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# Hydrology and Fire History Drive Patterns in Post-Fire Recovery in Everglades Wetland Ecosystem

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# HYDROLOGY AND FIRE HISTORY DRIVE PATTERNS IN POST-FIRE RECOVERY IN EVERGLADES WETLAND ECOSYSTEM

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Jenisha Oli

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To: Dean Michael R. Heithaus
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This thesis, written by Jenisha Oli, and entitled Hydrology and Fire History Drive Patterns in Post-Fire Recovery in Everglades Wetland Ecosystem, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this thesis and recommend that it be approved.

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DEDICATION

To parents and siblings

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ABSTRACT OF THE THESIS

HYDROLOGY AND FIRE HISTORY DRIVE PATTERNS IN POST-FIRE RECOVERY IN EVERGLADES WETLAND ECOSYSTEM

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Although fire-adapted ecosystems in Everglades require regular burning to maintain wetland ecosystems, land management and climate-change have altered natural fire-regime. Due to changes in climate and hydrology, historical fire-regimes may become irrelevant. To understand changing fire return intervals, I look at patterns in ecosystem recovery, where fast recovery is indicative of resilience and adaption with an objective of understanding post-fire recovery time in Everglades. I evaluated how post-fire recovery rates were influenced by hydrology and fire-history (1948-2019) by measuring changes in normalized difference vegetation index following fires that burned between 2005-2019 within Everglades. Hydrology had stronger effect on post-fire recovery compared to fire history. Increasing water-levels by 10% across Everglades either shortened (sawgrass marl prairie) or prolonged (cattail marsh, graminoid marsh, graminoid prairie, halophytic herbaceous prairie and sawgrass marsh) post-fire recovery estimates. Fire return intervals for Everglades were dynamic and fire-management must develop novel approaches to manage fire-regimes.

Keywords: Prescribed fire, water levels, fire return intervals, fire management, adaptive management solutions.

TABLE OF CONTENT

LIST OF TABLES

TABLE PAGE

LIST OF FIGURES

## Introduction

Although fire is often thought of as an agent of destruction (Rowell & Moore, 2000), it is an important component of fire-adapted ecosystems. Fires are essential to decrease excess accumulation of surface fuels, control invasive species, expose soil for seed germination (Doren et al., 1993), remove standing dead trees (Chang, 1996; La Puma et al., 2007) and prevent woody encroachment (Loveless, 1959; Platt & Gottschalk, 2001; Sah, Ross, Snyder, et al., 2010; Wade et al., 1980). The absence of fire will lead to changes in species composition and movement towards the climax community through the process of succession (J. K. Brown, 1975; Graham & Jain, 2005).

Fire regimes are complex and include the general pattern of fire in a specific area. It is a combination of fire frequency, fire return interval, the total area affected by fire, fire intensity, and fire severity (Franklin et al., 2016; Gill, 1975). Fire adapted ecosystems require specific fire regimes (Cissel et al., 1999; Drewa et al., 2002; Moritz et al., 2005) and deviance from the regime that species are adapted to can cause significant changes in the ecosystem structure and function (Glitzenstein et al., 1995; Platt et al., 1988, 2002).

Due to the risk of damage to people and property, natural fires across the world have been historically suppressed (Heines et al., 2019; Jazebi et al., 2020; Lentile et al., 2006). Long-term fire suppression has disrupted natural fire regimes and has led to the decline in the resilience of fire-adapted ecosystems (Bucher et al., 2014; Pyne, 2016; Williams, 1995). Over time, the increasing recognition of the role of fire in the fire-adapted ecosystems has shifted fire management's focus from suppression to using prescribed fire to simulate natural fire patterns (Bassett et al., 2020; Eloy et al., 2019; Marks-Block & Tripp, 2021; Slocum et al., 2003). Prescribed fire is now used in addition to lightning-ignited fires to maintain fire-adapted ecosystems (Williams, 1995) and to mitigate extreme fire behavior (Laris, 2002; Mistry et al., 2005). The use of fire as a management tool by managers in the southeastern United States of America (USA) has been a common practice since 1958 (Abrahamson, 1984a; T. J. Smith III et al., 2015).

The Everglades, one of the largest subtropical wetland complex in the USA, has fire-adapted ecosystems. Everglades fire-adapted ecosystems include both pinelands and wetlands (Brian Beckage et al., 2005; Loveless, 1959; Pyne, 2016). Within Everglades National Park, prescribed fire is used as an essential management tool to maintain the fire-adapted ecosystems (Brian Beckage et al., 2005; Davis & Ogden, 1994; Loveless, 1959). The wetland marshes and marl prairies are a large component of the landscape, occupying ~65% of the Everglades landscape (Loveless, 1959). In these wetlands, fast moving surface fires consume aboveground grasses and herbaceous species (Abrahamson, 1984b), and reduce the presence of woody species (Platt & Gottschalk, 2001; Sah, Ross, Snyder, et al., 2010). The meristems of a dominant species, sawgrass, is protected by overlapping leaf bases allowing sawgrass to resprout from these meristems after fire (Wade et al., 1980). The marshes and marl prairies are thought to recover from fire within 2-3 years (L. N. Brown et al., 2020; Cook & Hayes, n.d.; Salvatico, 2019). If left unburned for more than 3 years woody vegetation encroachment increases (Loveless, 1959; Wade et al., 1980).

Fire return intervals are a major defining feature of fire regimes (Ford et al., 2010; Gill, 1975; Safford & Van de Water, 2014) and are influenced by the frequency of ignition, fuel structure and species composition (Safford & Van de Water, 2014). Fire return intervals are also determined by ecosystem's capacity to recover from a fire. Ecosystems cannot burn at shorter intervals than they can recover from without marked changes in the structure and function of those ecosystems (Ford et al., 2010). A study on the effects of fire return intervals in long-leaf pine ecosystems showed that these ecosystems were strongly regulated by fire and fire-return intervals played a key role in species composition (Ford et al., 2010). In Everglades fire adapted ecosystems, fire return intervals range from 2-177 years (Snyder, 1991). While wetland marsh and marl prairies have a fire return interval of 2-3 years (L. N. Brown et al., 2020; Cook & Hayes, n.d.; Salvatico, 2019), the fire return interval for pinelands is 6-10 years (Snyder, 1991; Wade et al., 1980), 10-24 years for cypress (Wade et al., 1980), and hammocks have a fire return interval of 177 years (Snyder, 1991).

Similar to fire, hydrology can also have a significant effect on ecosystem structure and function, especially in Everglades wetland ecosystems. The difference in hydrology across Everglades landscape accounts for the varying pattern in species composition (John et al., 2021). Marshes often exhibit higher water levels and remain inundated throughout most years in the Everglades (Lockwood et al., 2003) whereas the marl prairies exhibit seasonal dry downs that can last anywhere from 3-6 months annually (Sah, Ross, & Stofella, 2010; M. S. Ross et al., 2006). Aside from influencing species composition, hydrology also interacts with fire to affect the amount of fuels consumed and the capacity to recover from fire. In general, drier conditions increase pre-fire fuel availability (Slocum et al., 2007), while wetter conditions limit the exposure of vegetation to fire and can protect against high severity fire effects (Wade et al., 1980). In wetlands, flooding after fire can increase post-fire recovery rates by suppressing vegetation growth, leading to a more sparsely vegetated landscape (Herndon et al., 1991; Ruiz et al., 2013). While hydrology and fire history have had a significant influence on vegetation and fire behavior in the Everglades (Lockwood et al., 2003; Loveless, 1959), the specific influence of the interaction between hydrology and fire on post-fire recovery rates is unknown (Herndon et al., 1991; Ponzio et al., 2004; Ruiz et al., 2013)

The primary objective of this study is to evaluate how hydrology and fire history influence post-fire recovery rates in Everglades wetlands to understand how patterns in post-fire recovery vary. Ecosystem recovery is the system's ability to return to its pre-disturbance state (Holling, 1973) and recovery time is the total time taken to reach the pre-disturbance state (D. L. DeAngelis & Waterhouse, 1987). Recovery is dependent on individual species response to fire (Shuman et al., 2017), pre-fire ecosystem condition (B. Beckage et al., 2003), fire severity, and post-fire climate (J. F. Johnstone & Chapin, 2006). Recovery rates can therefore vary based on the combination of the fire regime and post-fire conditions (Enright et al., 2014; Tepley et al., 2018). A major assumption of this approach is that ecosystems are adapted to regimes they recover quickly from (Maher & Baum, 2013; Ramón Vallejo et al., 2012; Spalding et al., 2014). I hypothesized that (H1) wet conditions after fire will increase post-fire recovery times. Herndon et al., (1991) found that recovery times for sawgrass (*Cladium jamaicense* Krantz) marshes were longer when hydroperiods were higher after fire. When water levels were higher than the canopy, recovery rates were approximately double the time required for clumps that were exposed. I also hypothesize that (H2) areas that burn more frequently should be more fire adapted and should recover faster from fire (Wilson et al., 2015). Areas that burn more frequently are more likely to maintain fire adapted species and may recover faster (Chmura et al., 2011; Halofsky et al., 2020).

Quantitative geospatial information on changes in ecosystem structure might be a useful approach on understanding the effects of fire and ecosystem recovery after fire. Satellite imagery and remote sensing techniques allow us to continuously measure changes in land cover and ecosystem structure over time (Kennedy et al., 2014) by detecting changes in surface reflectance. Remote sensing has been used to evaluate recovery after fire all over the world (Arévalo et al., 2014; Chu & Guo, 2013; Clemente et al., 2009; Puerta-Piñero et al., 2012). One of the most widely used methods in the disturbance recovery assessment is to compare burned areas to neighboring unburned areas (Foster & Tilman, 2000; Frolking et al., 2009). Changes in surface reflectance as vegetation recovers and regains coverage lost in a fire is used to assess recovery (Díaz-Delgado & Pons, 2001; Goetz et al., 2006; A. M. S. Smith et al., 2007; Wilson et al., 2015). The Normalized Difference Vegetation Index (NDVI) is commonly used for monitoring changes in vegetation cover and productivity. NDVI captures variation in vegetation density (Carlson & Ripley, 1997; Hernández-Clemente et al., 2009; Malak & Pausas, 2006) and has been shown to reflect spatio-temporal patterns in ecosystem productivity and biomass (Boelman et al., 2003; Box et al., 1989; Butterfield & Malmström, 2009; Freeman et al., 2007; Goswami et al., 2015; Jones, 2001; Walker et al., 1995; Wessels et al., 2006). Capturing variation in ecosystem structure and function, NDVI is a useful indicator of recovery patterns (Hope et al., 2007; Malone et al., 2016; Röder et al., 2008; Schroeder et al., 2007; Viedma et al., 1997; Wilson et al., 2015). Because of its sensitivity to changes in vegetation cover (Carlson & Ripley, 1997; Hernández-Clemente et al., 2009; Malak & Pausas, 2006; Viedma et al., 1997), NDVI has been used to detect post-fire recovery patterns (Carlson & Ripley, 1997; Meng et al., 2015; Ryu et al., 2018), and will be used here to understand patterns in post-fire recover in Everglades wetland ecosystems.

## Methods

### Study Site

The Florida Everglades (25°18′45″N, 80°41′15″W) is listed as a United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage Site and also as a Wetland of International Importance. The Everglades have a sub-tropical climate with hot and humid summers and mild winters, which produces a year-long growing season (L. H. Gunderson & Loftus, 1993). With distinct summer-wet and winter-dry seasons (Egler, 1952), the temperatures can reach a maximum of 40°C in the summer and drop to 17°C in the winter (L. H. Gunderson & Loftus, 1993). Precipitation (1380 mm $yr^{-1}$) is an important factor in regulating hydrology (L. Gunderson & Light, 2006). Mean annual rainfall ranges from 1300-1600 mm (Donald L. DeAngelis et al., 1998; L. H. Gunderson & Loftus, 1993; Lockwood et al., 2003) and the majority of the rainfall (~80%) occurs in the wet season which starts in May and ends in October (L. H. Gunderson & Loftus, 1993). Water levels increase throughout the wet season and peaks in October (B. Beckage et al., 2003).

The Everglades is a diverse landscape comprised of freshwater and saline wetlands, mangroves scrub, tall riverine mangrove forests, pinelands, tree islands, and hardwood hammocks (Donald L. DeAngelis et al., 1998; Milon & Scrogin, 2006; Pyne, 2016). Marshes and marl prairie wetland ecosystems occupy ~65% of the Everglades and Sawgrass (*Cladium jamaicense* Krantz) is a dominant species in both marshes and marl prairie wetlands (Loveless, 1959; Wade et al., 1980) (Figure 1). These ecosystems have a diverse hydrological regime. Water flow into the Everglades depends on local rainfall and regional runoff from adjacent lakes (Davis & Ogden, 1994). The surface water increases in the wet season (May to October) and decreases in the dry season (November to April) (Brian Beckage & Platt, 2003; Loveless, 1959). Canals and levees are constructed by South Florida Water Management District to control the water dynamics in Everglades (Davis & Ogden, 1994). These management implications have caused disruption in water flow and altered the hydroperiod of the Everglades (Jones et al., 2013). Variation in hydrology and the short fire return interval make these wetlands an excellent candidate to evaluate the effects of hydrology and a dynamic fire history on post-fire recovery.

The Everglades vegetation map produced by the Center for Remote Sensing and Mapping Science at The University of Georgia was used to develop a wetland layer for Everglades National Park (https://fce-lter.fiu.edu/data/GIS/). The original vegetation map was developed in 1995 and it classified Everglades vegetation into 91 classes. I simplified the vegetation classes in this detailed product to delineate marsh and marl prairie wetland types into six categories (Figure 1): cattail (*Typha* spp.) marsh, graminoid marsh, graminoid prairie, sawgrass marsh, sawgrass marl prairie and halophytic herbaceous prairie. The final wetland vegetation file consisted of just the six classes at 30-meter resolution. All processing was done in R (R Core Team, 2014).

Everglades Wetland Ecosystems

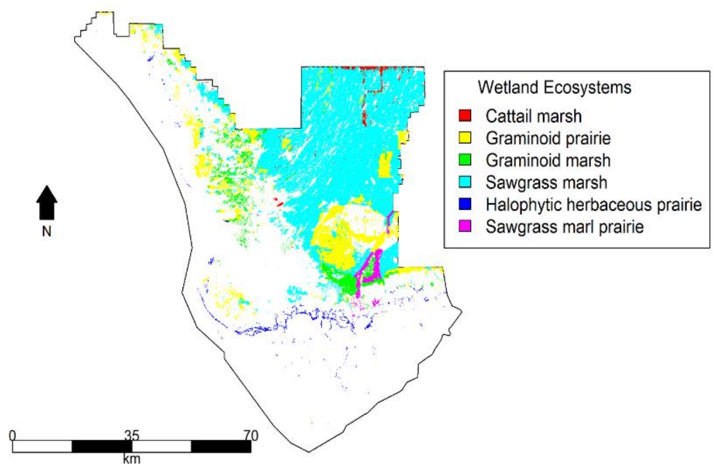


Figure 1. Map of Everglades marshes and marl prairie wetland ecosystems. Marshes and marl prairies of Florida Everglades were classified into six different types: cattail (*Typha* spp.) marsh, graminoid marsh, graminoid prairie, sawgrass (*Cladium jamaicense* Krantz) marsh, sawgrass marl prairie and halophytic herbaceous prairie.

Cattail marshes are found scattered across the Everglades in disturbed sites and at long-hydroperiod sites that remain inundated throughout most years (Sah, Ross, & Stofella, 2010; Wade et al., 1980). Cattail marshes are comprised of non-graminoid emergent marshes such as *Pontederia lanceolata*, *Sagittaria* spp., *Nymphaea odorata*, *Typha* spp., with *Ludwigia repens* and *Utricularia* spp. Graminoid marshes are semi-permanently flooded and present in the southern part of Shark River Slough, the stair step region, and the C-111 basin (Sah, Ross, & Stofella, 2010). Species such as maidencane (*Panicum hemitomon*), spike rush (*Eleocharis cellulosa*), black rush (*Juncus roemerianus*) and common reed (*Phragmites* spp.) make up the graminoid marsh. The graminoid prairies are inundated 3 to 7 months a year (Sah, Ross, & Stofella, 2010) and muhly grass (*Muhlenbergia filipes*), cordgrass (*Spartina* spp.), and a mix of maidencane-spike rush in shallow open water are definitive species in this wetland type. The marl prairies have an annual hydroperiod of 2 to 6 months (M. S. Ross et al., 2006) and muhly grass and sawgrass dominate this wetland type. Sawgrass marshes are present throughout the Everglades with an annual hydroperiod of 7-11 months (Lockwood et al., 2003) and dominated by sawgrass on the ridges. The halophytic herbaceous prairie is found scattered along the coastal areas in tidal zones in Cape Sable and south of West lake (Sah, Ross, & Stofella, 2010) and consists of saltgrass (*Distichlis spicata*), smutgrass (*Sporobolus* spp.) and keys grass (*Monanthochloe littoralis*); they also contain very salt tolerant species such as saltwort (*Batis maritima*), glasswort (*Salicornia* spp.) and sea purslane (*Sesuvium* spp.). These wetland types are often incorporated into two overall classes: marshes, and marl prairies in the Everglades, and are indicative of hydrological patterns.

**Overview**

To evaluate how hydrology and fire history influence post-fire recovery rates in Everglades wetlands, I used the NDVI to measure post-fire recovery for fires that occurred from 2005-2019 in Everglades wetlands. First, I developed a model to estimate the expected unburned NDVI (Baseline) for Everglades wetlands, controlling for vegetation type (cattail marsh, graminoid marsh, graminoid prairie, sawgrass marsh, sawgrass marl prairie and halophytic herbaceous prairie) and water level. For burned areas, I measured recovery time as the time it takes for a burned area to fall within the 95% CI of expected NDVI (Baseline). I then explored hydrology and fire frequency (1948-2000) as drivers of post-fire recovery and evaluated the impact of a 10% increase in water level on post-fire recovery. This approach required the development of Everglades fire history layers, designing a baseline model to understand expected unburned NDVI, measuring recovery rates for burned areas, and exploring drivers of recovery.

**Defining the Baseline NDVI**

I used the Normalized Difference Vegetation Index (NDVI; Eq 1), which captures changes in green vegetation based on chlorophyll absorption (Liu et al., 2018; Mahajan & Bundel, 2016).

$$NDVI = (Red - NIR) / (NIR + Red) \qquad \text{Eq. 1}$$

The NDVI was calculated from Landsat 7 (ETM+; Table 1). Landsat data are available at 16-day intervals and at a 30-meter resolution. All the measurement dates with fill values, saturated values and the values that were out of range for all the bands were not used in addition to measurements with low cloud confidence.

Table 1. Landsat 7 (ETM+) spectral bands and different vegetation indices calculated from these band values.

| Landsat Spectral Bands | Band range | Trait |
|---|---|---|
| Blue band (Band 1) | 0.45 - 0.52 µm | Distinguishing soil from vegetation, and deciduous from coniferous vegetation |
| Green band (Band 2) | 0.52 - 0.60 µm | Chlorophyll absorption, emphasizes peak vegetation for assessing plant vigor |
| Red band (Band 3) | 0.63 - 0.69 µm | Discriminates vegetation slopes |
| Near Infrared band (Band 4) | 0.77 - 0.90 µm | Emphasizes biomass content and shorelines |

| | | |
|---|---|---|
| Shortwave Infrared band 1 (Band 5) | 1.55 - 1.75 µm | Discriminates moisture content of soil and vegetation |
| Shortwave Infrared band 2 (Band 7) | 2.08 - 2.35 µm | Hydrothermally altered rocks with mineral deposits |

To understand what the expected NDVI should be for wetland ecosystems under variable hydrological regimes, I generated sample points (n=2,302) across wetland types that did not burn from 1948-2019. I used a stratified random sampling approach to distribute sample points by wetland type and observed water levels values for each wetland type using the *sampleRandom* function in the "Raster" package (Hijmans et al., 2013) in R (R Core Team, 2014) (Table 2). Sample points were at least 30-m apart.

Table 2. Sample design for the baseline model. Total unburned (1948-2019) wetland area within Everglades National Park, the total number of sample points (SP) and the fraction of sample points for each wetland type.

| **Wetland Type** | **Unburned Area ($km^2$)** | **Unburned Area (%)** | **Baseline SP (Total points)** | **Baseline SP (%)** |
|---|---|---|---|---|
| Cattail marsh | 0.36 | 0.14 | 102 | 4.44 |
| Graminoid prairie | 44.49 | 18.17 | 443 | 19.24 |
| Graminoid marsh | 37.95 | 15.51 | 340 | 14.77 |
| Sawgrass marsh | 118.99 | 48.62 | 1,011 | 43.91 |
| Halophytic herbaceous prairie | 23.95 | 9.79 | 236 | 10.26 |
| Sawgrass marl prairie | 19.04 | 7.77 | 170 | 7.38 |
| Total | 244.78 | 100 | 2,302 | 100 |

I obtained the daily median water level information from the Everglades Depth Estimation Network (EDEN; https://sofia.usgs.gov/eden/) from 1st Jan 2005 to 31st Dec 2019. I used the daily water level for the date of the NDVI measurement. At locations where water level stations were not available, the nearest station was used to calculate the water level for that location. The nearest neighboring water level station for each location was found using the *get.knnx* function in the package "FFN" (Li & Li, 2012) in R (R Core Team, 2014). Thus, 65 water level stations for unburned sample locations were selected. While this approach does not capture high resolution variability in water level for a particular location, it does capture relative change in conditions for a location and landscape level differences for different parts of the landscape.

I downloaded NDVI for all sample points from the Application for Extracting and Exploring Analysis Ready Samples (AppEEARS). While studies often use pre-fire conditions or neighboring unburned pixels to define the baseline (Foster & Tilman, 2000; Frolking et al., 2009), in the Everglades changes in water level and the ecosystem type were thought to have a strong impact on NDVI. The development of a baseline NDVI model would better capture expected NDVI for an unburned location under the existing conditions.

The baseline dataset (Table 2) was split into a training (80%) and a testing (20%) dataset. Data in both datasets were distributed across the following variables: wetland type, elevation, latitude, longitude, and water level. I fit a Generalized Additive Model (GAM) using the *gam* function in the *"mgcv"* package (S. Wood & Wood, 2015) in R (R Core Team, 2014). The GAM approach is an extension of GLM making an assumption of additive functions and smoothing components; where the coefficients can be expanded as smooth functions of covariates (Hastie & Tibshirani, 1987). GAM models are semiparametric models in which the relationships among the variables are not restricted to any shapes. With the use of a smoothing spline function to model non-linear relationships between the predictor and response variables. GAMs do not require prior knowledge of the response curves or relationships between the variables, which makes it easier to use when assumptions cannot be made on a specific link function for error distribution. GAMs are data driven rather than model driven (Lehmann, 1998). The over-fitting of the splines is avoided in GAM by determining an appropriate degree of smoothness (Levine et al., 2021; S. N. Wood, 2004). A backward selection method was used to select the best fit variables and to determine the effect of each variable on the final model (Poggio et al., 2013). Akaike's Information Criterion (AIC) (Akaike, 1974) and deviance explained were used to compare each of the models created. The AIC is used to rank models based on the closeness of fitted values and true values (Johnston et al., 2019; Littell et al., 1996; Tepley et al., 2017). The discrepancy between the observed and fitted values was measured by the deviance instead of $R^2$ (S. N. Wood, 2006).

From the initial pool of 23 variables (Band 1, Band 2, Band 3, Band 4, Band 5, Band 7, Normalized Burn Ratio (NBR), NDVI, Simple ratio (SR), maximum Band 1, maximum Band 2, maximum Band 3, maximum Band 4, maximum Band 5, mean Band 5, maximum Band 7, month, location, elevation, wetland types, maximum NDVI, maximum NBR and maximum SR), I used 9 variables. Month, location (latitude and longitude), elevation, wetland types, water level, maximum Band 5 (2005-2019), maximum NDVI (2005-2019), maximum NBR (2005-2019), and maximum SR (2005-2019; Table 3) were used to model NDVI. The final model had the lowest AIC and the highest deviance explained. Cross-validation was used to measure the validity of the baseline model with the test dataset to compare observed NDVI to predicted values.

Table 3. Explanatory variables used in the development of the baseline GAM model for Everglades wetlands (2005-2019).

| Variables | Interpretation | References |
|---|---|---|
| Month | Accounts for seasonal variation, where vegetation growth (biomass) directly depends on the growing season. | Hagenbo et al., 2019; Mateo-Sanchis et al., 2019 |
| Latitude<br>Longitude | Accounts for the spatial distribution of the points and landscape gradients in resources. | Drobyshev et al., 2017; Hanzelka et al., 2019 |
| Point elevation | Influences exposure/ Low elevation locations experience higher water levels | Westerling & Bryant, 2008; Wilson et al., 2015 |
| Wetland Type | Captures the variation in vegetation communities. Includes: cattail marsh, graminoid prairie, graminoid marsh, sawgrass marsh, halophytic herbaceous prairie and sawgrass marl prairie. | Mateo-Sanchis et al., 2019; Tian et al., 2018 |
| Maximum Band 5 | Differentiates between differences in moisture content of soil and vegetation in space and time. | Asner & Lobell, 2000; Oyama et al., 2015 |
| Maximum NDVI | Indicative of primary productivity and live green vegetation.<br>NDVI= (Band 4 - Band 3) / (Band 4 + Band 3) | Röder et al., 2008; Wessels et al., 2006 |
| Maximum NBR | Has been used to detect burn areas and fire intensity and severity.<br>NBR= (Band 4 - Band 7) / (Band 4 + Band 7) | Escuin et al., 2008; Miller & Yool, 2002 |
| Maximum SR | Differentiate between vegetation and water. Larger SRI indicates healthy vegetation while lower values denote soil, water, or ice. SR= Band 4 / Band 3 | Melillos & Hadjimitsis, 2020 |

## Estimating Post-Fire Recovery Time

Everglades National Park records the date of fires, the source of ignition (natural versus anthropogenic), and the type of fire (prescribed and wild) in fire perimeter shapefiles. These vector files extend from 1948-2019. Using this information from the Everglades National Park, I developed fire history layers. I determined which parts of the landscape burned from 1948 -2019 and calculated the total number of fires in the Everglades marshes and marl prairies matching the resolution of Landsat products.

To evaluate the patterns in post-fire recovery across Everglades wetlands, I randomly sampled 7,000 locations (Table 4) that burned from 2005-2019, that were distributed across all 6 marsh and marl prairie wetlands ecosystem types, the range of water levels observed within each ecosystem types, and the total number of fires in each marsh and marl prairie wetland ecosystem type using the *sampleRandom* function in the “Raster” package (Hijmans et al., 2013) in R (R Core Team, 2014). The sample points were at least 30 meters apart. I downloaded Landsat 7 data from AppEEARS for the sample point locations and calculated NDVI. For each sample point, I also estimated the baseline NDVI using the baseline model. Recovery time is the number of days it took to return to an NDVI value that fell within the 95% prediction interval for the baseline NDVI. To ensure that each sample point had enough NDVI measurements to get within 6 months of the actual recovery time, I made sure that all the fires had at least two NDVI measurements per year. A total of 5,667 points were used to evaluate drivers of recovery time.

Table 4. Sampling frequency for the burned wetlands within Everglades National Park (2005-2019). Sample points (SP) for data analysis were distributed across wetland types.

| Wetland Type | Burned Area ($km^2$) | Burned Area (%) | Recovery SP (total points) | Recovery SP (%) |
|---|---|---|---|---|
| Cattail marsh | 16.46 | 1.78 | 630 | 9 |
| Graminoid prairie | 176.72 | 19.03 | 1,750 | 25 |
| Graminoid marsh | 58.01 | 6.24 | 1,050 | 15 |
| Sawgrass marsh | 674.17 | 72.60 | 3,012 | 43.02 |
| Halophytic herbaceous prairie | 2.16 | 0.24 | 350 | 5 |
| Sawgrass marl prairie | 1.06 | 0.11 | 208 | 2.98 |
| Total | 928.58 | 100 | 7,000 | 100 |

**Drivers of Post-Fire Recovery**

Similar to the approach used to model baseline NDVI, GAMs were used to measure the effect of hydrology on post-fire recovery time. Explanatory variables included the water level on the day of the fire, mean, minimum and maximum water level six months after fire, one year after fire, and two years after fire. Hydrological information was obtained from the nearest water level station from 2005-2019 using 91 water level stations for burned sample points. I used a backwards selection process and only included variables in the final model that were significant and that led to the highest deviance explained and the smallest AIC.

To measure the effect of fire history on post-fire recovery, GAMs were developed using the total number of fires for each sample location (Halofsky et al., 2020; C. E. McMichael et al., 2004). The total number of fires represents the number of times each location burned since 1948. Using fire records from Everglades National Park, I developed fire history layers. I determined which parts of the landscape burned from 1948-2019 and calculated the total number of fire incidents in the Everglades marshes and marl prairies.

Following an evaluation of the individual effect of fire, I measured the interacting effects for hydrology and fire history using the same approach. I then increased observed daily water levels by 10%. An increase of 10% falls within projections for the Everglades marsh and marl prairie wetlands (Flower et al., 2019; Koch et al., 2015) and could potentially represent conditions that result from restoration activities. First, I increased the daily water level by 10%, other water level variables such as maximum water level six months after fire, maximum water level one year after fire, and maximum water level two years after fire were then calculated. Next, I estimated recovery time using the recovery model to evaluate how recovery time may change with a 10% increase in water levels.

## Results

Marsh and marl prairie wetland ecosystems within the Everglades exhibit different water level conditions. Three distinct hydrologic groups were evident among the wetland ecosystems: dry (average water level < 0 m), moderate (average water level 0.1 m - 1 m) and high (average water level > 1 m) water level wetlands. Dry wetlands include halophytic herbaceous prairies that occur along the coast. Graminoid marsh, graminoid prairie, and sawgrass marl prairie have moderate water levels and cattail marsh and sawgrass marsh are considered high water level wetlands (Figure 2a). The average number of fires from 1948 to 2019 also differed by wetland ecosystem type (Figure 2b). The highest fire frequencies were observed in the sawgrass marl prairie (5.74 ± 0.12), followed by the graminoid prairie (4.74 ± 0.05), cattail marsh (4.45 ± 0.04), sawgrass marsh (3.89 ± 0.04), graminoid marsh (2.08 ± 0.04), and the halophytic herbaceous prairie (1.89 ± 0.14). Post-fire recovery time was generally less than 2 years but can take more than 5 years for some wetland types (Figure 2c). The mean recovery time (± standard error) was 2.35 ± 0.08 years for cattail marsh, 1.74 ± 0.06 years for the graminoid marsh, 2.11 ± 0.05 years for the graminoid prairie, 1.33 ± 0.09 years for the halophytic herbaceous prairie, 4.74 ± 0.15 years sawgrass marl prairie and 2.89 ± 0.05 years for the sawgrass marsh. Although I estimated recovery for 5,667 points, there were 140 points that did not recover within the study period (2005- 2019). These points burned from 2005-2019 and limit my ability to consider locations that require long recovery times (> 14 years; Table 5).

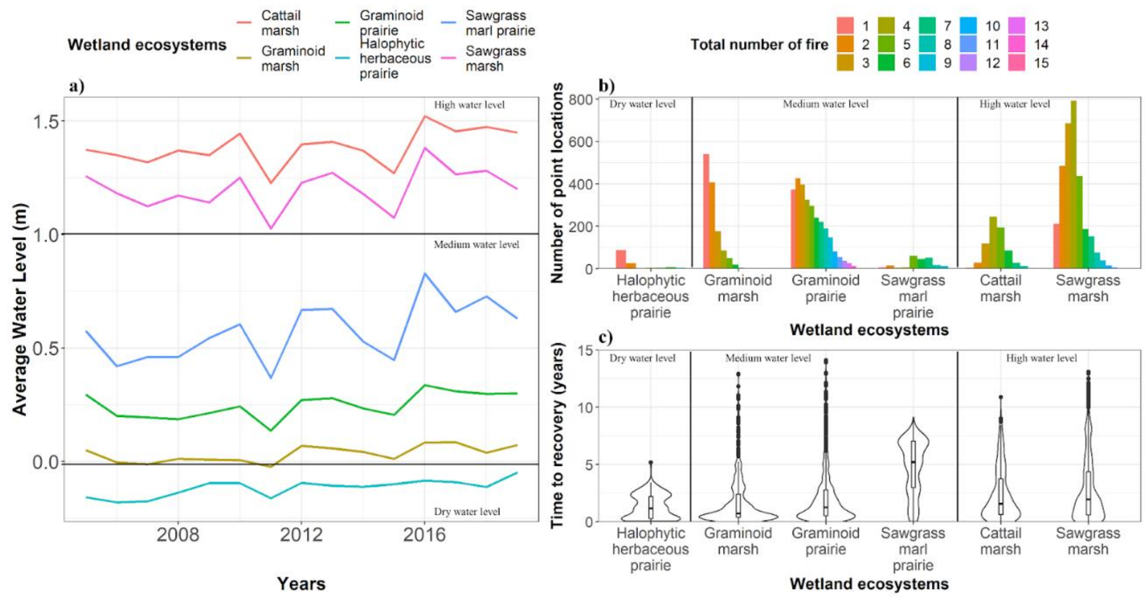


Figure 2. Average annual water levels (m) for wetland types from 2005-2019 in Everglades National Park. b) Total number of fires for wetland types from 1948-2019. c) Recovery time in years for wetland ecosystems.

Table 5: The frequency of sample points from 2005-2019 in Everglades National Park that did not recover during the sample period.

| Year of fire | Sample points that did not recover | Wetland types | | | | | |
|---|---|---|---|---|---|---|---|
| | | Cattail marsh | Graminoid marsh | Graminoid prairie | Halophytic herbaceous prairie | Sawgrass marl prairie | Sawgrass marsh |
| 2005 | 14 | 0 | 9 | 4 | 1 | 0 | 0 |
| 2006 | 2 | 0 | 0 | 0 | 0 | 0 | 2 |
| 2008 | 6 | 0 | 3 | 0 | 0 | 0 | 3 |
| 2009 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| 2011 | 18 | 0 | 0 | 0 | 0 | 0 | 18 |
| 2012 | 10 | 2 | 4 | 1 | 0 | 0 | 3 |
| 2013 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| 2014 | 5 | 0 | 4 | 1 | 0 | 0 | 0 |
| 2017 | 18 | 0 | 3 | 13 | 0 | 0 | 2 |
| 2018 | 17 | 0 | 12 | 1 | 0 | 0 | 4 |
| 2019 | 48 | 0 | 14 | 22 | 0 | 0 | 12 |
| Total | 140 | 2 | 49 | 44 | 1 | 0 | 44 |

## Baseline NDVI

Daily water level ($p < 0.001$), latitude ($p < 0.001$), longitude ($p < 0.001$), month ($p < 0.001$), point elevation ($p < 0.001$), elevation difference between point location and water level station ($p < 0.001$), maximum band 5 value ($p < 0.001$), maximum NBR ($p < 0.001$), maximum NDVI ($p < 0.001$) and maximum SR ($p < 0.001$) had a significant effect on baseline NDVI ($p < 0.001$; Table A1). Smoothing functions were significant by wetland type for daily water level, month, maximum band 5 value, maximum NBR, maximum NDVI and maximum SR. The baseline model explained 70.5% of deviance in NDVI for unburned wetlands. The mean baseline NDVI values (± standard deviation) for each wetland ecosystems were greatest for the halophytic herbaceous prairie (0.55 ± 0.16), followed by the cattail marsh (0.43 ± 0.12), graminoid marsh (0.39 ± 0.15), graminoid prairie (0.39 ± 0.14), sawgrass marl prairie (0.39 ± 0.14), and sawgrass marsh (0.37 ± 0.13). As water levels increased, NDVI decreased for all wetland ecosystems (Figure 3). The larger variation in prediction intervals for graminoid marsh, halophytic herbaceous prairie and sawgrass marl prairie shows that these ecosystems were not found in higher water levels (Figure 3).

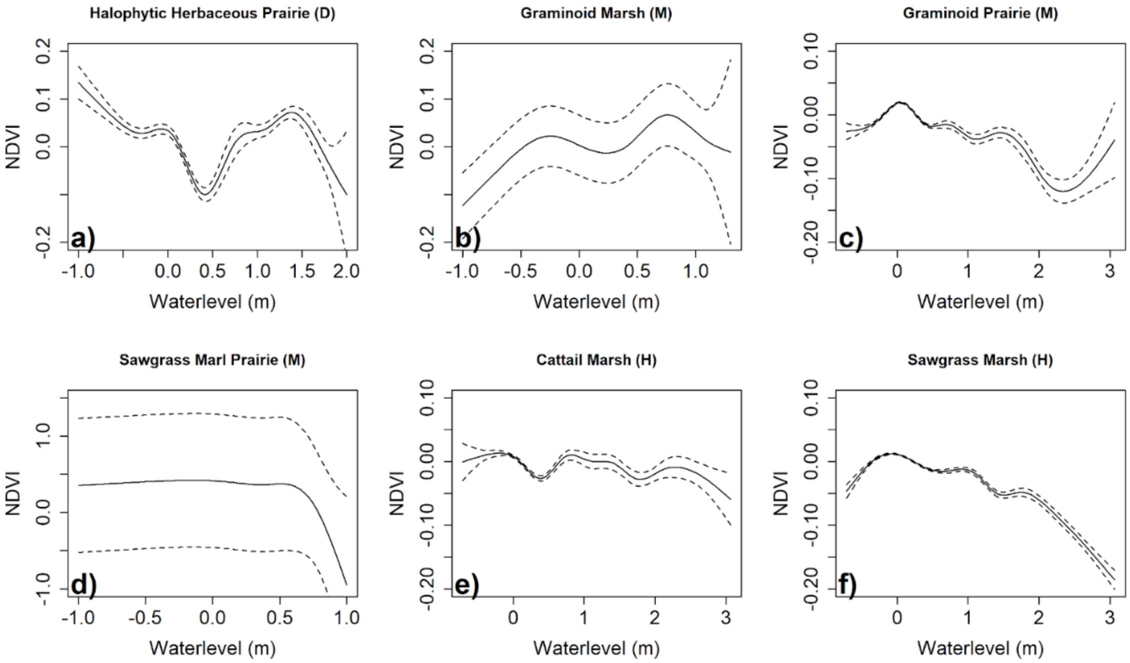


Figure 3: Variation of baseline NDVI with water level in Everglades marsh and marl prairie wetland ecosystem types (solid black line). The dotted lines show the 95% prediction interval. The X-axis differs between plots due to the observed differences in water level across wetland types and the variation in Y-axis is done to better represent the variation in NDVI. D, M, and H refers to dry, medium and high-water level conditions respectively exhibited by the ecosystems.

### Drivers of Post-Fire Recovery

Water level had a significant effect on recovery time for Everglades wetlands (deviance explained =16.7%). Maximum water level six months after fire ($p < 0.001$; 13.5% deviance explained) and maximum water level two years after fire ($p <0.001$; 11.2% deviance explained) both had significant effects on recovery time (Figure 4). Maximum water level six months after fire (Figure 4a) showed a negative relationship with the recovery time whereas maximum water level two years after fire (Figure 4b) showed a positive relationship with the recovery time. Higher water level during the early stages of recovery favored faster vegetation regrowth which then slowed over time (Figure 4).

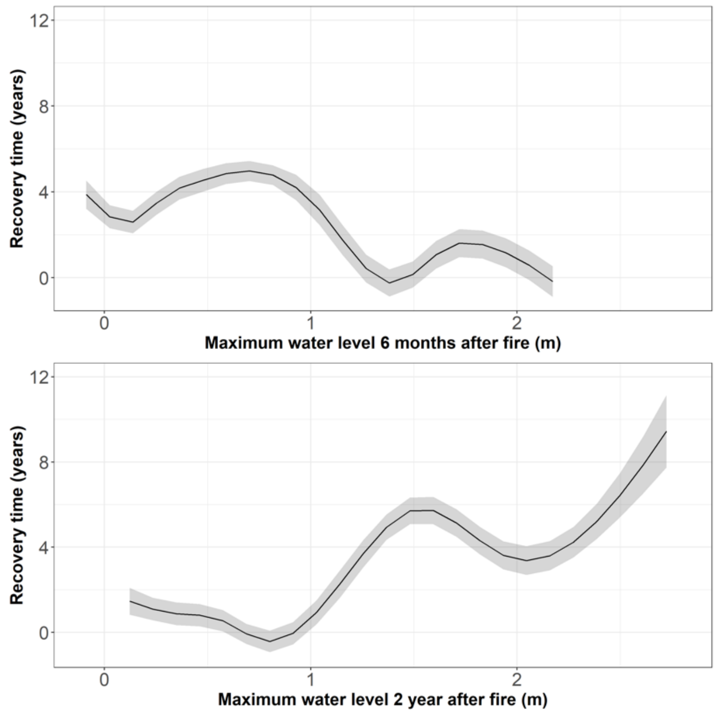


Figure 4: Generalized additive model results for post-fire recovery time (years) for (a) maximum water level six months after fire, and (b) maximum water level two years after fire for Everglades wetlands.

The total number of fires ($p < 0.001$) explained 1.14% of the deviance in recovery time (Figure 5). Time to recovery increased with the number of fires up to seven fires, after which it decreased with an increased number of fires (Figure 5). Results suggest that a threshold must be reached (i.e., seven fires) before fire history starts having a reducing effect on recovery time.

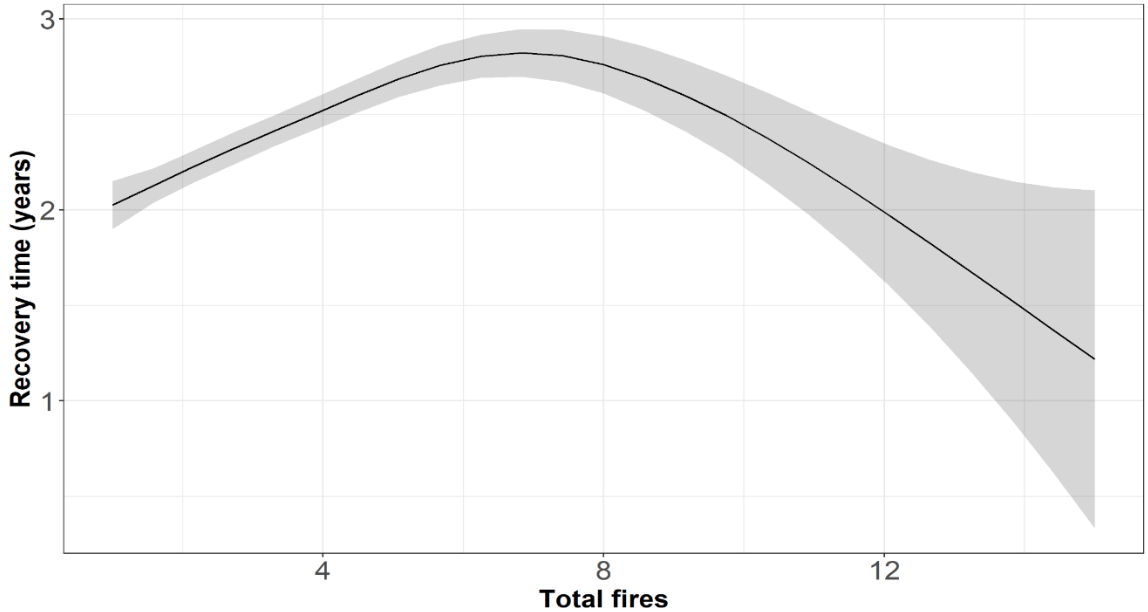


Figure 5: Generalized additive models result for post-fire recovery time in response to changes in the total number of fires in Everglades wetlands.

Including maximum water level six months after fire ($p < 0.001$), maximum water level two years after fire ($p < 0.001$), and total fires ($p < 0.001$) in a recovery model explained 25.2% deviance in post-fire recovery ($p < 0.001$). This combined hydrology and fire history model was used to predict the recovery time for each wetland type. With a projected increase in water level by 10%, the recovery time for all Everglades marsh and marl prairie wetlands increased except for sawgrass marl prairie (Figure 6). There was greater variability in wetland recovery time as well as a larger range of outlier values in recovery time for observed water levels compared to +10% water levels (Figure 6).

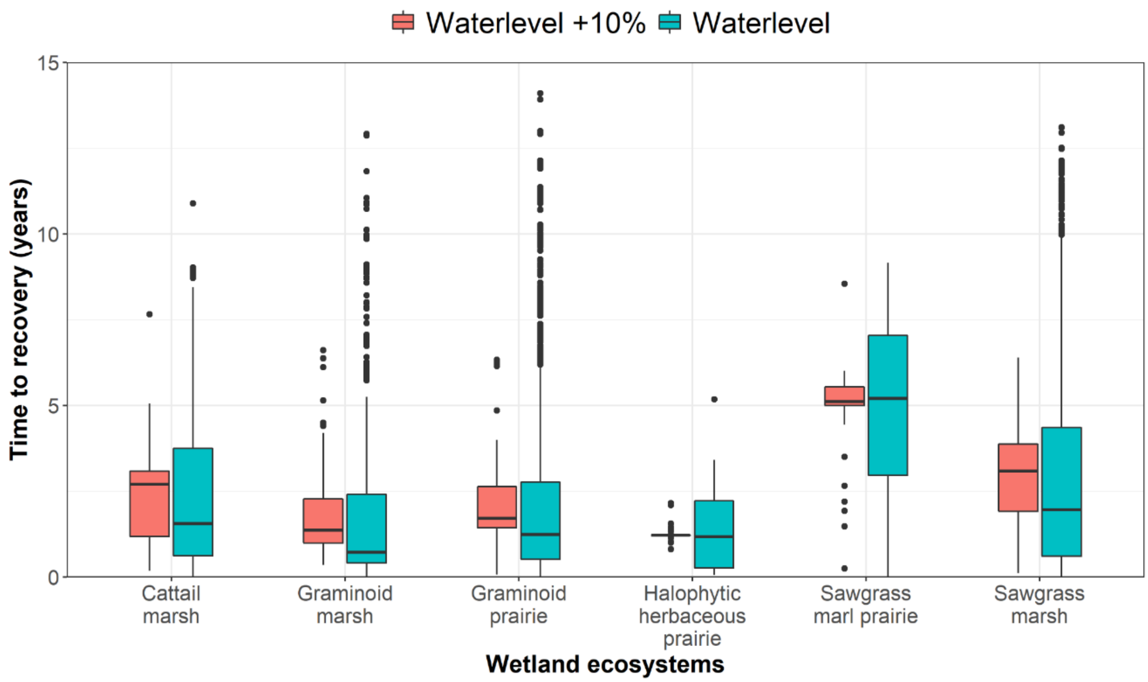


Figure 6: Box plot of recovery time in years for different Everglades wetlands under current water level (blue) and +10% water levels (pink).

**Discussion**

This study assessed the recovery rates of the Everglades wetland ecosystems under the influence of current and future hydrologic regimes and current fire regimes. The hydrology of the Everglades landscape had a greater influence on recovery than fire history and post-fire recovery rates varied by wetland type. The variation in post-fire recovery time among wetland types in this study is similar to the species-specific recovery rates reported by (P. M. Ross et al., 2019; Slapcinsky et al., 2010). Native rush (*Juncus effusus*) recovered within 1 year of fire whereas spiny rush (*Juncus acutus*), chenopod (*Chenopodioideae*) and salt couch (*Paspalum vaginatum*) did not recover within 1-year in salt marsh at Ash Island, New South Wales (P. M. Ross et al., 2019). Likewise, Slapcinsky et al., (2010) saw recovery of *Conradina glabra* in the 2nd and 3rd year after fire while the recovery of *Warea carteri* occurred within 1-year in Florida. Even though these studies were conducted in the same location, the recovery of different species varied possibly due to species specific responses to fire.

In this study, recovery time for wetlands ranged on average from about 1 to 5 years, which is within the range reported for other wetland species and ecosystems (Braswell et al., 2019; Clarkson, 1997; McAtee et al., 1979; P. M. Ross et al., 2019). Clarkson, (1997) reported 2-3 year recovery rates for *Baumea teretifolia* and *Schoenus brevifolius* at Whangamarino wetland and *Schoenus brevifolius* at the Moanatuatua wetland of New Zealand. Similarly, gulf cordgrass (*Spartina spartinae*) in Texas recovered in less than 2 years after fire (McAtee et al., 1979). Earlier studies have found rapid and prompt regrowth (more than 50% in less than a year) for sawgrass after fire (Loveless, 1959) if its meristems remain undamaged (Wade et al., 1980). Another study in Florida Lake Wales grasses and palmettos showed 90% recovery within 1 year in well drained sites whereas recovery was seen to be slower in drier sites (Abrahamson, 1984a, 1984b).

I hypothesized that high water levels would lead to increased post-fire recovery time. My results suggest that recovery time is lower when water levels are higher during the first six months after fire, indicating that there is either rapid regrowth immediately after fire or wetland types with higher water levels recover faster than with lower water levels. Since the Everglades wetland type is confounded with water level it is not possible to fully separate the overall water level effects from the effects of wetland type. All wetland types decreased in recovery time with an increase in water level within the first 6 months, except for the graminoid prairie and halophytic herbaceous prairie. This finding was similar to (Abrahamson, 1984b) where species recovered at different rates after fire due to factors like interactions with fire severity, nutrient content, and/or species moisture content (Ruiz et al., 2013). I also saw that the halophytic herbaceous prairie was adapted to low water level sites and the graminoid prairie to moderate water level sites (average below 0.25m), which suggest that species in these sits will have slower growth rates and therefore longer recovery times when water levels are high.

Recovery time increased with increase in water level two years post-fire. Because NDVI is positively correlated with vegetation cover (De Keersmaecker et al., 2014), productivity (Jobbágy et al., 2002) and leaf area index (Carlson & Ripley, 1997; Wang et al., 2005); the NDVI-based recovery indices might show a general pattern of fast recovery immediately after the fire and a gradual decrease in response speed (typically after 6–12 months), as observed by (Ireland & Petropoulos, 2015). João et al., (2018) found vegetation type and structure, and climate had significant effects on the early post-fire recovery whereas the resilience to maintain pre-fire structure and function determines more of the longer-term recovery process (Jill F. Johnstone et al., 2016). Besides hydrological conditions, fire and nutrient availability are known to be major influences on wetland ecosystems in the Everglades wetlands (Childers et al., 2003; Doren et al., 1997; Lockwood et al., 2003).

I hypothesized that recovery time would be shorter for areas experiencing frequent fires (Kinoshita & Hogue, 2011). However, Everglades wetlands exhibited this effect only after the total number of fires in an area exceeded 7. Only graminoid prairie and sawgrass marsh experienced more than 7 fires whereas other ecosystems experienced less than 7 fires from 1948 to 2019. The interval between fires is determined by the fuel accumulations where long intervals result in intense fires (Hobbs & Gimingham, 1984; Rothermel & Philpot, 1973; Van Wilgen, 1982) and short fire intervals reduce fuel biomass leading to less severe fires (Dodge, 1972; Van Wilgen & Kruger, 1981). The intervals observed in Everglades wetlands (+10 years) over the study period was not sufficient to maintain the effects of fire on recovery. Fire in these wetlands is essential to prevent hardwood dominance (Wade et al., 1980) and woody encroachment has been identified as a major issue across this landscape (Loveless, 1959; Platt & Gottschalk, 2001; Sah, Ross, Snyder, et al., 2010; Wade et al., 1980). Woody encroachment is an indication that the +10 years fire return interval currently observed in many areas is not sufficient to maintain short stature fire adapted wetlands.

A major assumption of this work is that ecosystems are adapted to regimes they recover quickly from (Maher & Baum, 2013; Ramón Vallejo et al., 2012; Spalding et al., 2014). Everglades wetlands show variation in recovery time, suggesting that the level of adaptation to fire differs and that fire return intervals between these wetlands also differ. Recovery occurs within 3 years in graminoid and marl prairies (L. H. Gunderson & Loftus, 1993; Wade et al., 1980). Unlike sawgrass, graminoid, and marl prairies, halophytes are more tolerant of altered hydrology, salinity stress and extreme temperatures than of fires (Bose et al., 2014; Kumari et al., 2015). Ground fires have been shown to increase cattail abundance (Ponzio et al., 2004; Wade et al., 1980) in areas dominated by sawgrass marsh as well as the graminoid marsh (Knickerbocker et al., 2009; Wade et al., 1980).

Though not taken into consideration in this study, fire severity also plays an important role in ecosystem recovery. In the presence of maximum fuel loads and dry conditions, fires can burn severely and consume a substantial portion of the above ground vegetation, affect soils and may even consume below ground vegetation (Rein et al., 2008; Wade et al., 1980). Such fires lead to changes in the vegetative community structure (Hayes & Robeson, 2011; João et al., 2018). The probability of experiencing high severity fire decreases as the total number of fires in an area increases because of the reduced fuel loads (Halofsky et al., 2020). A 10% increase in water level for Everglades wetlands showed an increase in the post-fire recovery time for the majority of wetland ecosystems, with the exception of the sawgrass marl prairie, which exhibited a slight decrease. Although climate change projections indicate that precipitation/water levels may increase or decrease (Flower et al., 2017, 2019; Maliva et al., 2021; Obeysekera et al., 2015), the Comprehensive Everglades Restoration Plan is expected to increase water levels throughout the park, in addition to recovery times. Therefore, fire regimes are going to change as well. Developing tools to estimate how and where recovery rates are changing will be essential for adaptive management programs.

Globally, fire management has been identified as a critical area of research for the preservation of ecosystems (Brian Beckage et al., 2005; Cole & Landres, 1996). The understanding of effective fire management and an effective fire regime under changing conditions is required to aid the successful restoration of the Everglades ecosystems (Brian Beckage et al., 2005; Lockwood et al., 2003). Although the proper management of fire adapted ecosystems must include a fire program that supports the management of wildfire and prescribed fire (Cissel et al., 1999; Williams, 1995), the management should consider recovery rates of vegetation. In the Everglades where both hydrology and fire are important drivers of ecosystem structure and function (Lockwood et al., 2003; Loveless, 1959), it is essential to understand the interaction between hydrology and fire to manage for an uncertain future.

Patterns in post-fire recovery can be used to evaluate resilience, which is the system's ability to adapt and return to pre-disturbance regime (L. Gunderson & Light, 2006) and the system's ability to maintain its fundamental functions after disturbance without differential changes in its internal properties (ecological resilience) (Holling, 1973; Virah-Sawmy et al., 2009). Patterns in post-fire recovery are a useful determinant of the effectiveness of managed fire regimes (Brewer & Platt, 1994; Platt et al., 1988; Safford & Van de Water, 2014).

**Study Limitations**

This study used NDVI as a proxy for post-fire vegetation recovery by assessing green biomass (Díaz-Delgado et al., 1998; Christine E. McMichael et al., 2006; Riaño et al., 2002; Röder et al., 2008). NDVI normalizes the difference between red and near-infrared bands of the satellite making it sensitive to the vegetation photosynthetic radiation (Gitelson et al., 1996). However, problems like atmospheric and soil reflectance are associated with NDVI (C. E. McMichael et al., 2004; Wittenberg et al., 2007) as NDVI simply is the measurement of the reflectance. Relating ground and satellite observations can increase the interpretability of satellite observations (Hudak et al., 2007), as well as provide a means for applying spatially limited ground observations across landscapes. This study would be further improved from an updated vegetation map, inclusion of fire severity, and higher resolution information on water level at the time of fire.

## Conclusion

Changes in climate have made it more important for us to understand the post-fire recovery of wetland ecosystems. This study provides important insights on key controls on post-fire recovery in wetland Ecosystems. Water level appears to be more important in post-fire recovery than fire history. This result may indicate that the fire regimes for these systems have been severely disrupted. Regardless, changes in hydrology in the future in response to climate change or CERP is likely to further alter fire regimes and an adaptive management strategy is key for maintaining these fire adapted ecosystems.

References


Abrahamson, W. G. (1984a). Post-fire recovery of Florida Lake Wales ridge vegetation. *American Journal of Botany*, *71*(1), 9–21.

Abrahamson, W. G. (1984b). SPECIES RESPONSES TO FIRE ON THE FLORIDA LAKE WALES RIDGE. *American Journal of Botany*, *71*(1), 35–43.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723.

Arévalo, J. R., Fernández-Lugo, S., Naranjo-Cigala, A., Salas, M., Ruíz, R., Ramos, R., & Moreno, M. (2014). Post-fire recovery of an endemic Canarian pine forest. *International Journal of Wildland Fire*, *23*(3), 403–409.

Asner, G. P., & Lobell, D. B. (2000). A Biogeophysical Approach for Automated SWIR Unmixing of Soils and Vegetation. *Remote Sensing of Environment*, *74*(1), 99–112.

Bassett, T. J., Landis, D. A., & Brudvig, L. A. (2020). Effects of experimental prescribed fire and tree thinning on oak savanna understory plant communities and ecosystem structure. *Forest Ecology and Management*, *464*, 118047.

Beckage, B., & Platt, W. J. (2003). Predicting severe wildfire years in the Florida Everglades. *Frontiers in Ecology and the Environment*, *1*(5), 235–239.

Beckage, B., Platt, W. J., & Panko, B. (2005). A Climate-Based Approach to the Restoration of Fire-Dependent Ecosystems. *Restoration Ecology*, *13*(3), 429–431.

Beckage, B., Platt, W. J., Slocum, M. G., & Panko, B. (2003). Influence of the El Nino Southern Oscillation on fire regimes in the Florida Everglades. *Ecology*. http://onlinelibrary.wiley.com/doi/10.1890/02-0183/full

Boelman, N. T., Stieglitz, M., Rueth, H. M., Sommerkorn, M., Griffin, K. L., Shaver, G. R., & Gamon, J. A. (2003). Response of NDVI, biomass, and ecosystem gas exchange to long-term warming and fertilization in wet sedge tundra. *Oecologia*, *135*(3), 414–421.

Bose, J., Rodrigo-Moreno, A., & Shabala, S. (2014). ROS homeostasis in halophytes in the context of salinity stress tolerance. *Journal of Experimental Botany*, *65*(5), 1241–1257.

Box, E. O., Holben, B. N., & Kalb, V. (1989). Accuracy of the AVHRR vegetation index as a predictor of biomass, primary productivity and net CO2 flux. *Vegetation*, *80*(2), 71–89.

Braswell, A. E., May, C. A., & Cherry, J. A. (2019). Spatially-dependent patterns of plant recovery and sediment accretion following multiple disturbances in a Gulf Coast tidal marsh. *Wetlands Ecology and Management*, *27*(2), 377–392.

Brewer, J. S., & Platt, W. J. (1994). Effects of fire season and soil fertility on clonal growth in a pyrophilic forb, Pityopsis graminifolia (Asteraceae). *American Journal of Botany*, *81*(7), 805–814.

Brown, J. K. (1975). Fire cycles and community dynamics in lodgepole pine forests. *The Bark Beetles, Fuels, and Fire Bibliography*, 2.

Brown, L. N., Rosencranz, J. A., Willis, K. S., Ambrose, R. F., & MacDonald, G. M. (2020). Multiple Stressors Influence Salt Marsh Recovery after a Spring Fire at Mugu Lagoon, CA. *Wetlands*, *40*(4), 757–769.

Bucher, M., Buchanan, B., Fulks, W., Kelly, J., Bates, P., Kauffman, G., Simon, S., Mohr, H., & Others. (2014). The Southern Blue Ridge Fire Learning Network: A collaborative partnership to restore fire-adapted ecosystems and build resilient forests and communities in the southern Blue Ridge. *Proceedings, Wildland Fire in the Appalachians: Discussions among Managers and Scientists. General Technical Report SRS-199, USDA Forest Service, Southern Research Station, Asheville, NC*, 193–200.

Butterfield, H. S., & Malmström, C. M. (2009). The effects of phenology on indirect measures of aboveground biomass in annual grasses. *International Journal of Remote Sensing*, *30*(12), 3133–3146.

Carlson, T. N., & Ripley, D. A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment*, *62*(3), 241–252.

Chang, C.-R. (1996). Ecosystem responses to fire and variations in fire regimes. *Sierra Nevada Ecosystem Project: Final Report to Congress*, *2*, 1071–1099.

Childers, D. L., Doren, R. F., Jones, R., Noe, G. B., Rugge, M., & Scinto, L. J. (2003). Decadal change in vegetation and soil phosphorus pattern across the Everglades landscape. *Journal of Environmental Quality*, *32*(1), 344–362.

Chmura, D. J., Anderson, P. D., Howe, G. T., Harrington, C. A., Halofsky, J. E., Peterson, D. L., Shaw, D. C., & Brad St. Clair, J. (2011). Forest responses to climate change in the northwestern United States: Ecophysiological foundations for adaptive management. *Forest Ecology and Management*, *261*(7), 1121–1142.

Chu, T., & Guo, X. (2013). Remote Sensing Techniques in Monitoring Post-Fire Effects and Patterns of Forest Recovery in Boreal Forest Regions: A Review. *Remote Sensing*, *6*(1), 470–520.

Cissel, J. H., Swanson, F. J., & Weisberg, P. J. (1999). Landscape management using historical fire regimes: Blue River, Oregon. *Ecological Applications: A Publication of the Ecological Society of America*, *9*(4), 1217–1231.

Clarkson, B. R. (1997). Vegetation recovery following fire in two Waikato peatlands at Whangamarino and Moanatuatua, New Zealand. *New Zealand Journal of Botany*, *35*(2), 167–179.

Clemente, R. H., Cerrillo, R. M. N., & Gitas, I. Z. (2009). Monitoring post-fire regeneration in Mediterranean ecosystems by employing multitemporal satellite imagery. *International Journal of Wildland Fire*, *18*(6), 648–658.

Cole, D. N., & Landres, P. B. (1996). Threats to Wilderness Ecosystems: Impacts and Research Needs. *Ecological Applications: A Publication of the Ecological Society of America*, *6*(1), 168–184.

Cook, D. G., & Hayes, M. P. (n.d.). *[No title]*. Retrieved August 31, 2021, from https://www.researchgate.net/profile/Marc-Hayes-2/publication/346807031_Post-fire_species_composition_and_abundance_of_a_lentic-_breeding_amphibian_assemblage_case_study_of_Ledson_Marsh/links/5fd1035292851c00f862003b/Post-fire-species-composition-and-abundance-of-a-lentic-breeding-amphibian-assemblage-case-study-of-Ledson-Marsh.pdf

Davis, S., & Ogden, J. C. (1994). Synthesis: Vegetation Pattern and Process in the Everglades Ecosystem. In *Everglades* (pp. 473–486). CRC Press.

DeAngelis, D. L., Gross, L. J., Huston, M. A., Wolff, W. F., Fleming, D. M., Comiskey, E. J., & Sylvester, S. M. (1998). Landscape Modeling for Everglades Ecosystem Restoration. *Ecosystems*, *1*(1), 64–75.

DeAngelis, D. L., & Waterhouse, J. C. (1987). Equilibrium and Nonequilibrium Concepts in Ecological Models. *Ecological Monographs*, *57*(1), 1–21.

De Keersmaecker, W., Lhermitte, S., Tits, L., Honnay, O., Somers, B., & Coppin, P. (2014). Linking NDVI and climate-based ecosystem stability with land cover in Europe. *2014 IEEE Geoscience and Remote Sensing Symposium*, 3938–3940.

Díaz-Delgado, R., Salvador, R., & Pons, X. (1998). Monitoring of plant community regeneration after fire by remote sensing. *Fire Management and Landscape Ecology*, 315–324.

Díaz-Delgado, R., & Pons, X. (2001). Spatial patterns of forest fires in Catalonia (NE of Spain) along the period 1975--1995: analysis of vegetation recovery after fire. *Forest Ecology and Management*, *147*(1), 67–74.

Dodge, M. (1972). Forest fuel accumulation--a growing problem. *Science*, *177*(4044), 139–142.

Doren, R. F., Armentano, T. V., Whiteaker, L. D., & Jones, R. D. (1997). Marsh vegetation patterns and soil phosphorus gradients in the Everglades ecosystem. *Aquatic Botany*, *56*(2), 145–163.

Doren, R. F., Platt, W. J., & Whiteaker, L. D. (1993). Density and size structure of slash pine stands in the everglades region of south Florida. *Forest Ecology and Management*, *59*(3), 295–311.

Drewa, P. B., Platt, W. J., & Moser, E. B. (2002). Fire effects on resprouting of shrubs in headwaters of southeastern Longleaf pine savannas. *Ecology*, *83*(3), 755–767.

Drobyshev, I., Bergeron, Y., & Girardin, M. P. (2017). Strong gradients in forest sensitivity to climate change revealed by dynamics of forest fire cycles in the post Little Ice Age era. *Journal of*. https://doi.org/10.1002/2017JG003826

Egler, F. E. (1952). Southeast saline Everglades vegetation, Florida and its management. *Vegetation*, *3*(4), 213–265.

Eloy, L., A. Bilbao, B., Mistry, J., & Schmidt, I. B. (2019). From fire suppression to fire management: Advances and resistances to changes in fire policy in the savannas of Brazil and Venezuela. *The Geographical Journal*, *185*(1), 10–22.

Enright, N. J., Fontaine, J. B., Lamont, B. B., Miller, B. P., & Westcott, V. C. (2014). Resistance and resilience to changing climate and fire regime depend on plant functional traits. *The Journal of Ecology*, *102*(6), 1572–1581.

Escuin, S., Navarro, R., & Fernández, P. (2008). Fire severity assessment by using NBR (Normalized Burn Ratio) and NDVI (Normalized Difference Vegetation Index) derived from LANDSAT TM/ETM images. *International Journal of Remote Sensing*, *29*(4), 1053–1073.

Flower, H., Rains, M., Carl Fitz, H., Orem, W., Newman, S., Osborne, T. Z., Ramesh Reddy, K., & Obeysekera, J. (2019). Shifting Ground: Landscape-Scale Modeling of Biogeochemical Processes under Climate Change in the Florida Everglades. *Environmental Management*, *64*(4), 416–435.

Flower, H., Rains, M., & Fitz, C. (2017). Visioning the Future: Scenarios Modeling of the Florida Coastal Everglades. *Environmental Management*, *60*(5), 989–1009.

Ford, C. R., Minor, E. S., & Fox, G. A. (2010). Long-term effects of fire and fire-return interval on population structure and growth of longleaf pine (Pinus palustris). *Canadian Journal of Forest Research. Journal Canadien de La Recherche Forestiere*, *40*(7), 1410–1420.

Foster, B. L., & Tilman, D. (2000). Dynamic and Static Views of Succession: Testing the Descriptive Power of the Chronosequence Approach. *Plant Ecology*, *146*(1), 1–10.

Franklin, J., Serra-Diaz, J. M., Syphard, A. D., & Regan, H. M. (2016). Global change and terrestrial plant community dynamics. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(14), 3725–3734.

Freeman, K. W., Girma, K., Arnall, D. B., Mullen, R. W., Martin, K. L., Teal, R. K., & Raun, W. R. (2007). By-Plant Prediction of Corn Forage Biomass and Nitrogen Uptake at

Various Growth Stages Using Remote Sensing and Plant Height. *Agronomy Journal*, *99*, 530–536.

Frolking, S., Palace, M. W., Clark, D. B., Chambers, J. Q., Shugart, H. H., & Hurtt, G. C. (2009). Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. *Journal of Geophysical Research*, *114*(G2), G00E02.

Gill, A. M. (1975). Fire and The Australian Flora: A Review. *Australian Forestry*, *38*(1), 4–25.

Gitelson, A. A., Kaufman, Y. J., & Merzlyak, M. N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment*, *58*(3), 289–298.

Glitzenstein, J. S., Platt, W. J., & Streng, D. R. (1995). Effects of Fire Regime and Habitat on Tree Dynamics in North Florida Longleaf Pine Savannas. *Ecological Monographs*, *65*(4), 441–476.

Goetz, S. J., Fiske, G. J., & Bunn, A. G. (2006). Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada. *Remote Sensing of Environment*, *101*, 352.

Goswami, S., Gamon, J., Vargas, S., & Tweedie, C. (2015). *Relationships of NDVI, Biomass, and Leaf Area Index (LAI) for six key plant species in Barrow, Alaska* (No. e1127). PeerJ PrePrints. https://doi.org/10.7287/peerj.preprints.913v1

Graham, R. T., & Jain, T. B. (2005). Ponderosa pine ecosystems. *In: Ritchie, Martin W.; Maguire, Douglas A.; Youngblood, Andrew, Tech. Coordinators. Proceedings of the Symposium on Ponderosa Pine: Issues, Trends, and Management, 2004 October 18-21, Klamath Falls, OR. Gen. Tech. Rep PSW-GTR-198. Albany, CA: Pacific Southwest Research Station, Forest Service, US Department of Agriculture: 1-32.*, *198*, 1–32.

Gunderson, L. H., & Loftus, W. F. (1993). The Everglades. *Biodiversity of the Southeastern United States: Lowland Terrestrial Communities*, 199–255.

Gunderson, L., & Light, S. S. (2006). Adaptive management and adaptive governance in the everglades ecosystem. *Policy Sciences*, *39*(4), 323–334.

Hagenbo, A., Hadden, D., Clemmensen, K. E., Grelle, A., Manzoni, S., Mölder, M., Ekblad, A., & Fransson, P. (2019). Carbon use efficiency of mycorrhizal fungal mycelium increases during the growing season but decreases with forest age across a Pinus sylvestris chronosequence. *The Journal of Ecology*, *107*(6), 2808–2822.

Halofsky, J. E., Peterson, D. L., & Harvey, B. J. (2020). Changing wildfire, changing forests: the effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA. *Fire Ecology*, *16*(1), 4.

Hanzelka, J., Horká, P., & Reif, J. (2019). Spatial gradients in country-level population trends of European birds. *Diversity & Distributions*, *25*(10), 1527–1536.

Hastie, T., & Tibshirani, R. (1987). Generalized Additive Models: Some Applications. *Journal of the American Statistical Association*, *82*(398), 371–386.

Hayes, J. J., & Robeson, S. M. (2011). Relationships between fire severity and post-fire landscape pattern following a large mixed-severity fire in the Valle Vidal, New Mexico, USA. *Forest Ecology and Management*, *261*(8), 1392–1400.

Heines, B., Lenhart, S., & Sims, C. (2019). Balancing Prevention and Suppression of Forest Fires with Fuel Management as a Stock. In G. Yin & Q. Zhang (Eds.), *Modeling, Stochastic Control, Optimization, and Applications* (pp. 235–259). Springer International Publishing.

Hernández-Clemente, R., Cerrillo, R. M. N., Hernández-Bermejo, J. E., Royo, S. E., & Kasimis, N. A. (2009). Analysis of postfire vegetation dynamics of Mediterranean shrub species based on terrestrial and NDVI data. *Environmental Management*, *43*(5), 876–887.

Herndon, A., Gunderson, L., & Stenberg, J. (1991). Sawgrass (Cladium jamaicense) survival in a regime of fire and flooding. *Wetlands*, *11*(1), 17–28.

Hijmans, R. J., van Etten, J., Mattiuzzi, M., Sumner, M., Greenberg, J. A., Lamigueiro, O. P., Bevan, A., Racine, E. B., & Shortridge, A. (2013). *Raster package in R*. Version. https://rspatial.org/raster/pkg/RasterPackage.pdf

Hobbs, R. J., & Gimingham, C. H. (1984). Studies on Fire in Scottish Heathland Communities: I. Fire Characteristics. *The Journal of Ecology*, *72*(1), 223–240.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*. https://www.annualreviews.org/doi/abs/10.1146/annurev.es.04.110173.000245?j

Hope, A., Tague, C., & Clark, R. (2007). Characterizing post-fire vegetation recovery of California chaparral using TM/ETM+ time-series data. *International Journal of Remote Sensing*, *28*(6), 1339–1354.

Hudak, A., Morgan, P., Bobbitt, M., Smith, A., Lewis, S., Lentile, L., Robichaud, P., Clark, J., & McKinley, R. (2007). The relationship of multispectral satellite imagery to immediate fire effects. Fire Ecology 3 (1): 64-90. *Fire Ecology Special Issue Vol*, *3*, 66.

Ireland, G., & Petropoulos, G. P. (2015). Exploring the relationships between post-fire vegetation regeneration dynamics, topography and burn severity: A case study from the Montane Cordillera Ecozones of Western Canada. *Applied Geography* , *56*, 232–248.

Jazebi, S., de León, F., & Nelson, A. (2020). Review of Wildfire Management Techniques—Part I: Causes, Prevention, Detection, Suppression, and Data Analytics. *IEEE Transactions on Power Delivery*, *35*(1), 430–439.

João, T., João, G., Bruno, M., & João, H. (2018). Indicator-based assessment of post-fire recovery dynamics using satellite NDVI time-series. *Ecological Indicators*, *89*, 199–212.

Jobbágy, E. G., Sala, O. E., & Paruelo, J. M. (2002). Patterns and controls of primary production in the Patagonian steppe: A remote sensing approach. *Ecology*, *83*(2), 307–319.

John, A., Fuentes, H. R., & George, F. (2021). Characterization of the water retention curves of Everglades wetland soils. *Geoderma*, *381*, 114724.

Johnstone, J. F., Allen, C. D., Franklin, J. F., Frelich, L. E., Harvey, B. J., Higuera, P. E., Mack, M. C., Meentemeyer, R. K., Metz, M. R., Perry, G. L. W., Schoennagel, T., & Turner, M. G. (2016). Changing disturbance regimes, ecological memory, and forest resilience. *Frontiers in Ecology and the Environment*, *14*(7), 369–378.

Johnstone, J. F., & Chapin, F. S. (2006). Fire Interval Effects on Successional Trajectory in Boreal Forests of Northwest Canada. *Ecosystems*, *9*(2), 268–277.

Johnston, J. D., Dunn, C. J., & Vernon, M. J. (2019). Tree traits influence response to fire severity in the western Oregon Cascades, USA. *Forest Ecology and Management*, *433*, 690–698.

Jones, J. W. (2001). Image and in situ data integration to derive sawgrass density for surface flow modelling in the Everglades, Florida, USA. *IAH S Pubi . No*, *267*. http://hydrologie.org/redbooks/a267/iahs_267_0507.pdf

Jones, J. W., Hall, A. E., Foster, A. M., & Smith, T. J. (2013). Wetland Fire Scar Monitoring and Analysis Using Archival Landsat Data for the Everglades. *Fire Ecology*, *9*(1), 133–150.

Kennedy, R. E., Andréfouët, S., Cohen, W. B., Gómez, C., Griffiths, P., Hais, M., Healey, S. P., Helmer, E. H., Hostert, P., Lyons, M. B., & Others. (2014). Bringing an ecological view of change to Landsat-based remote sensing. *Frontiers in Ecology and the Environment*, *12*(6), 339–346.

Kinoshita, A. M., & Hogue, T. S. (2011). Spatial and temporal controls on post-fire hydrologic recovery in Southern California watersheds. *Catena*, *87*(2), 240–252.

Knickerbocker, C. M., Leitholf, S., Stephens, E. L., Keellings, D. J., Laird, H., Anderson, C. J. R., Fauth, J. E., & Quintana-Ascencio, P. F. (2009). Tree Encroachment of A Sawgrass (Cladium jamaicense) Marsh within an Increasingly Urbanized Ecosystem. *Natural Areas Journal*, *29*(1), 15–26.

Koch, M. S., Coronado, C., Miller, M. W., Rudnick, D. T., Stabenau, E., Halley, R. B., & Sklar, F. H. (2015). Climate change projected effects on coastal foundation communities of the Greater Everglades using a 2060 scenario: need for a new management paradigm. *Environmental Management*, *55*(4), 857–875.

Kumari, A., Das, P., Parida, A. K., & Agarwal, P. K. (2015). Proteomics, metabolomics, and ionomics perspectives of salinity tolerance in halophytes. *Frontiers in Plant Science*, *6*, 537.

La Puma, D. A., Lockwood, J. L., & Davis, M. J. (2007). Endangered species management requires a new look at the benefit of fire: The Cape Sable seaside sparrow in the Everglades ecosystem. *Biological Conservation*, *136*(3), 398–407.

Laris, P. (2002). Burning the Seasonal Mosaic: Preventative Burning Strategies in the Wooded Savanna of Southern Mali. *Human Ecology, 30*(2), 155–186.

Lehmann, A. (1998). GIS modeling of submerged macrophyte distribution using Generalized Additive Models. *Plant Ecology*, *139*(1), 113–124.

Lentile, L. B., Holden, Z. A., Smith, A. M. S., Falkowski, M. J., Hudak, A. T., Morgan, P., Lewis, S. A., Gessler, P. E., & Benson, N. C. (2006). Remote sensing techniques to assess active fire characteristics and post-fire effects. *Www.publish.csiro.au/journals/ijwf International Journal of Wildland Fire*, *15*, 319–345.

Levine, J., de Valpine, P., & Battles, J. (2021). Generalized additive models reveal among-stand variation in live tree biomass equations. *Canadian Journal of Forest Research. Journal Canadien de La Recherche Forestiere*, *51*(4), 546–564.

Li, S., & Li, M. S. (2012). Package “FNN.” *Entropy* , *17*(3). http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.303.9509&rep=rep1&type=pdf

Littell, R. C., Milliken, G. A., Stroup, W. W., Wolfinger, R. D., & Schabenberger, O. (1996). *SAS system for mixed models* (Vol. 633). SAS institute Cary, NC.

Liu, L., Yang, X., Zhou, H., Liu, S., Zhou, L., Li, X., Yang, J., Han, X., & Wu, J. (2018). Evaluating the utility of solar-induced chlorophyll fluorescence for drought monitoring by comparison with NDVI derived from wheat canopy. *The Science of the Total Environment*, *625*, 1208–1217.

Lockwood, J. L., Ross, M. S., & Sah, J. P. (2003). Smoke on the water: the interplay of fire and water flow on Everglades restoration. *Frontiers in Ecology and the Environment*, *1*(9), 462–468.

Loveless, C. M. (1959). A study of the vegetation in the Florida Everglades. *Ecology*, *40*(1), 2–9.

Mahajan, U., & Bundel, B. R. (2016). Drones for normalized difference vegetation index (NDVI), to estimate crop health for precision agriculture: A cheaper alternative for spatial satellite sensors. *Proceedings of the International Conference on Innovative Research in Agriculture, Food Science, Forestry, Horticulture, Aquaculture, Animal Sciences, Biodiversity, Ecological Sciences and Climate Change (AFHABEC-2016), Delhi, India*, *22*. https://www.researchgate.net/profile/Ujjwal-Mahajan-

2/publication/312497233_Drones_for_Normalized_Difference_Vegetation_Index_NDVI_to_Estimate_Crop_Health_for_Precision_Agriculture_A_Cheaper_Alternative_for_Spatial_Satellite_Sensors/links/587f60c808aed3826af6cc80/Drones-for-Normalized-Difference-Vegetation-Index-NDVI-to-Estimate-Crop-Health-for-Precision-Agriculture-A-Cheaper-Alternative-for-Spatial-Satellite-Sensors.pdf

Maher, T. M., & Baum, S. D. (2013). Adaptation to and Recovery from Global Catastrophe. *Sustainability: Science Practice and Policy*, *5*(4), 1461–1479.

Malak, D. A., & Pausas, J. G. (2006). Fire regime and post-fire Normalized Difference Vegetation Index changes in the eastern Iberian peninsula (Mediterranean basin). *International Journal of Wildland Fire*, *15*(3), 407–413.

Maliva, R. G., Manahan, W. S., & Missimer, T. M. (2021). Climate change and water supply: governance and adaptation planning in Florida. *Water Policy*, *23*(3), 521–536.

Malone, S. L., Barr, J., Fuentes, J. D., Oberbauer, S. F., Staudhammer, C. L., Gaiser, E. E., & Starr, G. (2016). Sensitivity to Low-Temperature Events: Implications for CO2 Dynamics in Subtropical Coastal Ecosystems. *Wetlands*, *36*(5), 957–967.

Marks-Block, T., & Tripp, W. (2021). Facilitating Prescribed Fire in Northern California through Indigenous Governance and Interagency Partnerships. *Fire*, *4*(3), 37.

Mateo-Sanchis, A., Piles, M., Muñoz-Marí, J., Adsuara, J. E., Pérez-Suay, A., & Camps-Valls, G. (2019). Synergistic integration of optical and microwave satellite data for crop yield estimation. *Remote Sensing of the Environment*, *234*, 111460.

McAtee, J. W., Scifres, C. J., & Drawe, D. L. (1979). Improvement of gulf cordgrass range with burning or shredding. *Rangeland Ecology & Management/Journal of Range Management Archives*, *32*(5), 372–375.

McMichael, C. E., Hope, A. S., & Loaiciga, H. A. (2006). Distributed hydrological modelling in California semi-arid shrublands: MIKE SHE model calibration and uncertainty estimation. *Journal of Hydrology*, *317*(3), 307–324.

McMichael, C. E., Hope, A. S., Roberts, D. A., & Anaya, M. R. (2004). Post-fire recovery of leaf area index in California chaparral: A remote sensing-chronosequence approach. *International Journal of Remote Sensing*, *25*(21), 4743–4760.

Melillos, G., & Hadjimitsis, D. G. (2020). Using simple ratio (SR) vegetation index to detect deep man-made infrastructures in Cyprus. *Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XXV*, *11418*, 105–113.

Meng, R., Dennison, P. E., Huang, C., Moritz, M. A., & D'Antonio, C. (2015). Effects of fire severity and post-fire climate on short-term vegetation recovery of mixed-conifer and red fir forests in the Sierra Nevada Mountains of California. *Remote Sensing of Environment*, *171*, 311–325.

Miller, J. D., & Yool, S. R. (2002). Mapping forest post-fire canopy consumption in several overstory types using multi-temporal Landsat TM and ETM data. *Remote Sensing of Environment*, *82*(2), 481–496.

Milon, J. W., & Scrogin, D. (2006). Latent preferences and valuation of wetland ecosystem restoration. *Ecological Economics: The Journal of the International Society for Ecological Economics*, *56*(2), 162–175.

Mistry, J., Berardi, A., Andrade, V., Krahô, T., Krahô, P., & Leonardos, O. (2005). Indigenous Fire Management in the cerrado of Brazil: The Case of the Krahô of Tocantíns. *Human Ecology*, *33*(3), 365–386.

Moritz, M. A., Morais, M. E., Summerell, L. A., Carlson, J. M., & Doyle, J. (2005). Wildfires, complexity, and highly optimized tolerance. *Proceedings of the National Academy of Sciences of the United States of America*, *102*(50), 17912–17917.

Obeysekera, J., Barnes, J., & Nungesser, M. (2015). Climate sensitivity runs and regional hydrologic modeling for predicting the response of the greater Florida Everglades ecosystem to climate change. *Environmental Management*, *55*(4), 749–762.

Oyama, Y., Matsushita, B., & Fukushima, T. (2015). Distinguishing surface cyanobacterial blooms and aquatic macrophytes using Landsat/TM and ETM+ shortwave infrared bands. *Remote Sensing of Environment*, *157*, 35–47.

Platt, W. J., Beckage, B., Doren, R. F., & Slater, H. H. (2002). Interactions of large-scale disturbances: prior fire regimes and hurricane mortality of savanna pines. *Ecology*, *83*(6), 1566–1572.

Platt, W. J., Evans, G. W., & Davis, M. M. (1988). Effects of fire season on flowering of forbs and shrubs in longleaf pine forests. *Oecologia*, *76*(3), 353–363.

Platt, W. J., & Gottschalk, R. M. (2001). Effects of exotic grasses on potential fine fuel loads in the groundcover of south Florida slash pine savannas. *International Journal of Wildland Fire*, *10*(2), 155–159.

Poggio, L., Gimona, A., & Brewer, M. J. (2013). Regional scale mapping of soil properties and their uncertainty with a large number of satellite-derived covariates. *Geoderma*, *209-210*, 1–14.

Ponzio, K. J., Miller, S. J., & Lee, M. A. (2004). Long-term effects of prescribed fire on Cladium jamaicense crantz and Typha domingensis pers. densities. *Wetlands Ecology and Management*, *12*(2), 123–133.

Puerta-Piñero, C., Espelta, J. M., Sánchez-Humanes, B., Rodrigo, A., Coll, L., & Brotons, L. (2012). History matters: Previous land use changes determine post-fire vegetation recovery in forested Mediterranean landscapes. *Forest Ecology and Management*, *279*, 121–127.

Pyne, S. J. (2016). *Florida: A Fire Survey*. University of Arizona Press.

Ramón Vallejo, V., Smanis, A., Chirino, E., Fuentes, D., Valdecantos, A., & Vilagrosa, A. (2012). Perspectives in dryland restoration: approaches for climate change adaptation. *New Forests*, *43*(5), 561–579.

R Core Team. (2014). *The R project for statistical computing*. www.r-project.org

Rein, G., Cleaver, N., Ashton, C., Pironi, P., & Torero, J. L. (2008). The severity of smouldering peat fires and damage to the forest soil. *Catena*, *74*(3), 304–309.

Riaño, D., Chuvieco, E., Ustin, S., Zomer, R., Dennison, P., Roberts, D., & Salas, J. (2002). Assessment of vegetation regeneration after fire through multitemporal analysis of AVIRIS images in the Santa Monica Mountains. *Remote Sensing of Environment*, *79*(1), 60–71.

Röder, A., Hill, J., Duguy, B., Alloza, J. A., & Vallejo, R. (2008). Using long time series of Landsat data to monitor fire events and post-fire dynamics and identify driving factors. A case study in the Ayora region (eastern Spain). *Remote Sensing of Environment*, *112*(1), 259–273.

Ross, M. S., Sah, J. P., Ruiz, P. L., Jones, D. T., Cooley, H., Travieso, R., Tobias, F., Snyder, J. R., & Hagyari, D. (2006). *Effect of Hydrologic Restoration on the Habitat of The Cape Sable Seaside Sparrow, Annual Report of 2004-2005*. https://digitalcommons.fiu.edu/sercrp/85/

Ross, P. M., Harvey, K., Vecchio, E. M., & Beckers, D. (2019). Impact of fire and the recovery of molluscs in south-east Australian salt marsh. *Ecological Management & Restoration*, *20*(2), 126–135.

Rothermel, R. C., & Philpot, C. W. (1973). Predicting Changes in Chaparral Flammability. *Journal of Forestry*, *71*(10), 640–643.

Rowell, A., & Moore, P. F. (2000). *Global review of forest fires*. Citeseer.

Ruiz, P. L., Sah, J. P., Ross, M. S., & Spitzig, A. A. (2013). Tree Island Response to Fire and Flooding in the Short-Hydroperiod Marl Prairie Grasslands of the Florida Everglades, USA. *Fire Ecology*, *9*(1), 38–54.

Ryu, J.-H., Han, K.-S., Hong, S., Park, N.-W., Lee, Y.-W., & Cho, J. (2018). Satellite-Based Evaluation of the Post-Fire Recovery Process from the Worst Forest Fire Case in South Korea. *Remote Sensing*, *10*(6), 918.

Safford, H. D., & Van de Water, K. M. (2014). Using fire return interval departure (FRID) analysis to map spatial and temporal changes in fire frequency on national forest lands in California. *Res. Pap. PSW-RP-266. Albany, CA: US Department of Agriculture, Forest Service, Pacific Southwest Research Station. 59 P*, *266*. https://www.fs.usda.gov/treesearch/pubs/45476

Sah, J. P., Ross, M. S., Snyder, J. R., & Ogurcak, D. E. (2010). Tree Mortality following Prescribed Fire and a Storm Surge Event in Slash Pine (Pinus elliottii var. densa) Forests in the Florida Keys, USA. *International Journal of Forestry Research*, *2010*. https://doi.org/10.1155/2010/204795

Sah, J. P., Ross, M. S., & Stofella, S. (2010). *Developing a Data-Driven Classification of South Florida Plant Communities*. https://digitalcommons.fiu.edu/sercrp/93/

Salvatico, N. (2019). *Fire and soil in Florida: A review*. soils.ifas.ufl.edu. https://soils.ifas.ufl.edu/media/soilsifasufledu/sws-main-site/pdf/technical-papers/Salvatico_Nicole_Twelve_Month_Embargo_Period.pdf

Schroeder, T. A., Cohen, W. B., & Yang, Z. (2007). Patterns of forest regrowth following clearcutting in western Oregon as determined from a Landsat time-series. *Forest Ecology and Management*, *243*(2), 259–273.

Shuman, J. K., Foster, A. C., Shugart, H. H., Hoffman-Hall, A., Krylov, A., Loboda, T., Ershov, D., & Sochilova, E. (2017). Fire disturbance and climate change: implications for Russian forests. *Environmental Research Letters: ERL [Web Site]*, *12*(3), 035003.

Slapcinsky, J. L., Gordon, D. R., & Menges, E. S. (2010). Responses of Rare Plant Species to Fire in Florida's Pyrogenic Communities. *Natural Areas Journal*, *30*(1), 4–19.

Slocum, M. G., Platt, W. J., Beckage, B., Panko, B., & Lushine, J. B. (2007). Decoupling Natural and Anthropogenic Fire Regimes: a Case Study in Everglades National Park, Florida. *Natural Areas Journal*, *27*(1), 41–55.

Slocum, M. G., Platt, W. J., & Cooley, H. C. (2003). Effects of Differences in Prescribed Fire Regimes on Patchiness and Intensity of Fires in Subtropical Savannas of Everglades National Park, Florida. *Restoration Ecology*, *11*(1), 91–102.

Smith, A. M. S., Lentile, L. B., Hudak, A. T., & Morgan, P. (2007). Evaluation of linear spectral unmixing and ΔNBR for predicting post-fire recovery in a North American ponderosa pine forest. *International Journal of Remote Sensing*, *28*(22), 5159–5166.

Smith, T. J., III, Foster, A. M., & Jones, J. W. (2015). *Fire History of Everglades National Park and Big Cypress National Preserve, southern Florida*. pubs.usgs.gov. https://pubs.usgs.gov/of/2015/1034/

Snyder, J. R. (1991). *FIRE REGIMES IN SUBTROPICAL SOUTH FWRIDA*. https://talltimbers.org/wp-content/uploads/2018/09/303-Snyder1991_op.pdf

Spalding, M. D., Ruffo, S., Lacambra, C., Meliane, I., Hale, L. Z., Shepard, C. C., & Beck, M. W. (2014). The role of ecosystems in coastal protection: Adapting to climate change and coastal hazards. *Ocean & Coastal Management*, *90*, 50–57.

Tepley, A. J., Thomann, E., Veblen, T. T., Perry, G. L. W., Holz, A., Paritsis, J., Kitzberger, T., & Anderson-Teixeira, K. J. (2018). Influences of fire-vegetation feedbacks and post-fire recovery rates on forest landscape vulnerability to altered fire regimes. *The Journal of Ecology*, *106*(5), 1925–1940.

Tepley, A. J., Thompson, J. R., Epstein, H. E., & Anderson-Teixeira, K. J. (2017). Vulnerability to forest loss through altered postfire recovery dynamics in a warming climate in the Klamath Mountains. *Global Change Biology*, *23*(10), 4117–4132.

Tian, F., Wigneron, J.-P., Ciais, P., Chave, J., Ogée, J., Peñuelas, J., Ræbild, A., Domec, J.-C., Tong, X., Brandt, M., Mialon, A., Rodriguez-Fernandez, N., Tagesson, T., Al-Yaari, A., Kerr, Y., Chen, C., Myneni, R. B., Zhang, W., Ardö, J., & Fensholt, R. (2018). Coupling of ecosystem-scale plant water storage and leaf phenology observed by satellite. *Nature Ecology & Evolution*, *2*(9), 1428–1435.

Van Wilgen, B. W. (1982). Some Effects of Post-Fire Age on the Above-Ground Plant Biomass of Fynbos (Macchia) Vegetation in South Africa. *The Journal of Ecology*, *70*(1), 217–225.

Van Wilgen, B. W., & Kruger, F. J. (1981). Observations on the effects of fire in mountain fynbos at Zachariashoek, Paarl. *South African Journal of Botany: Official Journal of the South African Association of Botanists = Suid-Afrikaanse Tydskrif Vir Plantkunde: Amptelike Tydskrif van Die Suid-Afrikaanse Genootskap van Plantkundiges*. https://agris.fao.org/agris-search/search.do?recordID=US201302797938

Viedma, O., Meliá, J., Segarra, D., & Garcia-Haro, J. (1997). Modeling rates of ecosystem recovery after fires by using landsat TM data. *Remote Sensing of Environment*, *61*(3), 383–398.

Virah-Sawmy, M., Gillson, L., & Willis, K. J. (2009). How does spatial heterogeneity influence resilience to climatic changes? Ecological dynamics in southeast Madagascar. *Ecological Monographs*, *79*(4), 557–574.

Wade, D., Ewel, J., & Hofstetter, R. (1980). *Fire in south Florida ecosystems* (Vol. 017). U.S. Department of Agriculture, Forest Service, Southeastern Forest Experiment Station. https://doi.org/10.2737/se-gtr-17

Walker, D. A., Auerbach, N. A., & Shippert, M. M. (1995). NDVI, biomass, and landscape evolution of glaciated terrain in northern Alaska. *The Polar Record*, *31*(177), 169–178.

Wang, Q., Adiku, S., Tenhunen, J., & Granier, A. (2005). On the relationship of NDVI with leaf area index in a deciduous forest site. *Remote Sensing of Environment*, *94*(2), 244–255.

Wessels, K. J., Prince, S. D., Zambatis, N., MacFadyen, S., Frost, P. E., & Van Zyl, D. (2006). Relationship between herbaceous biomass and 1-km2 Advanced Very High Resolution Radiometer (AVHRR) NDVI in Kruger National Park, South Africa. *International Journal of Remote Sensing*, *27*(5), 951–973.

Westerling, A. L., & Bryant, B. P. (2008). Climate change and wildfire in California. *Climatic Change*, *87*(1), 231–249.

Williams, J. T. (1995). The role of fire in ecosystem management. *In: Weise, David R.; Martin, Robert E., Technical Coordinators. The Biswell Symposium: Fire Issues and Solutions in Urban Interface and Wildland Ecosystems; February 15-17, 1994; Walnut Creek, California. Gen. Tech. Rep. PSW-GTR-158. Albany, CA: Pacific Southwest Research Station, Forest Service, US Department of Agriculture; P. 139-140, 158*. https://www.fs.usda.gov/treesearch/pubs/27430

Wilson, A. M., Latimer, A. M., & Silander, J. A. (2015). Climatic controls on ecosystem resilience: Postfire regeneration in the Cape Floristic Region of South Africa. *Proceedings of the National Academy of Sciences*, *112*(29), 9058–9063.

Wittenberg, L., Malkinson, D., Beeri, O., Halutzy, A., & Tesler, N. (2007). Spatial and temporal patterns of vegetation recovery following sequences of forest fires in a Mediterranean landscape, Mt. Carmel Israel. *Catena*, *71*(1), 76–83.

Wood, S. N. (2004). Stable and Efficient Multiple Smoothing Parameter Estimation for Generalized Additive Models. *Journal of the American Statistical Association*, *99*(467), 673–686.

Wood, S. N. (2006). Generalized additive models: an introduction with R. Chapman and Hall/CRC. *Texts Stat. Sci.*, *67*, 391.

Wood, S., & Wood, M. S. (2015). Package “mgcv.” *R Package Version*, *1*, 29.