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- NDVI of wetland reduces for extreme hydrologic events
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- Wetlands recovery faster for drought impacts than hurricanes'

Correspondence to:
A. Singh,
Arvind.Singh@ucf.edu

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Resilience of coastal wetlands to extreme hydrologic events in Apalachicola Bay

Subrina Tahsin[1], Stephen C. Medeiros[1], and Arvind Singh[1]

[1] Department of Civil, Environmental and Construction Engineering, University of Central Florida, Orlando, Florida, USA

Abstract Extreme hydrologic events such as hurricanes and droughts continuously threaten wetlands which provide key ecosystem services in coastal areas. The recovery time for vegetation after impact from these extreme events can be highly variable depending on the hazard type and intensity. Apalachicola Bay in Florida is home to a rich variety of saltwater and freshwater wetlands and is subject to a wide range of hydrologic hazards. Using spatiotemporal changes in Landsat-based empirical vegetation indices, we investigate the impact of hurricane and drought on both freshwater and saltwater wetlands from year 2000 to 2015 in Apalachicola Bay. Our results indicate that saltwater wetlands are more resilient than freshwater wetlands and suggest that in response to hurricanes, the coastal wetlands took almost a year to recover, while recovery following a drought period was observed after only a month.

1. Introduction

Hurricanes and droughts are extreme hydrologic events that cause enormous ecosystem perturbation. Such extreme events occur frequently, and the corresponding change in the ecosystem can persist for varying lengths of time [*Yang et al.*, 2008]. Ecosystem resilience can be understood by investigating the effects of these extreme events, including their persistence through time [*Switzer et al.*, 2006]. The impacts of hurricanes or droughts on coastal wetlands can vary depending on the wetland type, i.e., freshwater forested wetland (FFW), freshwater emergent wetland (FEW), and saltwater wetland (SWW) ecosystems [*Mo et al.*, 2015].

Hurricanes cause physical damage to wetlands by high-velocity winds and flows as well as saltwater flood submergence [*Stanturf et al.*, 2007]. The effect of even a short duration of saltwater storm surge inundation can have devastating effects on freshwater wetlands (FWW; representing combined FFW and FEW) [*Conner*, 1995; *Stanturf et al.*, 2007], while SWW are more tolerant of elevated salinity. Depending on other hydrological factors such as rainfall [*Huang et al.*, 2014] and groundwater recharge, the salinity levels in the surface water can remain elevated for months following a hurricane [*Steyer et al.*, 2007], with freshening not occurring for as long as 1 year [*Chabreck and Palmisano*, 1973]. While hurricanes bring storm surge and large amounts of rainfall in a relatively short time period, droughts are another natural hazard that can last from months to years [*McKee et al.*, 2004; *Florida Climate Center, Florida State University*, 2014].

Remote sensing can be used to detect and track the wetland dynamics at the local and regional scales. Multiple satellite sensors such as Landsat [*Han et al.*, 2015; *Tian et al.*, 2015], Formosat [*Tian et al.*, 2015], Moderate Resolution Imaging Spectroradiometer [*Landmann et al.*, 2013], and advanced very high resolution radiometer (AVHRR) [*Ramsey et al.*, 1997] can provide data for this application; these data are often processed into vegetation indices. These vegetation indices can be obtained from sensor reflectance data in spectral bands that are responsive to vegetation characteristics. The most well known is the normalized difference vegetation index (NDVI), and it is frequently used to identify and characterize vegetated areas.

NDVI has been shown to be highly correlated with parameters associated with plant health and productivity such as vegetation density and cover [*Wiegand et al.*, 1974; *Ormsby et al.*, 1987], vegetation dynamics over time [*Wellens*, 1997], vegetation classification [*Evans and Geerken*, 2006], and many other related aspects [*Wang and Tenhunen*, 2004; *Pettorelli et al.*, 2011]. For example, *Ramsey et al.* [1997] analyzed forest damage caused by Hurricane Andrew in 1992 using NDVI derived from AVHRR multitemporal images. Their main finding was the utility of regionally averaged NDVI change as an indicator of damage severity. *Wang* [2012] identified severe mangrove forest damage, based on NDVI time series, after Hurricanes Katrina and Wilma that took 2 to 3 years to recover. Numerous other posthurricane studies also focused on damage to coastal mangrove forests, using Landsat imagery, owing to hurricane winds [*Middleton*, 2009, 2016] and storm surge [*Conner*, 1995; *Stanturf et al.*, 2007].

Although the effects of wind, surge duration, and salinity on wetlands ecosystem have been investigated previously, the differences between effects on FWW and SWW remains largely uninvestigated. A very limited number of studies have attempted to untangle the relative impacts of drought on SWW and FWW ecosystems [*Ji and Peters*, 2003; *Lloret et al.*, 2007]. In fact, it has been argued that drought coupled with sea level rise could cause sudden dieback of salt marshes resulting in rapid, widespread mortality of vulnerable coastal species *McKee et al.* [2004]. To the above aim, using Apalachicola Bay as the study area, in this paper we investigate the stress on SWW, FFW, and FEW ecosystems due to hurricanes and droughts using an NDVI.

2. Study Area and Data Description

2.1. Study Area: Apalachicola Bay

Apalachicola Bay in the Florida Panhandle is located in a high-risk hurricane zone and has received significant research attention in the past few decades [see, e.g., *Huang and Jones*, 2001; *Leitman et al.*, 2003; *Darst and Light*, 2007; *Edmiston et al.*, 2008; *Huang et al.*, 2014]. It is home to rich natural resources including oyster beds and a vast array of marshes. In fact, Apalachicola oysters account for 90% of Florida's oyster production and are a major economic driver in the region [*Huang and Jones*, 2001]. The typical vegetation in the marshes around Apalachicola Bay is composed mainly of tall grass species, such as, *Spartina cynosuroides* (big cordgrass), *Spartina alterniflora* (smooth cordgrass), and *Juncus roemerianus* (black needlerush) [*Livingston et al.*, 1974]. The lower marshes of the Apalachicola River are primarily composed of natural wetlands with few anthropogenic disturbances. The minimal human influence on wetlands for this region makes it an ideal candidate for assessing the impacts of extreme hydrologic events on wetland recovery.

The National Oceanic and Atmospheric Administration (NOAA) Coastal Change Analysis Program (C-CAP) classified wetlands along the eastern seaboard and Gulf coasts of the United States and is considered a reliable, integrated digital database that enables researchers to track development in coastal regions [*Klemas et al.*, 1993]. The C-CAP classifications are created from a combination of satellite imagery and fieldwork. C-CAP classifies land cover types into 22 standardized classes that include forested areas, urban areas, and wetlands. This study used the C-CAP classification as basis and resampled it to three wetland types — SWW, FFW, and FEW — based on salinity and height of vegetation. The resampling of SWW included all estuarine forested, emergent, and scrub wetlands; FFW represented freshwater forested wetlands; and FEW included freshwater emergent and scrub wetlands [*Klemas et al.*, 1993]. An elevated salinity gradient (>0.5%) characterized SWW, while low-salinity gradient (<0.5%) characterized FWW. The red box in Figure 1a represents the domain for the current study.

2.2. Hurricane and Drought Years: A Brief History

A number of significant hydrologic events impacted Aplachicola Bay from year 2000 to 2015 [*National Weather Service*, 2016]. Heavy rainfall in 2003 caused flooding in several counties adjacent to the study area and led to the declaring local state of emergency. Due to the localized intense rainfall, local rivers swelled to reach severe flood stages. Hurricane Frances made its second landfall near St. Marks, FL, in August 2004, after crossing the Florida peninsula and weakening to a tropical storm; however, storm surge impacts were still significant along the Florida Panhandle [*National Hurricane Center*, 2004]. Tropical Storm Bonnie and Hurricane Ivan also made landfalls in 2004 to the west of Apalachicola Bay with Ivan causing up to 3.65 m of surge along the coast in Apalachicola Bay [*Edmiston et al.*, 2008]. In July 2005, Hurricane Dennis caused a 2.74 m surge on the barrier islands protecting Apalachicola Bay [*Beven*, 2005]. Tropical Storm Claudette hit the Florida Panhandle in 2009; although the intensity of this storm was comparatively less than those in preceding years, Apalachicola Bay received significant surge as it was positioned in the northeast quadrant of the storm. Note that the eastern half of a hurricane, and the northeast quadrant in particular, contains the most intense winds, and therefore, storm surge due to the wind speed and the hurricane's forward velocity act in the same direction, compounding each other. Hurricane Isaac in 2012 caused 1.0 m of surge in Apalachicola Bay. A significant drought occurred in the Apalachicola River watershed from May 2011 to June 2012. Lastly, and most recently, Hurricane Andrea made landfall in Florida's big bend region in 2013. Storm surge inundation level in Apalachicola Bay during that time was as much as 1.7 m above mean sea level [*Beven*, 2013].

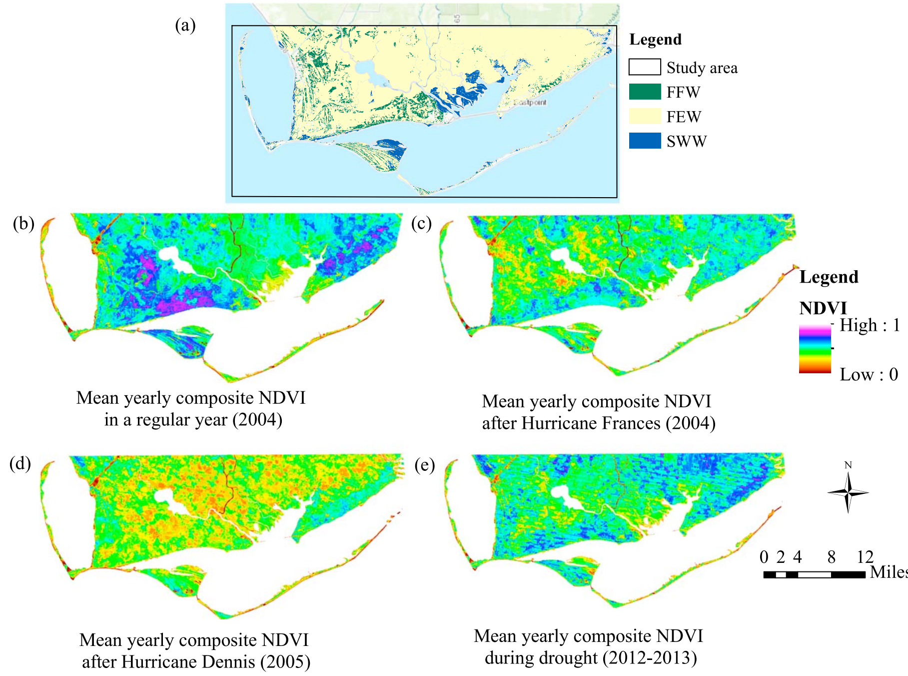

Figure 1. (a) Apalachicola Bay and lower river marshes, derived from C-CAP wetland classification (2006), used as the study area. Freshwater Forested Wetland (FFW) represents 8.36% of the total area, Freshwater Emergent Wetland (FEW) represents 73.77%, and Saltwater Wetland (SWW) represents 6.83%. The majority of "Other" is agricultural land, whereas the blue color represents open water. Yearly averaged NDVI values at the Apalachicola Bay (b) for a regular year and (c–e) for different extreme hydrologic events. The study area included a total of 1098 × 2035 pixels of each cell size 30 m × 30 m. In Figures 1b–1e water bodies are represented as white, whereas the blue color in the maps corresponds to healthy wetlands (vigorous, dense green biomass), and yellow to red color corresponds to stressed wetlands (less to no vegetation).

2.3. Data Collection and Preprocessing

NDVI is a vegetation index derived from optical remote sensors and represents the reflective and absorptive characteristics of vegetation in the red and near-infrared bands of the electromagnetic spectrum and conveys valuable information relating to vegetation properties on the land surface [*Justice et al.*, 1985; *Myneni et al.*, 1997, 1998]. The Landsat-derived composite multiband vegetation index imagery (processed to NDVI) was obtained from U.S. Geological Survey Earth Resources Observation and Science Center Science Processing Architecture (ESPA). Landsat visible (reflected light) bands in the spectrum of blue, green, red, near-infrared (NIR), and midinfrared have a ground resolution of 30 m and a revisit time of 16 day period. Landsat 5 was retired in 2013, and the orbital offset between Landsat 7 and Landsat 8 allows for an 8 day repeat cycle. Like other optical multispectral satellites, Landsat data can be contaminated by clouds and cloud shadows. ESPA provides standalone "cfmask" layers that account for atmospheric gases, aerosols, and clouds (including thin cirrus clouds). Landsat 7 imagery required additional processing for stripe removal due to the documented failure of the scan line corrector in 2003. From the Landsat imagery, the NIR and RED spectral bands were used to compute NDVI as follows:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})}, \tag{1}$$

where NIR and RED stand for the spectral reflectance measurements acquired in the near-infrared and visible regions, respectively. NDVI values range from 0.0 (i.e., no vegetation) to 1.0 (vigorous and dense green biomass) [*Lane et al.*, 2014]. Note that the NDVI can be negative for water bodies; however, areas of open water from the C-CAP data were excluded from our study area.

NDVI time series data have been used in the past to detect long-term land use/land cover changes [e.g., *Pirotti et al.*, 2014]. However, the utility of NDVI to detect vegetation stress in wetlands, as discussed above, is often limited by poor quality data resulting from atmospheric and other effects. For instance, only 134 months of data were directly usable out of the 192 months of the study time period. Studies typically assume that the NDVI time series follows seasonal cycles of growth and decline of vegetation and that clouds or poor atmospheric conditions usually depress observed NDVI values [*Chen et al.*, 2004]. Previous studies have suggested several methods to construct NDVI time series by filling gaps and smoothing out noise in the time series data. Overcoming missing or poor quality NDVI data has been primarily accomplished through spatial [*Myneni et al.*, 1998; *Lim and Kafatos*, 2002; *Potter et al.*, 2003] or temporal [*Justice et al.*, 1985; *DeFries et al.*, 1995; *Loveland et al.*, 2000] averaging/filtering. A particular method that has proven to be acceptable for constructing a high-quality NDVI time series is based on the Savitzky-Golay Filter [*Savitzky and Golay*, 1964; *Chen et al.*, 2004; *Luo et al.*, 2005] and is used in this study for both interpolating missing data and discounting negative and anomalously low NDVI values.

3. Results and Discussion

NDVI variability under extreme natural events. Flooding associated with storm surge was observed as a result of the major hurricanes Dennis, Frances, Claudette, and Andrea that made landfalls in the last decade in Apalachicola Bay. Figures 1b–1e show NDVI variability during a nonevent (regular) year (Figure 1b), after Hurricane Frances (Figure 1c), after Hurricane Dennis (Figure 1d), and during drought (Figure 1e). While 2002 was a nonevent year, 2004 and 2005 had significant storm surge from Hurricanes Frances and Dennis and 2012 was classified as a drought year. The overall mean annual NDVI values in the study area were found to be 0.52, 0.49, 0.34, and 0.41 in 2002, 2004, 2005, and 2012, respectively. Recall that low NDVI values represent wetland with less vigor and a high NDVI represents wetlands with more vigor; a decrease in the mean NDVI in 2004 and especially 2005 suggests that the most stress (loss of vigor) for wetlands occurred due to repeated hurricane strikes. Drought also impacted the average NDVI range in 2012–2013 (see Figure 1e where the color map changes from blue (seen in a regular year) to yellowgreen, indicating wetland stress).

The NDVI changes observed in Figures 1b–1e for different years can be further quantified by computing a threshold value of NDVI that can be used to compare differences in NDVI within a given year. To determine the threshold, we computed the 25th percentile (value representing 25% of the data and here this or smaller values indicate highly stressed wetlands) of the pixelized NDVI for each regular (nonevent) year from the total length of data considered in this study. We then took the average of all 25th percentiles from each year and considered it as the threshold value. We computed the threshold based on the three individual types of wetlands (i.e., FFW, FEW, and SWW) and compared the results with the combined overall wetland (Table 1). The average computed threshold values for the three different types of wetlands were very similar to the overall wetland threshold value. For example, the threshold value for FFW, FEW, SWW, and overall wetland were 0.66, 0.64, 0.6, and 0.6, respectively. Note that there were extreme events in 2003, 2004, 2005, 2009, 2011, 2012, and therefore, those years were excluded from the threshold calculation. Also note that although the later years after the extreme event year may be impacted by the extreme event, we only exclude the year of the extreme event from our calculation of the threshold as the impact is not as strong as in the current year of the event. To determine the yearly changes over the study area, we identified wetland areas that had NDVI values below the threshold. As shown in Table 1, 2003, 2004, 2005, 2006, 2009, 2011, and 2012 had higher percentages of wetland area below the threshold. In particular, 2005 had a significant percentage (~95%) of wetland that was below the threshold, indicating that the most stressed period for the study area wetland was 2005 due to chronic impacts that extended a year beyond the extreme events. There was also a single event in 2009 and then the drought in 2011 that impacted the wetlands but to a lesser degree than 2005.

As discussed in the section 1, hurricane and drought impacts on coastal wetlands can vary depending on the wetland types; thus, a better way to quantify wetland stress is based on wetland type. The box plots in Figure 2 show yearly NDVI for the three different wetland types studied here. As shown in Figure 2, SWW has a consistently lower range of NDVI (median value 0.37, Figure 2a) than FFW (median value 0.56, Figure 2b) and FEW (median value 0.51, Figure 2c) during the study period. The average 25th percentile NDVIs are also shown in Figure 2 for the three different wetland types, for comparison. The largest reduction occurred in 2005 following the 2004–2005 back to back hurricane landfalls (also evident from average annual NDVI for overall study area, shown in Figures 1b–1e and discussed above); NDVI was found to be the lowest during that period and the median values were 0.15 for SWW and 0.20 for both FFW and FEW. Other significant reductions were observed in 2009 after Hurricane Claudette and in 2013 during the drought period. We postulate that this significant NDVI reduction in FFW areas can be attributed to partial to total uprooting of the wetland and major foliage damage.

Table 1. Percentage of Wetland Areas Below the Computed Threshold[a]

Year	FFW 25th Percentile NDVI	FFW % Wetland Area Below Threshold	FEW 25th Percentile NDVI	FEW % Wetland Area Below Threshold	SWW 25th Percentile NDVI	SWW % Wetland Area Below Threshold	Overall Wetland 25th Percentile NDVI	Overall Wetland % Wetland Area Below Threshold
2000	0.60	51.56	0.65	58.21	0.58	62.62	0.62	58.09
2001	0.69	51.63	0.70	56.52	0.66	58.59	0.67	54.35
2002	0.67	59.13	0.67	58.84	0.61	57.41	0.54	56.58
2003	0.61	67.47	0.52	63.06	0.49	61.52	0.63	64.56
2004	0.52	75.54	0.44	74.83	0.41	73.01	0.61	76.61
2005	0.50	93.51	0.39	92.64	0.37	85.69	0.52	94.84
2006	0.69	69.47	0.56	69.63	0.54	64.41	0.54	70.46
2007	0.53	62.26	0.57	62.40	0.52	57.72	0.61	63.14
2008	0.65	59.17	0.66	59.30	0.60	54.86	0.66	56.62
2009	0.54	70.55	0.52	70.71	0.48	65.41	0.64	67.51
2010	0.73	57.89	0.66	58.03	0.63	59.23	0.62	55.4
2011	0.52	64.72	0.56	63.82	0.50	66.21	0.67	65.64
2012	0.53	68.13	0.54	67.18	0.51	69.70	0.54	69.1
2013	0.70	60.02	0.57	61.43	0.54	59.24	0.63	60.87
2014	0.71	56.20	0.70	57.53	0.67	55.47	0.61	53.78
2015	0.68	58.75	0.65	60.14	0.62	57.99	0.52	56.22

[a]The 25th percentiles of NDVI for each year and different types of wetlands as well as for overall wetland are also provided for comparison. The threshold was computed by averaging yearly 25th percentiles of NDVI based on different categories (FFW, FEW, SWW, and overall wetland).

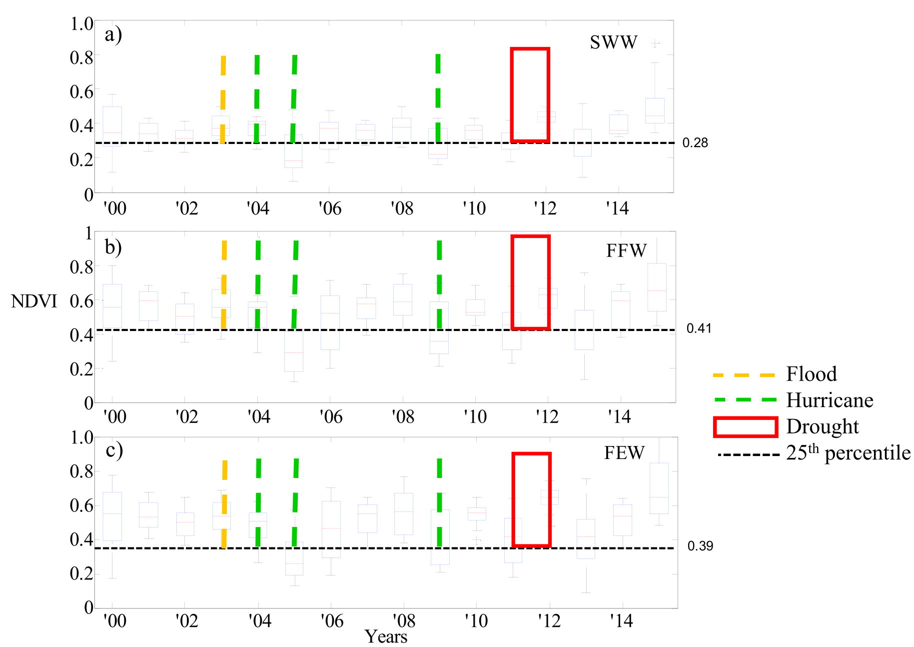

Figure 2. Box plots of the computed NDVI for the Freshwater Forested Wetland (FFW), Freshwater Emergent Wetland (FEW), and Saltwater Wetland (SWW) of the Apalachicola Bay. Horizontal line (black line) in each box indicates median demarkating 50% data either above or below the median whereas the dashed (black) horizontal line represents the average 25th percentile (value provided on the right-hand side of the panels) for different types of the wetlands studied here. Upper and lower quartiles of the box refer to 25% and 75% of the data from the median, whereas upper and lower whiskers indicate maximum and minimum values, respectively, excluding outliers. Plus symbols indicate outliers in the data. The dashed vertical lines represent flood and hurricanes, whereas column represents drought.

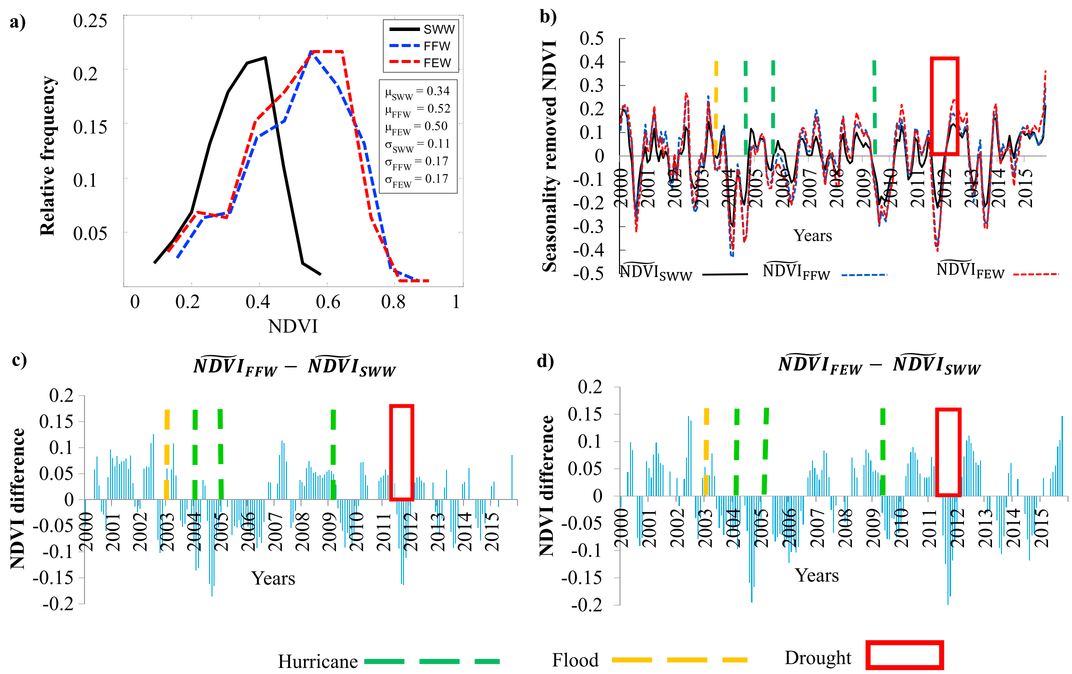

Figure 3. (a) Probability density function (pdf) of the NDVI and (b) seasonality removed time series of NDVI for the three different wetland types used in this study. The box inset in Figure 3a indicates the mean and the standard deviation of the NDVI, showing low values in the case of SWW, suggesting SWW to be more resilient than FFW and FEW, whereas in Figure 3b similar trends (as seen in Figure 2) of significant NDVI changes are observed. Time series of seasonality removed NDVI (shown in Figure 3b) differences between (c) FFW and SWW, and (d) FEW and SWW. The dashed vertical lines represent flood and hurricanes, whereas column represents drought. Note that in Figures 3c and 3d, the very small NDVI differences $\sim\pm0.014$ were excluded from the time series as a treatment to the instrumental or data collection error.

SWW versus FWW resilience to extreme natural events. Figure 3a shows the comparison between the probability density functions (pdfs) of NDVI for SWW, FFW, and FEW that include all the extreme events observed at Apalachicola Bay over the study period. As expected, the pdf of NDVI for the SWW is shifted to the left (low mean NDVI value) compared to FFW and FEW. In addition, the range of the NDVI (as well as the spread around the mean, see inset box in Figure 3a for the first- and second-order statistics) for SWW is narrower ($\sim$0.5) compared to FFW ($\sim$0.70) and FEW ($\sim$0.78) (see Figure 3a). We hypothesize that the narrow pdf of SWW indicates more stability over the study period which we interpret as an indicator of resilience, implying that the SWW demonstrated more resilience to hydrologic hazards over the study period.

In addition to changing mean and variance, NDVI time series of Apalachicola Bay wetlands showed significant seasonality for all three types. In general, seasonality describes the phenological dynamics of terrestrial ecosystems that reflect the response of the atmosphere to inter and intra-annual dynamics of the hydrologic regimes and Earth's climate [*White et al.*, 1997; *Schwartz*, 1999]. Specifically, seasonality of vegetation refers to the regular periodic change that a terrestrial ecosystem experiences. In order to further quantify the impacts of hurricanes and droughts, the seasonality in the Apalachicola Bay wetlands was filtered out, where seasonally adjusted $\widetilde{\mathrm{NDVI}}_{IJ}$ can be expressed as

$$\widetilde{\mathrm{NDVI}}_{IJ} = \mathrm{NDVI}_{IJ} - \mathrm{NDVI}'_{I}; \quad (2)$$

NDVI_{IJ} represents NDVI in month I of year J and NDVI'_{I} is the mean NDVI over the time series for month I. Here we use seasonally adjusted NDVI time series to indicate abnormal NDVI peaks or drops.

Figure 3b shows the time series plot of the three types of wetlands in Apalachicola Bay after filtering out the seasonality. Note that any sharp drop or peak in the time series (Figure 3b) can be attributed to some anomaly such as an extreme event. Figure 3b reveals significant NDVI reductions associated with major hurricane years 2004 and 2005. Hurricane Claudette is associated with the second highest NDVI reduction in 2009 since the

Table 2. Categorical Representation of Average Frequency of Anomalous (Negative NDVI Difference) Months Corresponding to Selected Years Based On Figure 3c (Left) and Based on Figure 3d (Right)[a]

	$\widetilde{\text{NDVI}}_{FFW} - \widetilde{\text{NDVI}}_{SWW}$ (Figure 3c)		$\widetilde{\text{NDVI}}_{FFW} - \widetilde{\text{NDVI}}_{SWW}$ (Figure 3d)	
	E-NDVI-C (in current year)	R-NDVI-C (in current year)	E-NDVI-C (in current year)	R-NDVI-C (in current year)
E-NDVI-C (in past year)	9.0 [−1.99]	8.33 [−1.89]	9.0 [−2.23]	7.00 [−1.92]
R-NDVI-C (in past year)	8.0 [−1.63]	5.33 [−0.70]	8.33 [−1.87]	5.83 [−0.78]

[a]The values in brackets represent the strength (sum of magnitudes over a year) of anomalous NDVI difference as well as the frequency of events.

second highest drop in Figure 3b is right after 2009. Another significant reduction was observed during the 2012–2013 period when a drought occurred concurrently with Hurricane Andrea.

Recovery after hurricanes and droughts. As discussed above, the ability of a wetland to recover after a hydrologic event depends on both the type of event and the type of wetland. SWW showed distinctly different responses compared to FWW for both hurricane and drought events. Figures 3c and 3d show the differences in seasonally adjusted NDVI between FFW and SWW (Figure 3c) and FEW and SWW (Figure 3d) over the 16 year study period. The period from 2004 to 2006 shows a negative difference indicating that the SWW NDVI was greater than that of FWW. In nonevent years, the FWW have consistently higher NDVI than SWW; therefore, a positive difference is considered normal. Along that line, a negative difference indicates an anomaly (or anomalies) and wetland damage by submergence, flattening, or uproot/extraction of the wetland vegetation by the hurricanes and their associated storm surge. Furthermore, a negative NDVI difference also suggests that the NDVI of SWW changed relatively less than that of FWW during that time period, indicating that when subjected to the same events, SWW is more resilient. The situation was exacerbated as a result of the repeated hurricanes in 2004 and 2005.

To further quantify the impact of extreme events, we identified the number of depressed (negative NDVI difference) months with respect to the occurrence of an extreme event. Table 2 shows the categorical representation of the average number of negative months within the corresponding year that has been impacted by an extreme event (as well as for nonevent case) in previous year, current year, vice versa, or both. We divided the categories of year by “Event-based anomalous NDVI change (E-NDVI-C)” and “Regular NDVI change (R-NDVI-C).” For the regular (nonevent) years we computed anomalous NDVI change for the 12 calendar months (January–December) of a year. For the event-based year, we considered year start time as the month when the extreme event occurred and the end time as 12 months from the start time. Table 2 shows that longer duration of anomalous NDVI change occurs when there is event in both past and current year (upper left cells in Table 2), whereas shorter duration occurs when there is no past or current event (bottom right cells in Table 2), for both the cases shown in Figures 3c and 3d. This is also confirmed by the sum of the magnitudes of anomalous NDVI, representing strength as well as repetition of events (larger magnitude correspond to stronger and more frequent events), shown in the brackets in Table 2.

Figures 3c and 3d also indicate that after 2005 hurricane year, the anomalous negative differences revert back to regular positive difference after approximately 1 year. However, in 2012 the difference remains negative during the drought period (lasting approximately 6 months, indicated on both Figures 3c and 3d as a yellow rectangular column) but reverts to positive toward the end in approximately 1 month.

4. Summary and Conclusions

Hydrologic disturbances like hurricanes and droughts cause variable levels of damage in different wetland ecosystems. Exploratory analysis of the NDVI showed that Hurricanes Frances, Dennis, Claudette, and Isaac combined with a drought and Tropical Storm Andrea from 2000 to 2015 caused stresses in the coastal wetlands of Florida’s Big Bend Region. Using NDVI derived from Landsat 5, 7, and 8 as a proxy for wetland health, we showed that both response and recovery are influenced by the event (flood, hurricane, and drought) and wetland (freshwater or saltwater) types. Hurricanes and their associated saltwater storm surge caused NDVI reductions (i.e., stress) lasting a year or more before recovery was indicated in the NDVI trend for all wetland types. Recovery after droughts was much shorter, often beginning at the tail end of the drought and requiring only a month to recover to baseline levels. Freshwater wetlands were observed to be less resilient than saltwater wetlands to these hazards demonstrated by larger reductions in NDVI postevent.

The results of our study suggest that with increasing frequency and magnitude of extreme hydrologic events, as seen under current conditions and projections of climate change and sea level rise, the wetlands may become more vulnerable to change and can have significant ecological consequences. These methods and findings (e.g., utilizing vegetation stress and tolerance level) can be used to further improve the predictive capabilities that enhance monitoring, restoration and ecosystem service assessment efforts. Furthermore, our results can also be used to guide resource management practices such as additional freshwater releases from upstream controls after a surge event to help flush and freshen freshwater wetlands. For example, the Apalachicola River is controlled by the Jim Woodruff Dam at Lake Seminole near the Florida-Georgia border. Additionally, future research to investigate the spatial distribution or zonation of wetlands as a function of the hydrologic attributes of hurricanes (storm surge followed by hydrologic flood) would be worthwhile.

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