SPECTRAL DETECTION OF AN INVASIVE GRASS SPECIES (COGONGRASS: *Imperata cylindrica*) AND ITS EFFECT ON HERBACEOUS VEGETATION CHARACTERISTICS IN AN EXPERIMENTAL SETTING

By

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A THESIS PRESENTED TO THE GRADUATE SCHOOL OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE

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SPECTRAL DETECTION OF AN INVASIVE GRASS SPECIES (COGONGRASS: *Imperata cylindrica*) AND ITS EFFECT ON HERBACEOUS VEGETATION CHARACTERISTICS IN AN EXPERIMENTAL SETTING

By

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Cogongrass is a detrimental invasive species in the Southeastern US. It invades longleaf pine ecosystems, an endangered ecosystem of conservation interest because of its high understory plant diversity. Cogongrass invasion in the southeastern US may alter flammability of longleaf pine systems by changing water status and producing large amount of senescent biomass after die back. Cogongrass cover and its impacts on vegetation properties are difficult to quantify on landscape scales using traditional field methods. Hyperspectral remote sensing offers the possibility of quantifying cogongrass and its impacts using airborne and satellite images. I used experimental cogongrass invasion plots to test whether hyperspectral data can quantify cogongrass cover and its impact on dead plant coverage and water content on a local scale as a step to measuring cogongrass and its impacts from airborne and satellite data.

I applied partial least squares regression (PLSR) to data from a common garden experiment at the University of Florida at Bivens Arm to predict and monitor cogongrass coverage, dead plant coverage, live to dead biomass ratio, and canopy equivalent water thickness (EWT). In this experiment, 40 3 x 3 m plots have one of four treatments: (1) rainfall exclosure
Cogongrass coverage varied significantly between the wet and dry seasons. Vegetation canopy characteristics varied across the seasons and showed different pattern between cogongrass-invaded and uninvaded (native) subplots. Dead plant coverage was high in the native subplots and low in the invaded subplots in dry season, but showed opposite pattern in wet season. Whereas, canopy EWT was high in the invaded subplots and low in the native subplots in dry season, but showed opposite pattern in wet season. PLSR models could not provide good predictions because of the interference under rain-out shelters, thus the data from drought treatment were excluded from the analyses. With data trained from both the wet and dry seasons, PLSR models were successful in predicting cogongrass coverage ($R^2_{adj} (P) = 0.69$), dead plant material coverage ($R^2_{adj} (P) = 0.57$), and canopy EWT ($R^2_{adj} (P) = 0.33$). Models trained with data from one season were generally not able to predict vegetation characteristics in another season. The results demonstrate that cogongrass coverage and its impact on vegetation characteristics varies seasonally, therefore tracking the seasonality of its canopy traits requires statistical models calibrated with data sampled over the whole year. The results of this research provide the potential to scale up the measurements to detecting cogongrass and its effects on a landscape scale by relating to remote imaging spectrometers.
CHAPTER 1
BIOLOGICAL CHARACTERISTICS OF COGONGRASS AND MECHANISMS OF ITS SUCCESS INVASIONS IN LONGLEAF PINE ECOSYSTEMS

Biology and Ecology of Cogongrass

Cogongrass is a C4 plant species most weedy in full sun, warm, moist to wet areas due to its high light saturation point and low rates of temperature dependent photorespiration (Holm et al., 1977).

Cogongrass has creeping and tough underground rhizomes which comprises more than 60% total plant biomass, providing a solid foundation to its rapid regrowth after cutting or burning (Sajise, 1973). Cogongrass rhizomes have prominent nodes and shortened internodes that are able to penetrate other plants’ roots while growing (Tominaga, 2003). There are protective sheath covering rhizomes and leaving brownish colored cataphylls (English, 1998). The sclerenchymous fibers in rhizomes facilitate them on water consistence, breakage resistance, and heat damage reduction (Holm et al., 1977), which contributes a lot to cogongrass’s adaptation to poor soils and drought (Brook, 1989). The production of rhizomes was estimated to reach over 40 tons’ fresh weight (Lee, 1978) and 2 million shoots (Soerjani, 1970) per hectare. Thus, cogongrass has fast regeneration rate after foliar loss taking benefit of these dense mat underground rhizomes (Eussen, 1979).

Cogongrass rhizome regeneration happens between 3rd and 4th leaf stages that is plagiotropic, or vertical at early growth stage and then becoming horizontal when it develops scale cataphylls (Sajise, 1973). Rhizomes form from subapical buds following the regeneration of shoot arises from the apical bud. Most buds can be found at the distal end of the rhizomes (Sajise, 1973).

Apical dominance was observed in cogongrass rhizomes, which is that shoot tip would sprout before other shoots along the rhizome because of the hormones (auxins) that keep the
subtending shoots sprouting secreted by shoot tips (Gaffney, 1996). Moreover, there is auxin-regulated apical dominance supported by axillary buds along cogongrass rhizomes with exogenous applications of synthetic auxins (English, 1998).

Given a stemless appearance, cogongrass leaves grow directly from rhizomes, having glabrous-to-pubescent sheaths and membranous ligules at the bottom (Ayeni, 1985) and flat and linear-lanceolate as the middle and top part where possesses serrated margins and an off-center prominent white mid-rib (Terry, 1996). Leaf height varies with habitats from short to 1.5 m under good fertility conditions (Holm et al., 1977).

Cogongrass has relative long cone inflorescence which can hold more than four hundred individual spikelets (Bryson & Carter, 1993). There are compacted and dense seed with fluffy and white plumes produced from inflorescence, which has cylindrical and spike-like shape, averaging 10 to 20 cm long (Wilcut et al., 1988). Flowering time generally occurs in the early spring in southeastern U.S. but varies in other region and environment (Shilling et al., 1997). Cogongrass spreads by both rhizomes and seed. As a prolific seed producer, a single cogongrass can output around 3000 seeds which have ability to spread over 15 miles in open area with their silky white hairs (Sajise, 1973). And most seeds have ability to remain their activity for at least three months if they were under cold and dry conditions (Dickens & Moore, 1974). However, some researches claimed that viable seed production only happened in geographically isolated and heterogenous populations (McDonald, et al., 1996). Therefore, seed would explain cogongrass first establishment into new sites over large geographic areas and rhizome spread is the major mechanism of invasion expansion nearby the introduction location (Wilcut et al., 1988).
Cogongrass seed germination requires light and 11 to 43 °C as optimal environmental condition (Dickens & Moore, 1974). Seedlings establishment tend to occur in groups and is favored in areas of limited competition, such as disturbed sites, and it was found to be unlikely to emerge in areas with more than 75% sod cover (Dozier et al., 1998).

Cogongrass can be distinguished from the other species of Imperata from external physical characteristics. For example, cogongrass has two flower anthers, while other species have only one anther, such as Brazilian satintail (Imperata brasiliensis) (Gabel, 1982).

There is an interesting genetic aspect of cogongrass that it has a non-aggressive, ornamental form under the names of Rubra, Red Baron and Japanese Blood and this sale form can be converted to the green, invasive form from under certain environmental conditions (Greenlee, 1992). Besides, another concern is the possibility of hybridization between ornamental ecotypes and weedy biotypes and the combination grass might be able to survive far north and cold areas, which would extend the host range of this invasive species dramatically (Hall, 1998).

**Invasion Mechanisms of Cogongrass**

As a detrimental invasive species in the Southeastern US, there are abundance of researches on explaining the cogongrass invasion mechanisms from its biological characteristics. First, the density of the belowground rhizome network makes cogongrass a physical barrier to growth of roots of native species. Cogongrass rhizome tips are sharp that they may even penetrate the roots of native species, leading to damage or mortality by infection (Eussen & Soerjani, 1975).

Second, cogongrass is extremely competitive with native and desirable nonnative species for light, water, nutrients, and space (Eussen, 1979). Specifically, its leaf blades have been observed to reach heights of 1.5 m under good moisture and fertility conditions, which suggests
that cogongrass may compete for light on the forest floor, especially with understory species and young tree seedlings (Holm et al., 1977). Also, the dense carpet of leaf blades may prevent sunlight from reaching the upper soil layer, eliminating the opportunity for seedling germination of other species. The rhizomes can extract available soil moisture from shallow soil layers making it difficult for other grass species to establish, particularly desirable perennial grasses (Dozier et al., 1998). For example, the soil water content in the soil layer of 8 to 16 inch is reduced as much as half by cogongrass compared to where grows Sandhill vegetation in Florida. This is associated with a two to threefold increase in the rhizome-root biomass of cogongrass (Lippincott, 1997). As for nutrients, cogongrass was shown to decrease soil nitrate and potassium levels in invaded compared with noninvaded pine flatwoods (Collins & Jose, 2008) and to be more competitive for phosphorus than native pine savanna species in the southern United States (Brewer & Cralle, 2003), corresponding to that phosphorus levels in the soil dropped with the presence of cogongrass. Brewer & Cralle (2003) also demonstrated that the extent of cogongrass invasion was negatively correlated to the number of legumes present, which would lead to the assumption that species that are capable of obtaining nitrogen from other sources (fixation) are better able to compete with the invasive grass. Then in the research of Daneshgar and Jose (2009), cogongrass is shown to be efficient at gathering nitrogen and thus may be hindering competing species from taking up available nitrogen in the soil.

Third, cogongrass may have ability to inhibit germination and the early development of other plant species by releasing allelopathic substance(s) (Eussen & Wirjahardja, 1973). Cogongrass can suppress the germinations of tomatoes (Solanum lycopersicum L.) and cucumbers (Cucumis sativus L.), especially at low pH condition, by increasing their growth inhibiting substances o-coumaric acid and gentisic acid. Jose and Bryson (2004) demonstrated
that extracts of these acids from cogongrass’s roots and foliage with concentrations 0.5% normally can raise to 62% when it competed with *Cynodon dactylon* (L.) and *Lolium multiflorum* (Lam.).

Fourth, cogongrass is especially harmful due to its impacts on, and interaction with, fire in longleaf pine ecosystems. Longleaf pine ecosystems have historically burned every 2-5 years, which is critical for regenerating and maintaining longleaf pine in the canopy, and for creating a highly diverse understory. Cogongrass alters fire behavior by stimulating a higher frequency and intensity of burns than historically experienced in longleaf pine ecosystems (Lippincott, 2000) mainly because biomass accumulation of cogongrass can be higher than that of native ground vegetation. Fires fueled by cogongrass may be hotter with temperatures reaching 450 °C at heights ranging from 0 to 5 feet due to its higher density and biomass (Lippincott, 2000). Cogongrass tends to grow in dense and continuous stands, as opposed to more sparsely and patchily distributed native grasses. This leads to more uniform burns instead of the patchy fire patterns observed in undisturbed sites (Lippincott, 2000). Fire-prone species like cogongrass tend to accumulate dead plant material, altering understory composition and fuel cover (Brooks et al., 2004). Thus, not only understory vegetation and tree seedlings, but also juvenile trees in plantations and natural areas would be killed (Jose et al., 2002).

Substantial fire-induced mortality of longleaf pine seedlings was observed in a Florida Sandhill ecosystem invaded by cogongrass compared to Sandhill with native ground vegetation (Lippincott, 2000). Fire could eliminate dense cogongrass thatch, which promotes very intense and hot fires that destroy most aboveground vegetation. But the regeneration of new cogongrass can occur from rhizome fragments weighing as little as 0.1 g (Ayeni & Duke, 1985). Therefore, the insulated subterranean rhizomes from fire and high root to shoot ratio promote cogongrass
survival and propagule establishment (Sajise, 1973). The hotter cogongrass-fueled fires can kill low herbs, shrubs, and even normally fire-tolerant longleaf pine saplings (Lippincott, 2000). Following fires, cogongrass quickly invades burned areas and creates cogongrass monocultures, which creates a positive feedback loop between cogongrass invasion and intense fire (King & Grace, 2000). Consequently, change in fire behavior induced by cogongrass may ultimately lead to disappearance of native herbaceous and woody plants and totally shift species composition to undesirable trees in natural stands or reduce productivity in plantations.

The seasonal dynamics of invasive grasses can alter intra-annual patterns of ecosystem properties and processes. For example, in western U.S. sagebrush plant communities, invasive cheatgrass (*Bromus tectorum* L.) can extend the fire season by a month or more (Davies & Nafus, 2013). Cogongrass may periodically die back (Ramsey, et al., 2003), creating a large amount of dead material that acts as fuel. The timing of the accumulation of dead cogongrass might alter current fire regimes. Historically, fires in longleaf pine systems occurred predominately during the growing season in areas near the Gulf of Mexico (Slash, 2004) and in the dormant season elsewhere (Bale, 2009). On the other hand, prescribed burning in longleaf pine predominantly occurs in the dormant season (Knapp, 2010). Fire timing impacts ecosystem properties, such as understory flowering and pine seedling germination (Shepherd et al., 2012), thus affecting species composition. Furthermore, cogongrass may alter the seasonal pattern of vegetation water content and phytomass structural characteristics (Baeza et al., 2006), such as the ratio of live to dead plant biomass.

Cogongrass, with its extensive and deep rooting system, is believed to be resistant to drought (Terry et al., 1996) which may allow it to become a more aggressive invader under drought conditions. Below normal precipitation and increased temperature in the southeastern
U.S. may facilitate the alternation of plant species and make longleaf pine systems more vulnerable to cogongrass invasion (Krasensky & Jonak, 2013).
CHAPTER 2
SPECTRAL DETECTION OF AN INVASIVE GRASS SPECIES (COGONGRASS) AND ITS EFFECT ON HERBACEOUS VEGETATION CHARACTERISTICS IN AN EXPERIMENTAL SETTING

Introduction

Cogongrass (*Imperata cylindrica*) is a rhizomatous, perennial grass native to tropical and subtropical areas of Asia (Bryson & Carter, 1993). Cogongrass was initially planted in the southeastern United States for forage and soil stabilization (Dozier et al., 1998) but has spread rapidly to roadsides, agricultural fields (Bryson & Carter, 1993) and native longleaf pine ecosystems (Lippincott, 1997) where it has many negative impacts. The impacts of cogongrass on longleaf pine ecosystems are particularly problematic as these ecosystems are both highly diverse and threatened. Longleaf pine ecosystems, which contain the highest understory plant richness outside the tropics (Peet & Allard, 1993), used to occupy as much as 60 million acres in the southeastern U.S. but now cover only 3.8 million acres (Outcalt & Sheffield, 1996). Threats to remnant and restored longleaf pine ecosystems include urban encroachment, both fire suppression and high-intensity fires, and invasion by non-native species such as cogongrass (Varner & Kush, 2004). Cogongrass threatens these forest ecosystems by reducing native herbaceous species diversity (Brewer, 2008), survival of pine seedlings, and productivity of pine forests (Daneshgar et al., 2008). The dense mats of vegetation created by cogongrass also decreases habitat for birds and ground-dwelling animals (Barnes et al., 2013).

Cogongrass and Fire

Cogongrass is especially harmful due to its impacts on, and interaction with, fire in longleaf pine ecosystems. Longleaf pine ecosystems have historically burned every 1-3 years, which is critical for regenerating and maintaining longleaf pine in the canopy, and for creating a highly diverse understory (Frost, 2000). Cogongrass grass alters fire behavior by stimulating a
higher frequency and intensity of burns than historically experienced in longleaf pine ecosystems (Lippincott, 2000). Cogongrass tends to grow in dense and continuous stands, as opposed to more sparsely and patchily distributed native grasses. This leads to more uniform burns instead of the patchy fire patterns observed in undisturbed sites (Lippincott, 2000). Fire-prone species like cogongrass tend to accumulate dead plant material, altering understory composition and fuel cover (Brooks et al., 2004). The hotter cogongrass-fueled fires can kill low herbs, shrubs, and even normally fire-tolerant longleaf pine saplings (Lippincott, 2000). Following fires, cogongrass quickly invades burned areas and creates cogongrass monocultures, which creates a positive feedback loop between cogongrass invasion and intense fire (King & Grace, 2000).

The seasonal dynamics of invasive grasses can alter intra-annual patterns of ecosystem properties and processes. For example, in western U.S. sagebrush plant communities, invasive cheatgrass (Bromus tectorum L.) can extend the fire season by a month or more (Davies & Nafus, 2013). Cogongrass may periodically die back (Ramsey et al., 2003), creating a large amount of dead material that acts as fuel. The seasonality of cogongrass properties, such as the accumulation of dead materials, and its impact on seasonality of fuel loads, have not been studied. The timing of the accumulation of dead cogongrass might alter current fire regimes. Historically, fires in longleaf pine systems occurred predominately during the growing season in areas near the Gulf of Mexico (Slash, 2004) and in the dormant season elsewhere (Bale, 2009). On the other hand, prescribed burning in longleaf pine predominantly occurs in the dormant season (Knapp, 2010). Fire timing impacts ecosystem properties, such as understory flowering and pine seedling germination (Shepherd et al., 2012), thus affecting species composition (Knapp, 2010). Furthermore, cogongrass may alter the seasonal pattern of vegetation water content and phytomass structural characteristics (Baeza et al., 2006), such as the ratio of live to
dead plant biomass, which are essential parameters that influence the biomass burning processes and are included in most fire risk models worldwide (Chuvieco et al., 2004).

The spread of cogongrass and its impact on ecosystem structure and function may be altered by drought, which periodically occurs in the southeastern United States (Seager et al., 2009). Cogongrass may be resistant to drought because of its allocation to extensive belowground structures (Dozier et al., 1998). In its native range in southeast Asia, the spread of cogongrass has been documented to accelerate during El Niño-induced droughts (Woods, 1989). At the same time, drought can increase the probability and intensity of dry-season (dormant season) fires in southern pine forests (Littell et al., 2016). Thus, drought-fire cycles may lead to greater dominance by cogongrass (Mitchell et al., 2014). However, there is little known about the seasonality of cogongrass growth and response to drought in the southern US. We are interested in whether predicted occurred extreme drying can exacerbate the impacts of cogongrass on longleaf pine ecosystem structure, function and diversity.

**Remote Sensing of Cogongrass**

Remote sensing can allow for frequent temporal measurements of both invasive species coverage (Asner et al., 2008), and the impact of invasive species on ecosystem characteristics, such as those that lead to greater fire risk (Tamhankar et al., 2002). Hyperspectral data are particularly well-suited to the simultaneous detection of multiple vegetation characteristics, such as invasive species coverage and its impacts on water content, because of the large number of wavelength bands that are measured. Several studies having developed algorithms to detect cogongrass from other grasses in pastures using hyperspectral data (Mathur et al., 2002; Huang et al., 2001). However, there has been no attempts to quantify cogongrass in longleaf pine savannas, which have a unique set of highly diverse species compared to savannas. In this study, we use hyperspectral data to quantify both cogongrass cover and its impact both non-
photosynthetic vegetation (Asner & Heidebrecht, 2002) and vegetation water content (Cheng et al., 2006), particularly in the context of fire fuel assessment (Varga & Asner, 2008).

In most cases, remote sensing of invasive species and their vegetation impacts are measured in natural field settings or in laboratory settings. Rarely are these measurements made in controlled field experiments where various factors, such as invasive plant cover or rainfall are controlled. In this study, we measured the predictive ability of remote sensing metrics to measure key vegetation characteristics - invasive grass cover, dead plant cover, ratio of live to dead plant material, and canopy water content - in an experiment that manipulated both cogongrass coverage and rainfall in a longleaf pine grass community (Alba et al., 2017). Our objectives are to: (1) quantify how well hyperspectral measurements can detect variation in cogongrass coverage, dead plant material and water content in an experimentally controlled field setting: and (2) determine how well an algorithm trained in one season can predict ecosystem characteristics in another time period. In examining individual leaves from forest trees, Yang, et al., (Seasonal variability of multiple leaf traits captured by leaf spectroscopy at two temperate deciduous forests, 2016) found that Partial Least Square Regression (PLSR algorithm) trained in one season performed poorly in predicting leaf traits in another season and that an algorithm calibrated by data from multiple seasons performed best in predicting leaf traits. Here we test how a PLSR algorithm used to predict whole vegetation community characteristics performs across seasons, and test the need for calibration data in multiple seasons.

Methods

Study Site

The study area is a common garden experiment at the Bivens Arm site (Latitude is 29° 37’ 42.4” N and Longitude is 82° 21’ 14.4” W) at the University of Florida in Gainesville, Florida, USA. Gainesville has a humid subtropical climate, with a summer wet season and a dry
season from early fall through late spring. The wet season has high humidity and frequent rainfall, with an average daily high temperature above 29.4 °C and 15.2 cm precipitation per. During dry season from late fall through spring, temperatures are cooler with average minimum and maximum monthly precipitation range between 4.6 cm and 9.1 cm. The soils are Portsmouth sandy loam (67% sand, 3% silt, and 30% clay) consist of Blichton sand (25%; 2% – 5% slope) and Bivans sand (75%; 5% – 8% slope; Natural Resources Conservation Service, Web Soil Survey) (Alba et al., 2017).

Forty experimental plots, each 3 m x 3 m, were established in an abandoned field in early spring 2012. Twenty longleaf pine seedlings and 36 native herbaceous seedlings were planted in each plot. A factorial combination of drought treatment and cogongrass invasion was applied in spring 2013. Drought conditions were simulated in half of the plots. The drought plots were covered at 2 m height with 60% spatial coverage of plastic roofing that had 92% light penetration. The plastic roofing diverts rainfall from these plots into the vegetation matrix surrounding the plots. The drought plots were also trenched to 1 m depth in 2013 to prevent lateral movement of soil water into the drought plots. Netting that provides an approximate equal amount of shading as the plastic roofs but does not divert rainfall was installed also at 2 m height in the non-drought control plots. In each plot designated for the invasion treatment, 16 rhizome fragments and 9 seedlings of cogongrass were planted. Further details of the experiment can be found in Alba et al. (Alba et al., 2017).

Each 3 x 3 m plot was divided into 16 subplots (75 cm × 75 cm) as the sampling unit for canopy reflectance and field measurements. Spectral measurements were conducted in the June 2015, February 2016, and June 2016 (Table 1). Between 25 and 106 number of subplots where measured at each time period, which covered all four experiments treatments
(cogongrass/drought; no cogongrass/drought; cogongrass/control; no cogongrass/control) (Table 1). All non-vegetation materials in the plot (such as flags marking measurement locations for other studies) were removed before spectral measurement. The same subplots were not always re-measured in each time period. Some subplots could not be measured because the vegetation was too tall, or because there was non-removable equipment in the subplot that would influence the subplot reflectance.

**Canopy Reflectance Measurements**

Canopy reflectance was measured with a PANalytical Analytical Spectral Devices (ASD) Inc. (Boulder, CO, USA) FieldSpec® 4. The spectroradiometer has a spectral range between 350 – 2500 nm sampling resolution of 1 nm. Handheld measurements were conducted on sunny days within 2 hours of solar noon to minimize solar zenith angle changes. Before measuring each subplot, the spectrometer was optimized and calibrated using a Spectralon® white reference panel to reduce spectral variation resulting from different roof materials over the drought and non-drought plots, and to correct for varying sun angle and intensity. The ASD fiber optic, which has a 25° field of view, was placed 1.7 m above the ground providing a 0.75 m diameter footprint on the ground. For each subplot, the average of 15 measurements over 15 seconds was used.

**Measurements of Vegetation Characteristics**

The aerial coverages of the following vegetation types were visually estimated in each subplot: live (green) cogongrass; senesced (brown) cogongrass, live non-cogongrass and senesced non-cogongrass. For the June 2015 measurements only, coverage for each non-cogongrass species was also visually estimated. For all sampling periods but the first (June 2015), all of the aboveground biomass in one randomly located 18 cm × 18 cm column was harvested within each subplot on the same day as the reflectance measurement for that subplot.
Each sample was sorted into four categories: green cogongrass, green non-cogongrass, brown cogongrass and brown non-cogongrass. All fractions were weighed separately and dried in the oven for at least 72 hours at 70 ℃. After drying, samples were weighed again to obtain dry weights. EWT, defined as the weight of water in the vegetation column per unit area, was calculated as (Danson et al., 1992):

$$EWT = \frac{FW - DW}{A} (g/cm^2)$$

where FW and DW stands for the plant fresh weight and dry weight, respectively, and A is the area sampled.

**Data Analysis**

Partial least squares regression (PLSR) was used to develop predictive relationships between subplot reflectance and vegetation characteristics (percent cogongrass cover, percent dead plant cover, live to dead material ratio, and canopy EWT). PLSR is a generalization of multiple linear regression, which is able to reduce collinear variables to a small set of noncorrelated variables (factors) and then perform least squares regression on these factors (Wold, et al., 2001). Thus, PLSR is useful for spectroscopy because it can consider all available hyperspectral wavelengths and handle these numerous highly collinear spectra data. In this analysis, we used untransformed wavelength band data as it performed better than the transformed bands (logarithmic and first derivative). The wavelength bands in the following wavelength regions were removed due to high amount of noise: 1100 nm – 1160 nm, 1340 nm – 1500 nm, 1750 nm – 2050 nm, and 2250 nm – 2500 nm.

First, we tested whether the plastic rain-out roofs for the drought treatment impact the reflectance even after use of the spectralon reference for each measurement. Because we found strong differences in the reflectance spectra between the drought treatments (with the plastic roofs) and non-drought treatments, we analyzed the two data sets separately (Supplement).
Second, we compared the ability of PLSR models trained using subsets of the data from different seasons to predict vegetation characteristics across the whole data set. We used PLSR trained on a single season’s data to predict variables from the other dates from the same season. Then we used PLSR trained on one season’s data to predict vegetation characteristics for the other season. Finally, the target variables and spectra from all time periods were combined as one dataset. The whole dataset was divided into two parts (two thirds-one third), for training and testing, respectively. The Kennard-Stone algorithm was used to select the training subset for providing uniform coverage over the reflectance variables (Kennard & Stone, 1969).

Lastly, we performed a power analysis for cogongrass coverage and dead plant coverage using PLSR to test how many training samples (subplots) are sufficient for prediction for these vegetation characteristics. We randomly selected 50 subplots (from all three dates) as a testing set to gauge performance of PLSR trained on a variable number of training points. Then 10, 20, 30, …, 140 training samples (separate from the 50 test samples) were randomly chosen to predict the testing set. The performance of the different sized training set was measured by $R^2$ of training models, and $R_{adj}^2$ and $R^2$ of independent testing models. $R^2$ is a statistical measure indicating the goodness of fit of a model. However, $R^2$ always increases with more predictors that cannot determine whether the coefficient and its predictions are prejudiced. $R_{adj}^2$ compensates for the addition of predictors to a model (Miles, 2014).

To build a solid model, there are some factors need to desirable: a small number of latent variables, a small error in calibration and validation, and a high coefficient of determination ($R^2$) and adjusted coefficient of determination ($R_{adj}^2$) (Wold et al., 2001). The optimal number of PLSR latent variables was selected by minimizing the predictive residual error sum of squares
(PRESS) and maximizing adjusted prediction $R^2_{adj}$ using the leave-one-out validation method to avoid over-fitting.

The performance of the model was measured by the coefficient of determination ($R^2$), the adjusted coefficient of determination ($R^2_{adj}$), the root mean square error (RMSE), and the relative error (RE) for calibration (C), cross validation using one out of bag (CV), and independent validation (P). They were calculated as shown in equations:

$$R^2 = 1 - \frac{\sum_i(y_i - \hat{y}_i)^2}{\sum_i(y_i - \bar{y})^2}$$

$$R^2_{adj} = 1 - (1 - \frac{\sum_i(y_i - \hat{y}_i)^2}{\sum_i(y_i - \bar{y})^2}) \frac{n - 1}{n - p - 1}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

$$\text{RE} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}}{\bar{y}} \times 100\%$$

where $y_i$ and $\hat{y}_i$ are measured, and predicted values respectively, $\bar{y}$ is the average measured value, p is the total number of explanatory variables in the model, and n is the number of samples. All analyses and calculations were carried out using R studio (packages: “pls” and “prospectr”).

Results

Although a white reference was used in all subplots to calibrate the spectral measurements to reflectance, the spectra taken under the rain-out shelter were visibly different than the spectra taken from the control plots and included a strong spectral signature of the plastic used in the rain-out shelters (Figure 2-1). Therefore, the drought (with rain-outs shelters) and non-drought plots were analyzed separately with the non-drought results presented in the results of this section and the drought results in the Table 2-2.
Vegetation characteristics varied seasonally and among treatments. In the subplots invaded by cogongrass, the range of cogongrass coverage was 2 to 100%. In the invaded subplots, cogongrass coverage was higher in February 2016, December 2016 and March 2017 (the dry, cool season) than in June 2015 and 2016 (the wet, warm season) (Figure 2-2). For the native subplots, cogongrass coverage was always zero as any cogongrass that was found in the native subplots was removed. The invaded and native subplots showed contrasting patterns of dead plant coverage. In dry season, dead plant material coverage was high in the native subplots, but low in the cogongrass-invaded subplots (Figure 2-2). The opposite occurred in the June 2015 wet season, when dead plant material coverage was lower in the native subplots than in the invaded subplots (Figure 2-2). In June 2016, dead plant coverage was similar between invaded and native subplots (Figure 2-2), but the cogongrass-invaded plots had much higher live to dead plant material ratio (Figure 2-2). In February 2016 (dry season), canopy equivalent water thickness (EWT) was lower in the native subplots than in the invaded subplots (Figure 2-2). In the June 2015, wet season, the reverse was true. Canopy EWT was higher in the native plots than in the invaded subplots. In the December 2016, dry season, canopy EWT was similar for native and invaded subplots (Figure 2-2).

Cogongrass coverage had strong effects on other vegetation characteristics (Figure 2-3). With all subplots considered together, higher cogongrass coverage was associated with lower dead plant coverage ($r = -0.41$), higher live to dead ratio ($r = 0.34$), and higher canopy EWT ($r = 0.49$). These relationships are stronger if only the invaded subplots are considered, removing the native subplots that had no cogongrass coverage. With just the invaded subplots, the correlations between cogongrass coverage and other vegetation characteristics were $r = -0.94$ (dead plant coverage), $r = 0.40$ (live to dead ratio), and $r = 0.49$ (canopy EWT). Amongst the other
vegetation characteristics, canopy EWT and dead plant coverage had the strongest relationship ($r = -0.50$) that canopy EWT decreasing with dead plant coverage increasing.

Different levels of cogongrass coverage, dead plant coverage and canopy equivalent water thickness (EWT) affected the shape of the spectral curve and the magnitude of reflectance in different wavelength ranges (Figure 2-4, Figure 2-5). High cogongrass cover showed some features typical of increasing layering of vegetation (Roberts et al., 1990), such as high increased NIR and green reflectance (Figure 2-4). However, high cogongrass did not show greater absorption in the red region (Figure 2-5). High coverage of dead material showed a pattern typical for non-photosynthetic vegetation (NPV) including low red absorption, low NIR reflectance and high SWIR reflectance (Li & Guo, 2016) (Figure 2-4, Figure 2-5). Subplots with low canopy EWT showed similar patterns in reflectance as the subplots with high coverage of dead material (Figure 2-4, Figure 2-5). The power analysis showed that as the number of training subplots in the model increased, the model prediction power increased at a little expense to calibration accuracy. For cogongrass cover, prediction accuracy started to plateau at 50 samples (Figure 2-6). For dead plant cover, prediction accuracy plateaued at 30 samples (Figure 2-6). Therefore, in subsequent analysis we chose training samples that included at least 50 subplots.

The PLSR trained with hyperspectral data collected in wet season (June 2015) cannot predict data collected in the other wet period (June 2016) (Table 2-3, $R^2_{adj} < 0$). However, the algorithm trained with data collected in February 2016 and December 2016 dry seasons is able to predict cogongrass coverage ($R^2_{adj}(P) = 0.41$) and dead plant coverage ($R^2_{adj}(P) = 0.39$) also collected in the March 2017 dry season (Table 2-4). The PLSR trained to predict cogongrass and dead plant coverage from hyperspectral data on one season data (wet or dry) cannot predict cogongrass coverage and dead plant coverage for the other season data (dry or wet) (Table 2-3,
Table 2-4). The one exception to this is that the dead plant coverage trained with data from the dry season can predict dead plant coverage in the wet season ($R_{adj}^2(P) = 0.61$). The best prediction with highest $R^2$ and lowest RMSE was achieved when PLSR is trained on a subset of data from all five periods ($R_{adj}^2(P) = 0.69$ and 0.57 for cogongrass coverage and dead plant coverage, respectively).

Based on the information above, the PLSR algorithm was trained with two-thirds of the dataset from all time periods combined to predict the remaining one-third of data for all vegetation characteristics. PLSR models using hyperspectral data produced good estimation for cogongrass coverage (Figure 2-7, $R^2(P) > 0.70$) and dead plant coverage (Figure 2-7, $R^2(P) = 0.58$), but a poorer ability to predict live to dead plant tissue ratio (Figure 2-7, $R^2(P) = 0.08$) and canopy EWT (Figure 2-7, $R^2(P) = 0.38$) (Table 2-5). Considering the significant influence of sampling period, we added sampling date as an explanatory variable to predict the vegetation characteristics (Figure 2-8, Table 2-6). The addition of sampling date as an explanatory variable improved the $R^2$ significantly for live to dead ratio (0.20 $R^2$ increase), slightly for cogongrass coverage (0.05 $R^2$ increase) and dead plant coverage (0.05 $R^2$ increase), but not at all for canopy EWT (0.05 $R^2$ decrease).

The importance of spectral region to PLSR calibration models is revealed by the PLS regression coefficients, which represent the contribution of each predictor in determining model performance. The red edge (690 – 730 nm) and near infrared (NIR) regions (1000 – 1050; 1160 – 1200; 1500 – 1550 nm) were represented highly related with cogongrass coverage estimation in PLSR model (Figure 2-9). For dead plant coverage, green (≈ 520 – 590 nm), red (650 – 700 nm), NIR regions (900 – 950; 1500 – 1550 nm) and SWIR region (2050 – 2250 nm) were important in the PLSR models (Figure 2-9) For live to dead ratio, red edge (690 – 730 nm), NIR (1160 –
1340 nm) and SWIR (1600 – 1700; 2050 – 2250 nm) contributed significantly. For canopy EWT, green to red regions (500 – 730 nm), the NIR around 950 and 1100 nm and the SWIR region from 1650 – 1750 nm were particularly important (Figure 2-9). Regression coefficients of both live to dead ratio and canopy EWT showed value peak at 1240 nm, which is consistent with NDWI index ((ρ860 – ρ1240) / (ρ860 + ρ1240)). For both dead plant coverage and canopy EWT, important red region (620 – 730 nm) was present for bands related to NDVI index ((ρ816 – ρ681) / (ρ816 + ρ681)). Wavelength regions that had strong weighting for all four vegetation characteristics were centered around 700, 950, 1500, and 2050nm.
CHAPTER 3
DISCUSSION AND CONCLUSION

Seasonal Changes in Vegetation Properties Caused by Cogongrass Invasion

Cogongrass changed the dynamics of the vegetation composition and characteristics seasonally. In the dry season, the cogongrass-invaded subplots had less dead plant material cover and higher canopy water content than subplots with only native plants, which tended to die off in the dry season. Conversely, in the wet season, native subplots tended to be green, whereas cogongrass-invaded plots had greater dead plant material cover and lower canopy water content. Not only do these seasonal changes in vegetation characteristics have potential impacts on ecosystem status and functioning, but they impact the ability of hyperspectral data to predict cogongrass coverage and vegetation characteristics.

Wildfires are ignited by lightning in many longleaf pine ecosystems in the wet summer period. These fires tend to be high-frequency, low-severity surface fire regimes due to humid condition and limited coverage of dead vegetation (Outcalt, 2008). However, if cogongrass invaded areas tend to have more dead plant coverage and lower canopy water content during summer, it might lead to higher intensity ground fires or even crown fires that could cause elevated mortality of longleaf pine saplings and trees. For dry season prescribed fires, cogongrass coverage may alter the spread of the fires by elevating water content and decreasing dead plant coverage that serves as fire fuels.

Hyperspectral Prediction of Cogongrass Coverage

Hyperspectral data could simultaneously predict cogongrass coverage, dead plant material and canopy water content in an experimental setting. In this way, hyperspectral data can be used as a tool to non-destructively sample herbaceous plant communities. To accurately
predict these properties through time, it is important to having training data from different seasons.

We found that using PLSR models trained from data measured in one season (either wet or dry) could not explain the variability in cogongrass and dead plant coverage from the other season. Similar results were obtained from Yang, et al. (2016) examining leaf traits of several deciduous tree species from northeastern US forests. They found that PLSR models developed from leaf spectral data from one season (winter/summer) could not predict leaf traits in another season (spring/fall). The inability of predict leaf traits between season was likely due to the seasonal changes in leaf traits (Fajardo & Siefert, 2016). Seasonal changes in the leaf traits of cogongrass and the native species most likely contributed to the inability to predict cogongrass coverage using training data from the other season. However, the fact that a classifier could be developed when trained with data from both the dry and wet season suggests there are characteristics of cogongrass that are stable between seasons that are distinct from the native species and can be detected spectrally. For example, cogongrass is high in silica content (Dozier et al., 1998) compared to other species. Furthermore, cogongrass leaf blades are long, tough and oriented vertically unlike the co-occurring native plant species.

When trained with data from both the wet and dry seasons, percent cogongrass coverage can be estimated well using hyperspectral data and PLSR models. Previously, cogongrass was discriminated successfully from other grass species via hyperspectral data (Mathur et al., 2002). However, the spectral data used by Mathur et al. (2002) was from pure, single species plots. In this study, we showed that the percent cover of cogongrass, over a wide range of coverages and mixed with other herbaceous species, could be estimated from hyperspectral data. For applications of this method to real landscapes, cogongrass is most likely to occur both in dense
monocultures and mixed with other species, especially where cogongrass is invading new areas. Also, at the scale of airborne and especially satellite images, even pure cogongrass stands will likely be mixed with other vegetation in a single pixel (Ichoku & Karnieli, 1996) making the detection of cogongrass mixed with other species important.

Other methods, such as spectral unmixing (Miao et al., 2006) and vegetation indices (Narumalani et al., 2009), could be used to quantify cogongrass coverage. However, PLSR has some advantages over these other methods for quantifying invasive species coverage. Miao et al. (2006) used spectral unmixing to quantify the coverage the invasive yellow starthistle in California's Central Valley grasslands, which required identifying the spectral signature of other dominant plants and the soil background to define all endmembers. Using PLSR, on the other hand, does not require spectral signatures of the other dominant plant or soil coverages, and thus is more targeted and efficient.

**Hyperspectral Prediction of Dead Plant Coverage**

As expected, hyperspectral data could quantify the coverage of dead plant material well. Reflectance differences between dead plant material and green vegetation can be found in the shape of the green and red bands and the magnitude of reflectance in near-infrared and shortwave-infrared bands (Figure 2-7), which is consistent with the findings distinguishing green vegetation from non-photosynthetic vegetation (NPV) in AVIRIS data (Roberts et al., 1993). Numerous other studies have indicated hyperspectral data can quantify dead vegetation (Vargas & Asner, 2008; Guerschman et al., 2009) and fire fuel load of (Mutlu et al., 2008) which NPV is an important component (Chuvieco et al., 2004). However, NPV can be hard to quantify if landscapes have exposed soil because NPV and soil are spectrally similar (Okin, 2007). In the wet season, all our plots had very little soil exposed. In the dry season, especially in native species plots where most vegetation had died, significant amounts of soil were exposed, which
may explain why dead plant material could not be predicted in dry season when the PLSR model was trained in the wet season.

**Hyperspectral Detection of Canopy Water Content**

Using hyperspectral data and sampling date, PLSR models could predict canopy EWT, but with higher uncertainties compared to predictions of cogongrass and dead plant material coverage. Other studies have predicted canopy water content from AVIRIS (Serrano et al., 2000), MODIS (Cheng et al., 2008) and SPOT (Ceccato et al., 2002) sensors with greater accuracy than our study. There are several reasons that may explain why our study had lower than expected predictive ability for canopy EWT. First, the methods and spatial scale at which canopy EWT is measured in the field varies greatly among studies. We directly measured canopy water content in a small column of vegetation within the measurement footprint. It is more common to estimate canopy EWT indirectly by measuring water content of a subsample of leaves then scaling up the leaf level water content to the canopy via estimates of leaf area index (Ceccato et al., 2002). It is possible that using these more indirect measurements of canopy EWT, the hyperspectral signature is responding to some of the quantities used in the field measurement scaling process, such as leaf area index, rather than canopy EWT itself.

It is also possible that the small size of the vegetation column for which we directly measured canopy EWT was not representative of the variability in canopy EWT found in the footprint of the hyperspectral sensor. In some subplots, especially the high diversity native species assemblages, vegetation in the 0.75 m diameter footprint of the sensor was very heterogenous, with patches of live and dead vegetation, plants with different heights, different levels of exposed soil in the dry season, and different densities of woody stems. This heterogeneity was difficult to characterize with a single 75 cm column. A stronger relationship between hyperspectral data and canopy EWT was found in Clevers et al. (2010) in an herbaceous
floodplain community, but only subplots that were relatively homogeneous were used in the analysis. Also, for the cogongrass plots, the upper part of the dense grass canopy tended to be green, while the lower layers tended to be dead. It is likely that the upper part of the grass canopy had a stronger influence on the spectral signature, whereas our canopy EWT scheme equally measured water content from the whole vertical profile of the grass canopy.

**Specific Spectral Region Related to Vegetation Properties**

Examining the PLSR regression coefficients weightings can help determine what spectral regions allow quantification of the vegetation characteristics. Regions of the near infrared and shortwave infrared were important for quantifying cogongrass coverage. Because of the structure of cogongrass forming densely packed partially vertical grass blades, increasing coverage of cogongrass leads to higher infrared reflectance that is characteristic of increasing levels of leaf area index (Price & Bausch, 1995). Similar to cogongrass coverage, the near infrared and shortwave infrared were important wavelength regions for quantifying dead plant material. In addition, the visible red region between 670 – 690 nm was important for quantifying dead plant coverage, which could be explained by chlorophyll content differences between live and dead plant.

**Use of Spectral Data in Experimental Settings – Opportunities and Challenges**

Manipulative field experiments are becoming more common in ecology to understand ecosystem level changes in response to climate changes such as increased temperature and drought (Alba et al., 2017; Runion et al., 2015; King & Grace, 2000). These experiments can provide excellent opportunities to investigate how vegetation change can be detected through remote sensing (Asner et al., 2004). We intended to use hyperspectral data to study vegetation characteristics in both drought treatments and control plots. However, this was not possible because plastic roofs were used to divert rainfall in the experiment, and light coming through the
plastic contaminated the spectral signature of the drought treatment measurements. Thus, in some cases, equipment needed to generate the field-based experimental settings can hinder spectral measurements. If possible, experiments should be designed in such a way to make spectral measurements of the whole vegetation canopy possible.

We found that including sampling date as an explanatory variable in the PLSR models improved the prediction accuracy for cogongrass coverage, dead plant coverage and live to dead ratio significantly. Sampling date as an explanatory variable can help account for variation in illumination angle and intensity that occurred between sampling dates. Potentially including explicit information on direct and diffuse radiation during sampling throughout the year could potentially provide better predictive models.

**How Could This Study be Used in Applications?**

With the PLSR models developed to predict cogongrass coverage and vegetation characteristics, we can now use spectral data collected from the field spectroradiometer to noninvasively and efficiently measure cogongrass coverage and vegetation characteristics in the experimental plots. In this way, we can monitor long-term seasonal changes in cogongrass coverage and the effects of cogongrass on native plant community diversity, plant water status, and look at responses of the experimental plots to perturbations such as prescribed fire, which are planned for the plots. However, separate PLRS models must be built separately for control and drought plots.

At a larger spatial scale than the experimental plots, remote sensing methods can be used to map and monitor invasive species at landscape levels (Olsson et al., 2011; Asner et al., 2008). This study supports that cogongrass coverage should be detectable from airborne or satellite hyperspectral sensors both where cogongrass is invading natural systems (this study) or pastures (Johnson & Bruce, 2005). The increasing availability of airborne hyperspectral data, for example
from campaigns associated with the National Ecological Observatory Network, new government and commercial satellite hyperspectral sensors, such as HyspIRI (Lee et al., 2015) and Hyperion (Pengra et al., 2007), and even hyperspectral sensors carried by unmanned aerial vehicles (Dvorak et al., 2015; Hill et al., 2017), provide important data sources for mapping this invasive species. This study suggests spectral regions, especially near infrared and shortwave regions, that may be important for landscape-scale mapping of cogongrass. This study supports that large-scale mapping of cogongrass coverage could be important for detecting important ecosystem consequences driven by cogongrass invasion, such as seasonal build-up of dead plant material, alteration of vegetation water content, and changes to fire fuel loads.
Table 2-1. The number of plant samples in each field campaign.

<table>
<thead>
<tr>
<th>Period Treatment</th>
<th>Cogon Cover Control</th>
<th>Cogon Cover Drought</th>
<th>Dead Plant Cover Control</th>
<th>Dead Plant Cover Drought</th>
<th>L/D Material Ratio Control</th>
<th>L/D Material Ratio Drought</th>
<th>Canopy EWT Control</th>
<th>Canopy EWT Drought</th>
</tr>
</thead>
<tbody>
<tr>
<td>June 2015</td>
<td>54</td>
<td>52</td>
<td>54</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Feb 2016</td>
<td>28</td>
<td>34</td>
<td>28</td>
<td>34</td>
<td>27</td>
<td>34</td>
<td>27</td>
<td>34</td>
</tr>
<tr>
<td>June 2016</td>
<td>10</td>
<td>15</td>
<td>10</td>
<td>15</td>
<td>10</td>
<td>15</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>Dec 2016</td>
<td>29</td>
<td>24</td>
<td>29</td>
<td>24</td>
<td>26</td>
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<td>26</td>
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<tr>
<td>Mar 2017</td>
<td>16</td>
<td>26</td>
<td>16</td>
<td>26</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>137</td>
<td>151</td>
<td>137</td>
<td>151</td>
<td>64</td>
<td>73</td>
<td>64</td>
<td>73</td>
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Table 2-2. Predictive ability of hyperspectral estimation of vegetation characteristics using data from drought plots.

<table>
<thead>
<tr>
<th>Vegetation Characteristic</th>
<th>NL</th>
<th>$R^2$(C)</th>
<th>RMSE(C)</th>
<th>RE(C)</th>
<th>$R^2$(CV)</th>
<th>RMSE(CV)</th>
<th>RE(CV)</th>
<th>$R^2$(P)</th>
<th>Adjusted $R^2$(P)</th>
<th>RMSE(P)</th>
<th>RE(P)</th>
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<tr>
<td>Cogon Cover</td>
<td>15</td>
<td>0.79</td>
<td>0.12</td>
<td>49.64%</td>
<td>0.55</td>
<td>0.19</td>
<td>79.12%</td>
<td>0.47</td>
<td>0.46</td>
<td>0.21</td>
<td>86.68%</td>
</tr>
<tr>
<td>Dead Plant Cover</td>
<td>9</td>
<td>0.68</td>
<td>0.15</td>
<td>28.61%</td>
<td>0.53</td>
<td>0.18</td>
<td>38.36%</td>
<td>0.47</td>
<td>0.46</td>
<td>0.19</td>
<td>46.17%</td>
</tr>
<tr>
<td>L/D Ratio</td>
<td>6</td>
<td>0.48</td>
<td>1.78</td>
<td>140.97%</td>
<td>0.22</td>
<td>1.93</td>
<td>163.44%</td>
<td>0.29</td>
<td>-1.16</td>
<td>1.88</td>
<td>186.70%</td>
</tr>
<tr>
<td>Canopy EWT</td>
<td>4</td>
<td>0.21</td>
<td>0.03</td>
<td>55.75%</td>
<td>0.04</td>
<td>0.04</td>
<td>67.38%</td>
<td>0.09</td>
<td>0.06</td>
<td>0.04</td>
<td>70.86%</td>
</tr>
</tbody>
</table>

Note: For cogongrass and dead plant cover, these dates were used for both training and test data: June 2015, February 2016, June 2016, December 2016, and March 2017. For L/D ratio and canopy EWT, these dates were used for both training and test data: February 2016, June 2016, and December 2016. RMSE = root mean square error; C = calibration models using training data; P = independent validation models using testing data.
Table 2-3. Performance of PLSR reflectance models on cogongrass coverage that were calibrated and validated using data from different time periods.

<table>
<thead>
<tr>
<th>Training Data</th>
<th>Test Data</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>Season</td>
<td>Sample Size</td>
</tr>
<tr>
<td>Same Season</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6/2015</td>
<td>wet</td>
<td>54</td>
</tr>
<tr>
<td>2/2016+12/20</td>
<td>dry</td>
<td>57</td>
</tr>
<tr>
<td>6/2015+6/2016</td>
<td>wet</td>
<td>56</td>
</tr>
<tr>
<td>16+3/2017</td>
<td>dry</td>
<td>56</td>
</tr>
<tr>
<td>Different Season</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6/2015+2/201</td>
<td>wet &amp; dry</td>
<td>91</td>
</tr>
<tr>
<td>6+6/2016+12</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: RMSE = root mean square error; C = calibration models using training data; P = independent validation models using testing data.
Table 2-4. Performance of PLSR reflectance models on dead plant coverage that were calibrated and validated using data from different time periods.

<table>
<thead>
<tr>
<th>Training data</th>
<th>Test data</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date</td>
<td>Season</td>
<td>Sample Size</td>
</tr>
<tr>
<td>6/2015</td>
<td>wet</td>
<td>54</td>
</tr>
<tr>
<td>2/2016+12/2016</td>
<td>dry</td>
<td>57</td>
</tr>
<tr>
<td>6/2015+6/2016</td>
<td>wet &amp; dry</td>
<td>56</td>
</tr>
<tr>
<td>02/2016+12/2016+03/2017</td>
<td>dry</td>
<td>56</td>
</tr>
<tr>
<td>6/2015+2/2016+6/2016+12/2016+3/2017</td>
<td>wet &amp; dry</td>
<td>91</td>
</tr>
</tbody>
</table>

Note: RMSE = root mean square error; C = calibration models using training data; P = independent validation models using testing data.
Table 2-5. Predictive ability of hyperspectral estimation of vegetation characteristics in an experimental setting without date as an additional explanatory variable.

<table>
<thead>
<tr>
<th>Vegetation Characteristic</th>
<th>NL</th>
<th>$R^2$(C)</th>
<th>RMSE(C)</th>
<th>RE(C)</th>
<th>$R^2$(CV)</th>
<th>RMSE(CV)</th>
<th>RE(CV)</th>
<th>$R^2$(P)</th>
<th>Adjusted $R^2$(P)</th>
<th>RMSE(P)</th>
<th>RE(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogon Cover</td>
<td>11</td>
<td>0.83</td>
<td>0.123</td>
<td>39.78%</td>
<td>0.65</td>
<td>0.196</td>
<td>59.50%</td>
<td>0.73</td>
<td>0.69</td>
<td>0.206</td>
<td>55.99%</td>
</tr>
<tr>
<td>Dead Plant Cover</td>
<td>9</td>
<td>0.87</td>
<td>0.105</td>
<td>20.91%</td>
<td>0.74</td>
<td>0.151</td>
<td>35.49%</td>
<td>0.58</td>
<td>0.57</td>
<td>0.155</td>
<td>57.01%</td>
</tr>
<tr>
<td>L/D Ratio</td>
<td>3</td>
<td>0.23</td>
<td>1.095</td>
<td>111.64%</td>
<td>0.10</td>
<td>1.048</td>
<td>107.81%</td>
<td>0.08</td>
<td>-0.08</td>
<td>0.712</td>
<td>74.45%</td>
</tr>
<tr>
<td>Canopy EWT</td>
<td>5</td>
<td>0.45</td>
<td>0.025</td>
<td>43.75%</td>
<td>0.28</td>
<td>0.032</td>
<td>51.22%</td>
<td>0.38</td>
<td>0.33</td>
<td>0.033</td>
<td>44.94%</td>
</tr>
</tbody>
</table>

Note: For cogongrass and dead plant cover, these dates were used for both training and test data: June 2015, February 2016, June 2016, December 2016, and March 2017. For L/D ratio and canopy EWT, these dates were used for both training and test data: February 2016, June 2016, and December 2016. RMSE = root mean square error; RE = relative error; C = calibration models using training data; CV = cross-validation models using leave one out on training data; P = independent validation models using testing data.
Table 2-6. Predictive ability of hyperspectral estimation of vegetation characteristics in an experimental setting with date as an additional explanatory variable.

<table>
<thead>
<tr>
<th>Vegetation Characteristic</th>
<th>NL</th>
<th>$R^2$(C)</th>
<th>RMSE(C)</th>
<th>RE(C)</th>
<th>$R^2$(CV)</th>
<th>RMSE(CV)</th>
<th>RE(CV)</th>
<th>$R^2$(P)</th>
<th>RMSE(P)</th>
<th>RE(P)</th>
<th>Adjusted $R^2$(P)</th>
<th>RMSE(CV)</th>
<th>RE(CV)</th>
<th>RMSE(P)</th>
<th>RE(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cogon Cover</td>
<td>12</td>
<td>0.81</td>
<td>0.132</td>
<td>41.57%</td>
<td>0.65</td>
<td>0.196</td>
<td>59.50%</td>
<td>0.78</td>
<td>0.73</td>
<td>0.188</td>
<td>53.23%</td>
<td>0.196</td>
<td>59.50%</td>
<td>0.78</td>
<td>0.188</td>
</tr>
<tr>
<td>Dead Plant Cover</td>
<td>10</td>
<td>0.87</td>
<td>0.100</td>
<td>20.57%</td>
<td>0.73</td>
<td>0.153</td>
<td>35.97%</td>
<td>0.64</td>
<td>0.63</td>
<td>0.165</td>
<td>54.56%</td>
<td>0.153</td>
<td>35.97%</td>
<td>0.64</td>
<td>0.165</td>
</tr>
<tr>
<td>L/D Ratio</td>
<td>3</td>
<td>0.23</td>
<td>0.745</td>
<td>85.55%</td>
<td>0.14</td>
<td>1.020</td>
<td>104.88%</td>
<td>0.27</td>
<td>0.16</td>
<td>1.298</td>
<td>111.42%</td>
<td>1.020</td>
<td>104.88%</td>
<td>0.27</td>
<td>1.298</td>
</tr>
<tr>
<td>Canopy EWT</td>
<td>6</td>
<td>0.53</td>
<td>0.021</td>
<td>36.53%</td>
<td>0.26</td>
<td>0.032</td>
<td>51.75%</td>
<td>0.29</td>
<td>0.26</td>
<td>0.038</td>
<td>53.89%</td>
<td>0.032</td>
<td>51.75%</td>
<td>0.29</td>
<td>0.038</td>
</tr>
</tbody>
</table>

Note: For cogongrass and dead plant cover, these dates were used for both training and test data: June 2015, February 2016, June 2016, December 2016, and March 2017. For L/D ratio and canopy EWT, these dates were used for both training and test data: February 2016, June 2016, and December 2016. RMSE = root mean square error; RE = relative error; C = calibration models using training data; CV = cross-validation models using leave one out on training data; P = independent validation models using testing data.
Figure 2-1. Reflectance of 10 subplots randomly selected from (a) non-drought, cogongrass-invaded subplots, (b) non-drought, non-cogongrass subplots, (c) drought, cogongrass-invaded subplots, and (d) drought, non-cogongrass subplots.
Figure 2-2. Box-plots showing the following vegetation characteristics in non-drought subplots for native and cogongrass-invaded subplots through time: (a) cogongrass coverage, (b) dead plant coverage, (c) live to dead material ratio, and (d) canopy equivalent water thickness (EWT). Sample periods from the wet season are in bold and from the dry season are not in bold. For figure (a), cogongrass coverage for the native subplots in all time periods is zero.
Figure 2-3. Pearson correlation between the vegetation characteristics under non-drought treatment. The relationship between cogongrass coverage and dead plant coverage was developed from data taken in June 2015, February 2016, June 2016, December 2016, and March 2017 (N = 137). The other relationships were developed from data taken in February 2016, June 2016, and December 2017 (N = 64).
Figure 2-4. Mean hyperspectral reflectance for different quantiles of the following vegetation characteristics: (a) cogongrass coverage, (b) dead plant coverage, (c) live to dead ratio, and (d) canopy EWT for the full spectral range.
Figure 2-5. Mean hyperspectral reflectance in just the visible wavelength ranges for different quantiles of the following vegetation characteristics: (a) cogongrass coverage, (b) dead plant coverage, (c) live to dead ratio, and (d) canopy EWT.
Figure 2-6. Coefficient of determination (R²) of Partial Least Square Regression (PLSR) using field spectral data to predict (a) cogongrass and (b) dead plant coverage using training sets of different sizes.
Figure 2-7. The results of PLSR models for cogongrass coverage, dead plant coverage, live to dead ratio, and canopy EWT with training and testing data drawn from all dates combined for calibration (column a) and independent validation (column b). The black lines are 1:1 line. R2 = coefficient of determination, aR2 = adjusted coefficient of determination.
Figure 2-8. The results of PLSR models with date as an additional explanatory variable for objective variables with training and testing data drawn from all dates combined for calibration (column a) and independent validation (column b).
Figure 2-9. The PLSR model regression coefficients plot by wavelength for 4 objective variables in this study. The wavelength center of Water Band Index (WBI) in red, Normalized Difference Water Index (NDWI) in yellow, Normalized Difference Infrared Index (NDII) in blue, and Normalized Difference Vegetation Index (NDVI) in green are presented as the vertical lines as reference.
LIST OF REFERENCES


BIOGRAPHICAL SKETCH

Yuxi Guo graduated from Beijing Forestry University in 2015 with a bachelor degree in Wildlife and Nature Reserve Management. During undergraduate studies, she carried out two experiments concentrated on soil carbon sequestration and greenhouse gas emissions. Yuxi was accepted as a Master student by the School of Forest Resources and Conservation at University of Florida. She studied hyperspectral quantification on a specific invasive grass supervised by Dr. Stephanie Bohlman. She was interested in scaling up remote sensing technique on ecology questions into landscape scale. Yuxi would like to pursue a higher level degree in the future.