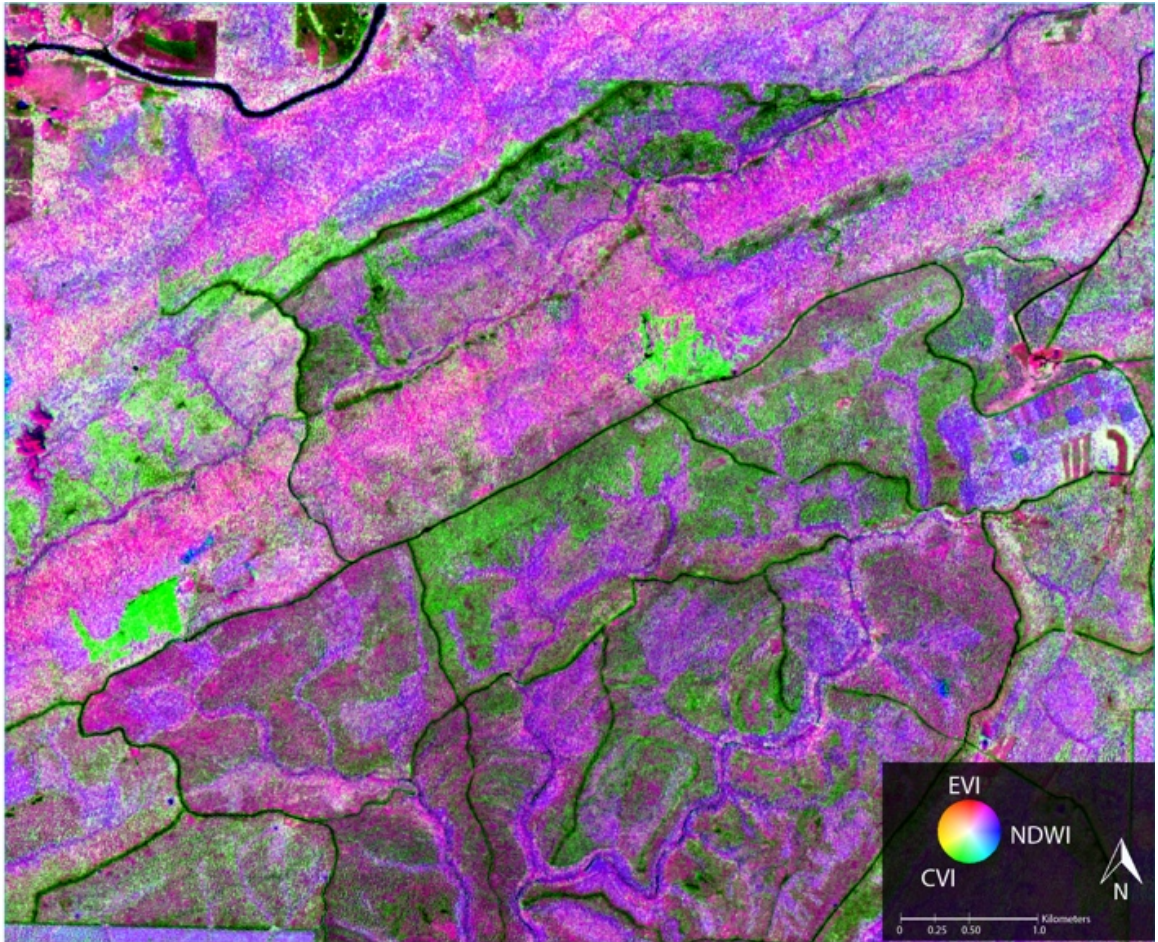


**Figure 4.2 Moving Window Analysis for Assessing Functional Diversity.**

Demonstration of moving window analysis to calculate functional diversity at various scales. False color composite of vegetation indices covering approximately 6,500 ha across the Pushmataha Wildlife Management Area in southeastern Oklahoma is displayed (A) with a subset covering an approximate 15 ha (B). Indices are plotted as Enhanced Vegetation Index (EVI, red), Chlorophyll Vegetation Index (CVI, green), and Normalized Difference Water Index (NDWI, blue). Pixel size is 10 m for all rasters. Moving window analysis was used to calculate metrics of functional diversity with various window sizes, ranging from 3 x 3 neighborhood of pixels (900 m<sup>2</sup>) to a neighborhood of 11 x 11 pixels (12,100 m<sup>2</sup>; C). Window sizes with total square meters (m<sup>2</sup>) covered in each analysis are displayed in B and C.

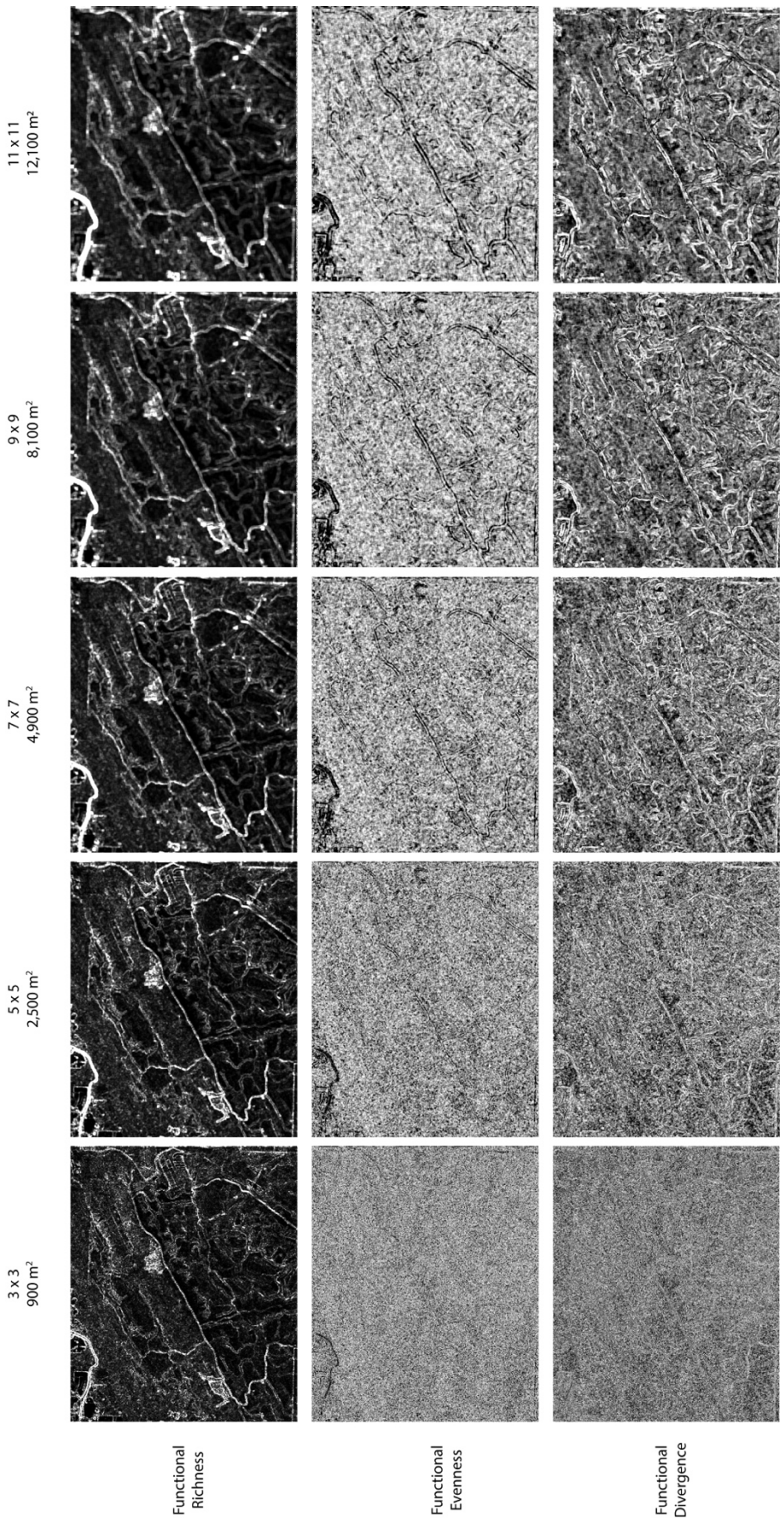


**Figure 4.3 Boxplots of Vegetation Indices.** Boxplots of Enhanced Vegetation Index (EVI), Chlorophyll Vegetation Index (CVI), and Normalized Difference Water Index (NDWI), including all pixels in the study area at Pushmataha Wildlife Management Area. For each box, the center line represents the median, while the upper and lower extents of the box represent the 3<sup>rd</sup> and 1<sup>st</sup> quartiles, respectively. Outliers are indicated by black circles above and below the whiskers.

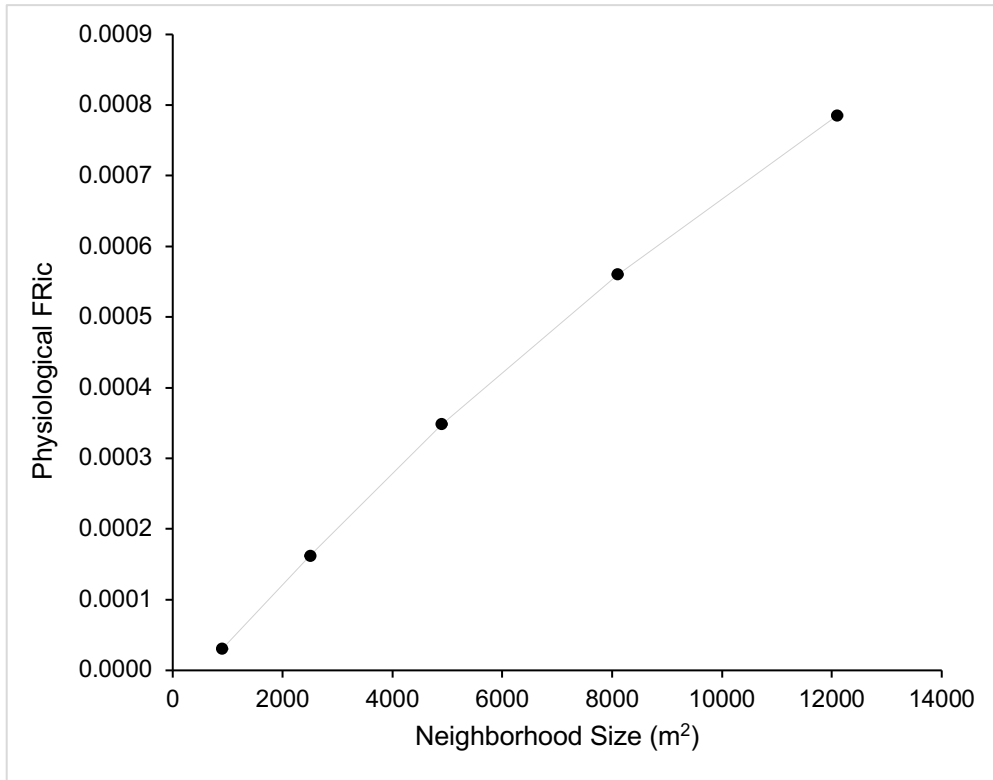


**Figure 4.4 False Color Composite of Vegetation Indices.** RGB color composite of vegetation indices across the Pushmataha Forest Habitat Research Demonstration Area. Indices are plotted as Enhanced Vegetation Index (EVI, red), Chlorophyll Vegetation Index (CVI, green), and Normalized Difference Water Index (NDWI, blue).



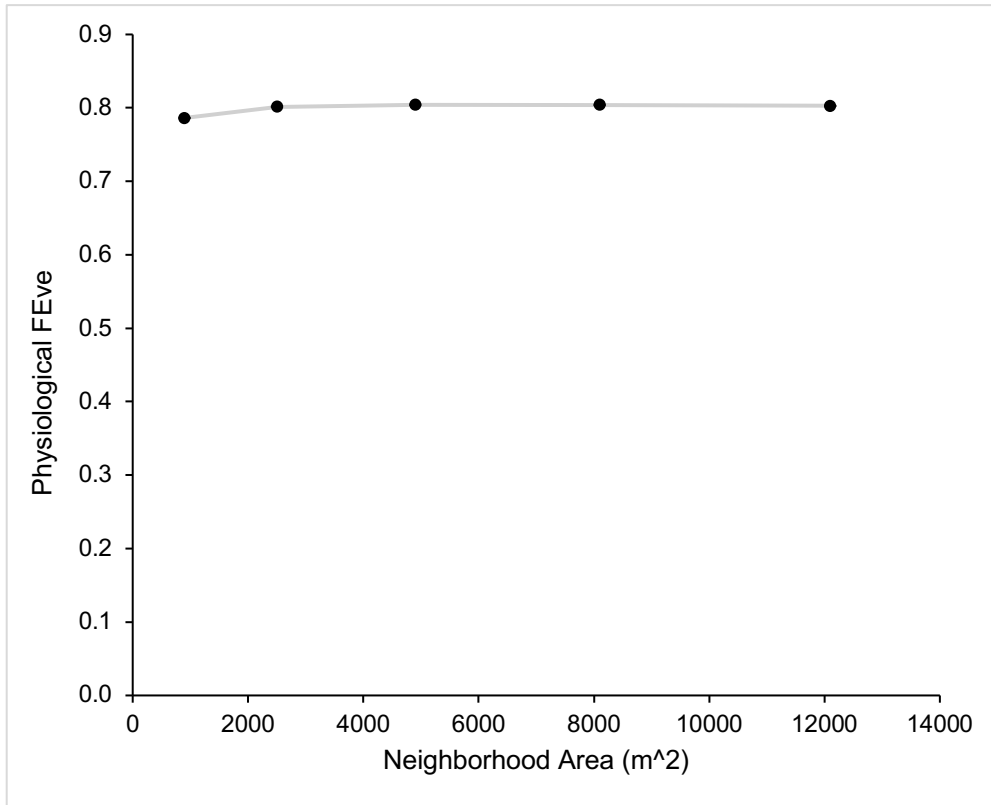


**Figure 4.5 Functional Diversity Metrics Across PWMA.** Visualizing window size dependency of functional richness, evenness, and divergence across the Pushmataha Wildlife Management Area (PWMA). Each scene covers the same 650,000 ha of the PWMA. Window size increases from 3 x 3 cell neighborhoods to 11 x 11 cell neighborhoods.

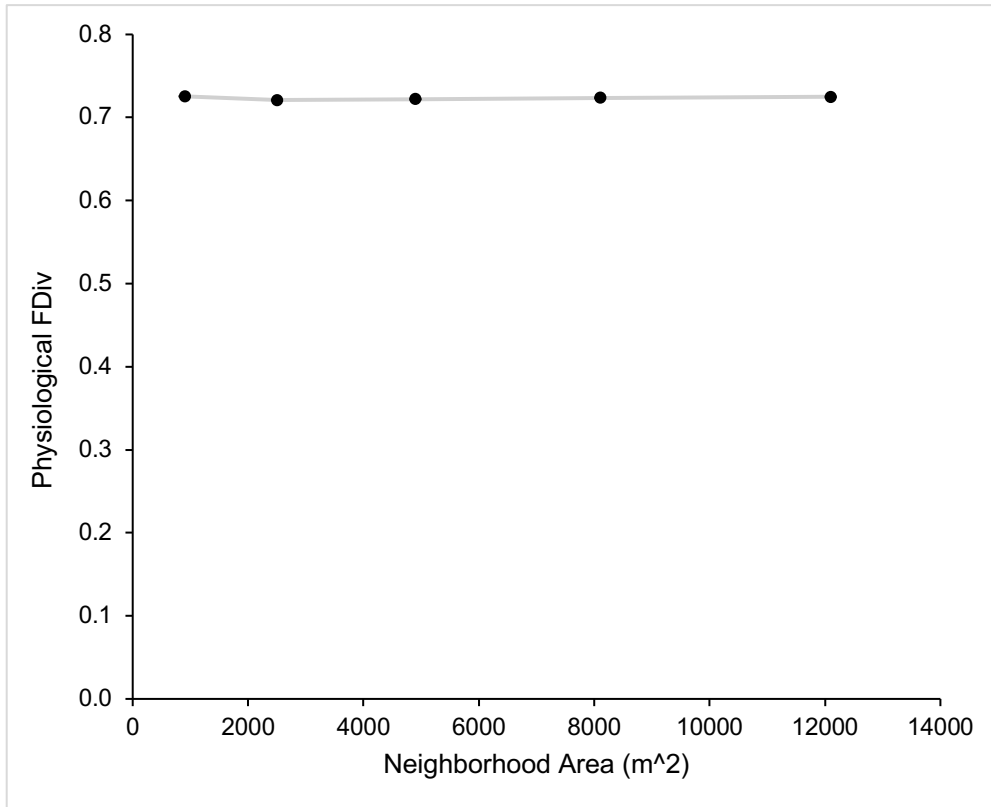


**Figure 4.6 Spatial Extent Dependency of Physiological Functional Richness.** Spatial extent dependency of physiological functional richness (FRic) across Pushmataha Wildlife Management Area. Mean FRic values for the study area are displayed with standard error. Standard errors are less than  $1.32 \times 10^{-6}$  for all five FRic values. Neighborhood size is reported as the total area in square meters (m<sup>2</sup>) included in the moving window analysis to calculate FRic.





**Figure 4.7 Spatial Extent Dependency of Physiological Functional Evenness.** Spatial extent dependency of physiological functional evenness (FEve) across Pushmataha Wildlife Management Area. Mean FEve values for the study area are displayed with standard error. Standard errors are less than  $9.03 \times 10^{-5}$  for all five FEve values. Neighborhood size is reported as the total area in square meters (m<sup>2</sup>) included in the moving window analysis to calculate FEve.



**Figure 4.8 Spatial Extent Dependency of Physiological Functional Divergence.**

Spatial extent dependency of physiological functional divergence (FDiv) across Pushmataha Wildlife Management Area. Mean FDiv values for the study area are displayed with standard error. Standard errors are less than  $6.99 \times 10^{-5}$  for all five FDiv values. Neighborhood size is reported as the total area in square meters (m<sup>2</sup>) included in the moving window analysis to calculate FDiv.

## CHAPTER V

### CONCLUSION

Biodiversity loss, land-use change, and modified disturbance regimes, amongst other effects of human development, are having significant consequences for the function and overall productivity of biological communities (Carreño-Rocabado et al. 2012). Functional diversity is a component of biodiversity that can provide valuable insight into a community's function, resilience, and response to environmental change (Tilman 2001). In plant communities, such as forests and savannas, measuring functional diversity often relies on the collection of functional trait data, examining plant characteristics associated with the plant's ability to obtain, utilize, and conserve resources (Reich et al. 2003). Assessing functional diversity of vegetation across a landscape is a time and labor-intensive process when completed with traditional field data collection, which can be improved with remote sensing methods. Satellite-borne sensors provide global multispectral imagery coverage and are capable of collecting valuable information on plant physiology and biochemistry (Ustin and Gamon 2010), while LiDAR can be used to capture variation in vegetation morphology (Reutebuch et al. 2005). The methodology I provide in this study utilizes both multispectral imagery and LiDAR to continuously map functional traits and metrics of functional diversity across a landscape with large

environmental gradients. I demonstrate the utilization of this remote sensing methodology to examine the effects of various forest management practices on the functional diversity of mixed pine-oak forests in southeastern Oklahoma at the Pushmataha Forest Habitat Research Demonstration Area (FHRA). I detected differences in vegetation morphology and physiology, assessed using environmental remote sensing, between treatments with an analysis of multivariate space. At FHRA, management practices affected the canopy height (CH), vertical diversity (FHD), density (TVD), water content (NDWI), and morphological functional evenness and divergence of plots. Fire frequency appeared to have the biggest impact on average trait and functional diversity values for treatments, with lower mean CH, FHD, and TVD, and lower morphological functional evenness and divergence associated with frequent prescribed burning.

Building upon the initial study, I extended these techniques to map metrics of functional diversity across the much larger Pushmataha Wildlife Management Area (PWMA). While the PWMA, and the FHRA within it, provided a suitable study area for the development of the methodology, the applications are not limited to the study of functional diversity in Oklahoma or forest-savanna landscapes. The methodology can be applied to a variety of vegetation communities and regions, limited only by the availability and resolution of the remotely sensed data. Increasing access to publicly-available multispectral and hyperspectral imagery from spaceborne missions is expanding the potential for global coverage of functional diversity monitoring. Capturing and visualizing the variation in functional diversity across landscapes is vital to understanding the resilience of Earth's ecosystems and predicting responses to future environmental change (Jetz et al. 2016).

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APPENDICES

**Table A.1 Post-hoc Test Results for Morphological Functional Evenness.** Table containing the results of Mann-Whitney U pairwise comparison post-hoc tests for morphological functional evenness. The two treatments being compared, the test statistic, and associated significance value is listed, with \* designating significance values less than 0.05.

<b>Treatments Compared</b>	<b>Mann-Whitney U Test Statistic</b>	<b>P-value</b>
CONT-HNT1	14.000	0.011*
CONT-HT	13.000	0.019*
CONT-HT1	17.000	0.002*
CONT-HT2	6.333	0.253
CONT-HT3	6.833	0.270
CONT-HT4	6.333	0.253
CONT-RRB	2.667	0.630
HNT1-HT	-1.000	0.857
HNT1-HT1	3.000	0.588
HNT1-HT2	-7.677	0.166
HNT1-HT3	-7.167	0.247
HNT1-HT4	-7.677	0.166
HNT1-RRB	-11.333	0.041*
HT-HT1	4.000	0.470
HT-HT2	-6.667	0.229
HT-HT3	-6.167	0.319
HT-HT4	-6.667	0.229
HT-RRB	-10.333	0.062
HT1-HT2	-10.667	0.054
HT1-HT3	-10.167	0.101
HT1-HT4	-10.667	0.054
HT1-RRB	-14.333	0.010*
HT2-HT3	0.500	0.936



HT2-HT4	0.000	1.000
HT2-RRB	-3.667	0.508
HT3-HT4	-0.500	0.936
HT3-RRB	-4.167	0.501
HT4-RRB	-3.667	0.508

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**Table A.2 Post-hoc Test Results for Morphological Functional Divergence.** Table

containing the results of Mann-Whitney U pairwise comparison post-hoc tests for

morphological functional divergence. The two treatments being compared, the test

statistic, and associated significance value is listed, with \* designating significance values

less than 0.05.

<b>Treatments Compared</b>	<b>Mann-Whitney U Test Statistic</b>	<b>P-value</b>
CONT-HNT1	13.333	0.016*
CONT-HT	4.333	0.434
CONT-HT1	11.000	0.047*
CONT-HT2	12.333	0.026*
CONT-HT3	6.167	0.319
CONT-HT4	1.667	0.763
CONT-RRB	-3.333	0.547
HNT1-HT	-9.000	0.104
HNT1-HT1	-2.333	0.673
HNT1-HT2	-1.000	0.857
HNT1-HT3	-7.167	0.247
HNT1-HT4	-11.667	0.035*
HNT1-RRB	-16.667	0.003*
HT-HT1	6.667	0.229
HT-HT2	8.000	0.149
HT-HT3	1.833	0.767
HT-HT4	-2.667	0.630
HT-RRB	-7.667	0.166
HT1-HT2	1.333	0.810
HT1-HT3	-4.833	0.435
HT1-HT4	-9.333	0.092
HT1-RRB	-14.333	0.01*
HT2-HT3	-6.167	0.319
HT2-HT4	-10.667	0.054
HT2-RRB	-15.667	0.005*
HT3-HT4	-4.500	0.467
HT3-RRB	-9.500	0.125
HT4-RRB	-5.000	0.367

## VITA

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