A New Picture of Fire Extent, Variability, and Drought Interaction in Prescribed Fire Landscapes: Insights From Florida Government Records

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Abstract Florida, United States, government records provide a new resource for studying fire in landscapes managed with prescribed fire. In Florida, most fire area (92%) is prescribed. Current satellite fire products, which underpin most air pollution emission inventories, detect only 25% of burned area, which alters airborne emissions and environmental impacts. Moreover, these satellite products can misdiagnose spatiotemporal variability of fires. Overall fire area in Florida decreases during drought conditions as prescribed fires are avoided, but satellite data do not reflect this pattern. This pattern is consistent with prescribed fire successfully reducing overall fire risk and damages. Human management of prescribed fires and fuels can, therefore, break the conventional link between drought and wildfire and play an important role in mitigating rising fire risk in a changing climate. These results likely apply in other regions of the world with similar fire regimes.

Plain Language Summary Wildfires and prescribed (i.e., controlled) fires are major sources of air pollution, greenhouse gases, and aerosols. Accurately estimating emissions from fires is critical to understanding their impacts on the environment and for designing sound fire management policies. We show that for Florida, United States, current satellites—the primary tools for identifying the extent, location, and time of these fires—dramatically underestimate the amount of fire, poorly identify its variation in space and time and can mischaracterize its relationship to drought. Using government records of fires, where available, can overcome some satellite shortcomings and provide a more accurate picture of fire extent and variability. In Florida, these records show that land area consumed by fire decreases during drought conditions due to less prescribed burning, but this pattern is not detected by satellites. Similar results may be expected in other parts of the world with similar fire characteristics, including agricultural and savanna regions of South America, Africa, Europe, and Asia. Using prescribed fire can help land managers adapt to climate-driven changes in wildfire activity.

1. Introduction

Vegetation fires are major sources of air pollutants and climate-forcing agents that degrade air quality and perturb regional and global climate (Al-Saadi et al., 2008; Bond et al., 2013; Brey et al., 2018; Dwyer et al., 2000; Kaufus et al., 2017; Randerson et al., 2012; Schroeder et al., 2016; Schultz et al., 2008; Soja et al., 2006, 2011; Tosca et al., 2010; van der Weer et al., 2010). Satellite observations are critical for quantifying fires and these impacts over most of the globe because ground-based fire reporting is uncommon and may be incomplete (Giglio et al., 2009; Hawbaker et al., 2017b; Soja et al., 2006, van der Weer et al., 2017; Wiedinmyer et al., 2010). Current satellite-based fire data sets have been evaluated extensively in landscapes dominated by large wildfires, where high-quality ground-based data are available, and generally perform well (Giglio et al., 2009; Randerson et al., 2012; Soja et al., 2006). However, small, prescribed fires contribute a large fraction of global fire area (Randerson et al., 2012). There are limited data to assess satellite performance in detecting these small fires (Amiro et al., 2001; Eidenshink et al., 2007; Kasischke et al., 2002; Laris, 2005; Marques et al., 2011; McCarty et al., 2009; NIFC, 2012; Parisien et al., 2006), but available information suggests that many of them are undetected (Al-Saadi et al., 2008; Hu et al., 2016; Larkin et al., 2014; Soja et al., 2009).

The southeastern United States burns more land area than the rest of the contiguous United States combined, and Florida accounts for over 10% of all fire area in the United States (EPA, 2016; Melvin, 2015;
Randerson et al., 2017). Most of these fires are prescribed fires for agriculture, forestry, conservation, and wildfire mitigation, and most of them are small, under 20 ha (0.02 km$^2$) in size. These small, prescribed fires are difficult to detect from space due to their short duration (hours or less), low intensity, and small size relative to the resolution of many satellite instruments (Giglio et al., 2003; Hawbaker et al., 2008; Hu et al., 2016; McCarty et al., 2009; Yokelson et al., 2011; Zhu et al., 2017). Unlike many other regions, however, records of these prescribed fires are available from Florida and some other U.S. state governments. The southeastern United States, therefore, provides a valuable test case for evaluating the performance of satellite-based fire products in detecting small and prescribed fires, which are widespread globally. Florida’s fires also occur on land cover types that host a large fraction of global fire activity (cropland, rangeland, savanna, grassland, shrubland, and temperate forest; van der Werf et al., 2017).

Satellite sensors can detect fires from thermal infrared signatures of active fires, changes in surface reflectance, which linger after the fire ceases, or both. All of these approaches face challenges in the southeastern United States. Active fires may be undetected if they burn under clouds, under tree canopies (typical of silvicultural fires), or when no satellite is overhead at the time of the fire (Cardoso et al., 2005; Giglio & Schroeder, 2007; Hawbaker et al., 2008; Prins et al., 1998). After a fire, vegetation can regrow quickly in the humid climate of the southeastern United States and obscure reflectance signatures of burned area before the next cloud-free satellite overpass (Picotte & Robertson, 2011). In Georgia, one common satellite product detected only 12% of fires and 60% of their total area (Hu et al., 2016, using Hazard Mapping System). For cropland fires, which are important in the southeastern United States and elsewhere, another product detected only 13% of burned area in Asia (Zhu et al., 2017, using Moderate Resolution Imaging Spectroradiometer, MODIS). Both of those studies, however, were limited to one year, so broader evaluations are needed.

Our work presents insights from a comprehensive data set of open biomass fires, meaning prescribed fires and wildfires, based on government reporting data in Florida. The data set provides a new tool for detecting patterns and trends of open fires and for evaluating remotely sensed products. These results can be applied to other regions of the world that have similar fire characteristics but lack comprehensive ground records. Government records avoid the fire detection challenges of remote sensing but require a critical assessment of their accuracy, which we do through comparisons to high-quality spatial fire records maintained by several land management organizations in Florida (sections 2 and 3). We show that the government data represent the magnitude and patterns of fires with similar or better accuracy to the common satellite-based methods in this region. We then examine the spatiotemporal patterns of prescribed fires and wildfires, including their relationship to climate variables (section 4), assess the ability of several common satellite-based fire products to detect these patterns, and discuss the other regions across the world that would likely have similar results to Florida (section 5).

2. Fire Data Sources and Methods

Prescribed fires in Florida are regulated by the Florida Forest Service (FFS), a state agency. Among the regulations, fire managers in Florida are required to request and obtain an open burn authorization (OBA) from FFS before starting a prescribed fire (Florida Statute, 2004). FFS generally approves OBA requests when weather conditions allow safe burning, provide good smoke dispersion, minimize smoke impacts on sensitive areas (roads, residential areas, hospitals, etc.), and when emergency response resources are available (Peterson et al., 2018). Approved OBAs are saved in a database that provides a comprehensive historical record of prescribed fire in Florida.

FFS provided us with anonymized OBA records of every authorized fire during 2004–2015. Each OBA includes a point location (latitude and longitude), date, burn area requested, and purpose (silviculture, agriculture, or land clearing for development). The FFS silviculture category includes commercial forestry and wildland management fires in forest, savanna, and shrubland. Pile burns are also recorded but not analyzed here. The accuracy of the FFS database requires evaluation because there are several potential sources of error. For example, location inaccuracies can occur when fire managers provide FFS with imprecise coordinates, a street address, or township and range within the Public Land Survey System, which FFS then converts to latitude and longitude. Area inaccuracies can occur when managers cancel a prescribed fire after an OBA is issued, or if part of the requested area contains ponds or other unburnable terrain. Since OBA requests are often approved in Florida, there is little incentive for land managers
to deliberately underestimate burn area or to avoid requesting permits. Therefore, our expectation is that
OBAs may overestimate burned area.

We evaluate the accuracy of the FFS database against comprehensive, high-quality prescribed fire records
from four large sites in Florida (Table S1 and Figure S1 in the supporting information): Tall Timbers
Research Station (TTRS, a private entity), Avon Park Air Force Range, Eglin Air Force Base, and Tyndall Air
Force Base. These four evaluation sites comprise 4% of Florida’s land area and 5% of the FFS-authorized fire
area during the study period. Each landowner’s fire records include the dates, areas, and fire perimeter poly-
gons of all prescribed fires that occurred during 2004–2015. The perimeters are either mapped by GPS after a
fire or are predetermined tracts that were previously mapped by GPS and are routinely burned as a block. At
TTRS, the burned area calculated from predetermined tracts differed from a subset of postfire measurements
using GPS by 5% or less, so both are sufficiently accurate for our purposes. We match each fire recorded by a
land manager with the nearest FFS OBA issued for the same day (Figure S2 and Text S1). The difference in
area and location between the OBA and known fire is considered error in the OBA database.

Wildfire information for Florida was obtained from the Fire Program Analysis Fire Occurrence Database (FPA
FOD; Short, 2014, 2017). The FPA FOD combines wildfire reports from federal, state, tribal, and local govern-
ments, making it the most comprehensive database available for Florida and the United States. Nevertheless,
it may omit some wildfires, including fires on private land that were managed entirely by private
fire crews.

We compare the Florida OBA and FPA FOD wildfire records to several widely used satellite data sets: the
National Oceanic and Atmospheric Administration Hazard Mapping System (HMS; National Oceanic and
Atmospheric Administration, 2017; Ruminer et al., 2006), Landsat Burned Area Essential Climate Variable
(BAEVCV version 1.1; Hawbaker et al., 2017a, 2017b), and the Global Fire Emissions Database (GFED version
4.1s; Randerson et al., 2017). HMS uses thermal detections of active fires from multiple satellites (1–4 km reso-
lution), while BAEVCV uses Landsat-series sensors (30-m resolution) to detect burn scars from changes in sur-
face reflectance. GFED combines both of these approaches using MODIS data (0.5-km sensor reported at
0.25°; Giglio et al., 2013; Randerson et al., 2012, 2017), classifying fires as small if they are detected by thermal
anomalies but not detected by the MODIS burned area product (MCD64A1; van der Werf et al., 2017). BAECV
and GFED both provide fire area, but HMS does not. For HMS, we assume an average size of 19 ha per fire
detection, which is the average size of HMS-detected fires in Georgia (Text S2; Hu et al., 2016). In addition,
we examine an agriculture fire product used in the 2014 National Emission Inventory (NEI; Pouliot et al.,
2017) and the Monitoring Trends in Burn Severity product (MTBS; USDA-FS & USGS, 2018), which includes
only large fires (>202 ha in the Eastern United States; Eidenshink et al., 2007). We also relate the fire variability
to the Palmer Drought Severity Index (PDSI; Hedinghsaus & Sabol, 1991; Palmer, 1965), normalized against
data from 1931 to 1990, and the Keech-Byram Drought Index (KBDI; Keetch & Byram, 1968). Both indices
are calculated from precipitation and air temperature, but KBDI is sensitive to subseasonal moisture changes
that affect fine fuels, while PDSI tracks prolonged moisture imbalance that persists for months to years and
affects deep soil moisture and deep-rooted plants.

3. Evaluation of Florida Open Burn Authorizations
The four study sites conducted 4,300 prescribed fires during 2004–2015. All but 198 can be matched with an
FFS OBA, meaning that the state database contains 95.4% of known prescribed fires. The median difference
between the area of a fire and its OBA ranges from –0.4% to –13% (0.1 to 11 ha, range across our four study
sites), so fires are typically a little smaller than requested. However, the range of error among individual fires is
–37% to +23% of the OBA area (±20%–25% median absolute deviation). Few fires (20%–28%) differ from
their OBA area by more than a factor of two (Figure S3); most of those are smaller than authorized. Other mea-
sures of FFS OBA accuracy are summarized in Table S1 and Figure S3.

The metrics above reflect the accuracy of the OBAs for a single fire on a single day. Accuracy of time-averaged
burn area is a better measure of the ability of OBAs to represent the overall extent and distribution of fires in
Florida. Accumulated over the study years, the actual fire area at the four study sites ranged from 14% less
than to 18% more than the OBA total (Table S1). Aggregated over all test sites and years, the OBA database
has a cumulative area error of 9% (i.e., 504,000 ha in OBAs versus 555,000 ha mapped as burned). Thus, the
OBA fire area has a typical error of 20%–40% for any given location and day, but the errors are under 20% at a
single site when averaged over the study period, and less, around 10%, when averaged over large regions of the state. For comparison, common satellite products may miss 40%–90% of fire area in the southeastern United States or in other agricultural regions (Hu et al., 2016; Zhu et al., 2017).

OBA location errors were 0.7–0.8 km (median, Table S1) and fewer than 20% of OBAs were located more than 2 km away from the actual fire (Figure S3). Although modest, these displacement errors mean that most OBA point locations are outside the actual fire perimeter (50%–98% of fires, Table S1), particularly for small fires and when a single OBA is requested for multiple fires, which is common at TTRS. As a result, OBAs can represent the general distribution of fires within Florida, but not the exact location of individual fires.

4. Current Status of Prescribed Fires, Wildfires, and Their Drought Interactions

Having established the accuracy of FFS prescribed fire data, we combine it with FPA FOD wildfire data to examine the patterns and variability of all open fires in Florida. Prescribed fires vastly exceed wildfires in Florida by area and number, as seen in Figure 1 and Table 1. Over the period 2004–2015, fires burned 9.9 ± 0.7 × 10^5 ha/year in Florida (multiyear mean ± standard deviation), which is 7% of the state’s land area each year. Wildfires burned only 8% of this area area (0.8 ± 0.6 × 10^5 ha/year). Of the prescribed fire types, silviculture fires consumed the most area (5.5 ± 6.7 × 10^5 ha/year), burning 50% more than agricultural fires. However, agricultural fires were much more numerous (15,000 year^{-1} versus 6,000 year^{-1}), reflecting their smaller average size (Figure S4). Figure 1a shows that most silviculture and land-clearing fires occur in northwest Florida, while agricultural fires dominate south Florida especially around Lake Okeechobee, where sugarcane agriculture is concentrated. Wildfires occur all across the state, but their area is concentrated in south Florida.

Prescribed fires in Florida are much more extensive on weekdays (Monday–Friday) than weekends (Figures 2a and S5). On Tuesday–Thursday, fires burn 3,400 ha/day compared to 1,000–1,500 ha/day on Saturday and Sunday. Monday and Friday are intermediate.

Table 1
Open Fire Characteristics for the Entire State of Florida During 2004–2015 Compared With Satellite-Based Fire Productsa

|                          | Number (year^{-1}) | Area (10^3 ha/year) |
|--------------------------|--------------------|---------------------|
| Prescribed (FFS)         |                    |                     |
| Agriculture              | 15,180 ± 1,380     | 354 ± 31            |
| Silviculture              | 6,480 ± 710        | 553 ± 67            |
| Land clearing             | 240 ± 50           | 3 ± 1               |
| Total prescribed          | 21,900 ± 1,800     | 909 ± 88            |
| Wildfire (FPA FOD)        | 3,270 ± 1,100      | 78 ± 56             |
| Total                    | 25,160 ± 1,400     | 987 ± 73            |
| Satellite products        |                    |                     |
| GFEDb                    | —                  | 268 ± 53            |
| BAECVc                   | —                  | 235 ± 91            |
| MTBSd                    | 200 ± 160          | 189 ± 121           |
| HMSe                     | 14,440 ± 3,020     | 274 ± 57            |
| NEI/HMS agriculturef     | —                  | 92                  |

Note. FFS = Florida Forest Service; FPA PPOD = Fire Program Analysis Fire Occurrence Database; GFED = Global Fire Emissions Database; BAECV = Burned Area Essential Climate Variable; MTBS = Monitoring Trends in Burn Severity; HMS = Hazard Mapping System; NEI = National Emission Inventory.

aValues are mean ± standard deviation across years.

bVersion 4.1s (van der Werf et al., 2017)
cVersion 1.1 (Hawbaker et al., 2017a)
dUSDA-FS and USGS (2018)
eNOAA (2017). Area assumes an average size of 19 ha per detection. See Text S2.
fData for 2014 only (Pouliot et al., 2017)
Although this weekly cycle might be expected from labor customs, the NEI of air pollutants does not account for it (Text S3 and Figure S5; EPA, 2015a, 2015b, 2016, 2017, 2018) nor do past regional studies mention it (Larkin et al., 2014; Park et al., 2007; Schichtel et al., 2017; Schweizer et al., 2017; Zeng et al., 2008). Moreover, the day-of-week effect seen here for prescribed fires in Florida is much stronger than what NEI specifies for emissions in any state (see Text S3 and Figure S5; EPA, 2015a, 2015b, 2016, 2017, 2018). Surrounding states likely have similar weekly cycles of fire emissions and including them could improve future emission inventories. In contrast, wildfires in Florida show no weekly cycle (Figure 2a).

Prescribed fires and wildfires have different seasonal cycles (Figure 2b) and longer-term variability (Figures 2c and 2d). Prescribed fires are usually most active in December through April, because managers and government agencies prefer burning during cool and wet conditions for fire control and safety. Florida’s wildfires peak in late spring, which is warmer and drier. On multiyear time scales, wildfire and prescribed fire area anomalies—the residual variability after removing the median seasonal cycle—are anticorrelated ($R = -0.53, R^2 = 0.28, p < 0.001$), meaning that years with extensive wildfires have below-normal prescribed fire area and vice versa.

**Figure 2.** Fire area in Florida (a) by day of week, (b) by seasonal cycle, (c) monthly over the study period, and (d) monthly anomalies, with (e) drought indices for comparison. Prescribed fire data from Florida Forest Service (this work), wildfire data from Fire Program Analysis Fire Occurrence Database (Short, 2017), and Global Fire Emissions Database (GFED) from version 4.1s (van der Werf et al., 2017). Vertical lines in panels a and b show standard errors of the mean, which is smaller than some plot symbols. Anomalies in panel d are calculated with respect to the median annual cycle, shown in panel b, and smoothed with a 3-month running mean. Drought indices are the Palmer drought severity index (PDSI) and Keetch-Byram drought index (KBDI), both averaged over Florida. Dry conditions are associated with negative PDSI and large positive KBDI. The PDSI axis is reversed so that up indicates drought for both KBDI and PDSI.
As seen in Figures 2c–2e, wildfire area increases during dry conditions ($R^2 = 0.28$, 0.22 for area anomalies versus PDSI and KBDI drought indices, respectively, $p < 0.001$). In particular, a prolonged drought identified by PDSI from 2006 to 2008 produced three of the four highest wildfire area anomalies in the record. This pattern of wildfires increasing during drought is common around the world (Balch et al., 2015; Charlés, 2017; Prichard et al., 2017; Westerling et al., 2006). The link between drought and prescribed fire, which has been studied much less, follows a different pattern that is not detected by satellite burned area data sets (section 5). In Florida, prescribed fires are less extensive during dry conditions. This decline during drought is driven by a combination of land managers choosing not to burn as well as FFS denying authorizations. Prescribed fire area is more strongly anticorrelated with short-term drought (KBDI $R^2 = 0.28$, $p < 0.001$) than with long-term drought (PDSI $R^2 = 0.14$, $p < 0.001$), likely because KBDI, not PDSI, is used by FFS and others to predict fire risk. This means that prescribed fires can be and are conducted during long-term drought, as long as sufficient precipitation falls to occasionally moisten shallow soil and fine fuels.

Prescribed fire area dwarfs wildfire area in Florida by a factor of 12 during our study period (Table 1). As a result, during drought conditions the total fire area decreases because the prescribed fire area decreases. Figure 2d shows that the largest reductions (i.e., negative anomalies) in prescribed fires occurred during the 2006 to 2008 drought and are as large, or larger, than the simultaneous wildfire increase. Conversely, in wet years, like 2010 and 2013–2015, wildfires burned slightly less area than normal while prescribed fire area increased much more. These patterns repeat throughout the data set. Overall, anomalies in total fire area in Florida are uncorrelated with long-term drought (PDSI; $R = 0.12$, $R^2 = 0.01$, $p = 0.17$) and anticorrelated with short-term drought (KBDI: $R = -0.34$, $R^2 = 0.12$, $p < 0.001$). Using the standardized precipitation index shows the same relationships with drought on multiple time scales. A more detailed discussion can be found in Text S4 (Hall & Brown, 2003; McKee et al., 1993; Vicente-Serrano et al., 2010). The lack of overall fire increase during drought suggests that prescribed fire policy is succeeding on a large scale to reduce fire risks to people and property in Florida.

Numerous case studies of individual wildfires show that prior prescribed fires can reduce the occurrence, severity, and area of wildfire (Fernandes & Botelho, 2003 and references therein), but there is much less evidence of whether current levels of prescribed fire are achieving their risk reduction goals on larger state or regional scales (Addington et al., 2015; Prestemon et al., 2010). Wildfire risk assessments should recognize the dominance of prescribed fire in the southeastern United States and account for the complex relationships, shown here, between drought and different fire types. However, recent assessments have not accounted for these features (Balch et al., 2017; Prestemon et al., 2016; Stephens et al., 2013). As a result, their prediction of large increases in wildfire activity in the southeastern United States in future climate scenarios may be overstated (Liu et al., 2013; Prestemon et al., 2016).

5. Evaluation of Satellite-Based Fire Area Products

The Florida fire data provide a new tool for evaluating the accuracy of satellite-based fire products over a large region with multiple fire types that are common worldwide. Since the satellite sensors have resolutions of 30 m to 4 km while OBAs are typically 0.5–1 km away from actual fires (section 3), the OBAs are not expected to exactly overlap space-borne detections of the same individual fires. As a result, we conduct comparisons at coarser spatial resolution (Figure 1, Table 1).

Over 2004–2015, GFED detected fires covering $2.7 \pm 0.5 \times 10^5$ ha/year in Florida, BAECV detected $2.4 \pm 0.9 \times 10^5$ ha/year, and HMS detected $2.7 \pm 0.6 \times 10^5$ ha/year. All of these are far less than the actual total fire area of $9.9 \pm 0.7 \times 10^5$ ha/year recorded by the FFS OBA and the FPA FOD (Table 1). Although there is some uncertainty in the HMS burned area, the total is certainly less than actual fire area (Text S2). Large biases also appear in specialized fire databases that rely on satellite data. For example, MTBS reported only $1.9 \pm 1.2 \times 10^5$ ha/year across Florida; however, it is designed to map and track trends in large fires only (Eidenshink et al., 2007) and thus excludes most Florida fires by design. The product that underpins NEI 2014 agricultural fire emissions detected $0.9 \times 10^5$ ha of crop and pasture fires in 2014 (Pouliot et al., 2017), the only year reporting data, while the comparable number from FFS agricultural OBAs is $3.9 \times 10^5$ ha. Thus, the fire area recorded by FFS and FPA FOD is consistently about 4 times greater than detected by any of these satellite products. Even accounting for 10–20% error in the government data
Overall, the Florida data suggest that a large fraction of global prescribed burning, but the multiyear GFED area anomalies (Figure 2d) closely resemble wildfire areas. Figure 2 evaluates the temporal variability of GFED over Florida against FFS and FPA FOD data and drought high-resolution sensors do not guarantee unbiased burn area estimates. In many cases, these sensors overestimate true burned area. This detection bias is worst for small fires, and the mean bias for GFED presumes 30% of the detected fire area, the mean bias is a factor of 5, but the mean bias falls to 2.7 where large fires dominate the detected fire area (Figure 1c and Text S5). The only region where GFED approaches FFS OBA and FPA FOD is on the southern shore of Lake Okeechobee, where large sugar cane fields are burned prior to harvest. BAECV, however, performs poorly in this region, due to a known weakness in detecting agricultural fires (Hawbaker et al., 2017b). Both the maps and statewide totals are consistent with fires being about four times greater than recognized from any of these satellites. Some past literature has treated Landsat-derived fire area products as more accurate than products derived from lower-resolution sensors (e.g., Boschetti et al., 2006; Giglio et al., 2009; Zhu et al., 2017), but the Florida results here caution that high-resolution sensors do not guarantee unbiased burn area estimates.

Figure 2 evaluates the temporal variability of GFED over Florida against FFS and FPA FOD data and drought indicators. Despite its overall bias, GFED reproduces the seasonal cycle of fire area, which is dominated by prescribed burning, but the multiyear GFED area anomalies (Figure 2d) closely resemble wildfire anomalies \( R^2 = 0.43, p < 0.001 \). In fact, GFED area anomalies are uncorrelated with both total fire anomalies \( R^2 = 0.04, p = 0.01 \) and prescribed fire anomalies in Florida \( R^2 = 0.03, p = 0.05 \). For example, in the first half of 2010, 2014, and 2015, GFED and wildfire areas were anomalously low, but total fire area was actually well above average. These patterns are consistent with the better detection efficiency for large wildfires compared to small prescribed fires, and it means that MODIS-based sensor products may misrepresent temporal changes in fire and fire emissions in regions where humans and climate exert opposing controls on fires of various sizes. Furthermore, the satellite products can give a misleading picture of the relationship between fires and drought. GFED fire area in Florida is nearly constant or increases slightly during drought (KBDI: \( R^2 = 0.1, p < 0.001 \); PDSI: \( R^2 = 0.01, p = 0.15 \); see Text S4 for standardized precipitation index), which differs from the actual drought relationship (section 4). Thus, current satellites can misdiagnose the relationship between fire and its human and environmental drivers due to their tendency to detect large wildfires and undetect smaller prescribed burns.

These satellite detection biases likely extend to other regions of the world with similar fire regimes to Florida. The main fire types in Florida are agriculture, savanna, and shrubland, with some temperate forest and grasslands (Figures 1 and S7); satellites undetect fire area for all of these. Similar fire types are found throughout the world (Figure S7 and Text S5). Agricultural burning is widespread on every inhabited continent (Korontzi et al., 2006), and frequent intentional burning is used in similarly structured woodlands and savannas within parts of the U.S. Great Plains (Engle & Bidwell, 2001), South America (Cano & Leynaud, 2010; Harris et al., 2007; Mistry, 1998), sub-Saharan Africa (Coetsee et al., 2010; Savadogo et al., 2007), and Australia (Price et al., 2012; Price & Bradstock, 2010). These analogous areas account for about half of global fire emissions (Figure S7, van der Werf et al., 2017). Additionally, Florida data suggest that only 20% of fire area is detected in places where small fires, as defined by GFED, provide more than 30% of the fire area (Figure 1c). Since small fires exceed this 30% threshold in GFED data across most of the world (Figure S7), that would significantly alter detected fire area everywhere outside the boreal wildfire belt, western North America, Australia, and African savannas. Overall, the Florida data suggest that a large fraction of global fire activity and extent is currently undetected.

6. Conclusions

The combination of FFS prescribed fire data and FPA FOD wildfire data provides the most comprehensive record of fire available in Florida. Together, they report fire area of 9.9 ± 0.7 × 10^6 ha/year, with uncertainty of 10%–20%. From these records, we show that multiple satellite-derived fire products underestimate burned area in Florida by approximately a factor of 4, likely due to the small size and low intensity of agricultural and silvicultural fires. Other states in the southeastern United States have similar fire regimes, so the biases documented here likely apply throughout the region and many other parts of the world with frequent prescribed burning. Correcting these biases could significantly increase the contribution of open vegetation fires to...
global pollutant emissions and air quality impacts. However, updated emission estimates should also consider the accuracy of fuel load, fuel consumption, and emission factors. In particular, fuel loads tend to decrease as fires become more frequent, particularly in forests, which could partially offset changes to burn area in an emission inventory.

Emission inventories, such as NEI, could also benefit from incorporating the strong day-of-week variation seen in prescribed fire activity. The current approach of assuming uniform emissions throughout the week underestimates peak smoke emission and exposure on weekdays and overestimates them on weekends. Similar weekly patterns likely occur in other areas where prescribed fire is a common land management practice. Given that very few states and regions currently track prescribed fire, our results underscore the need for other areas to develop more comprehensive fire databases from burn authorizations and wildfire reports.

Florida fires decrease in area during drought but this is not detected by current satellite products. This relationship between fire and drought in Florida is opposite to what has been reported elsewhere, such as the Western United States, boreal zones, and the tropics (Abatzoglou & Kolden, 2013; Abatzoglou & Williams, 2016; Anderson et al., 2015; Aragão et al., 2018; Duncan et al., 2003; Randerson et al., 2012; Tosca et al., 2010; van der Werf et al., 2004, 2010; Westerling et al., 2003, 2006). Florida, likely much of the southeastern United States, and possibly other regions of the world follow a different pattern for several interlinked reasons. Prescribed fires are dominant in Florida but are restricted during drought because safety and management considerations favor burning during periods of normal rainfall. In addition, the widespread use of prescribed fires over decades likely reduces the extent and severity of wildfires, limiting their growth during drought. The Florida data therefore demonstrate that with extensive prescribed fire management, drought does not inevitably increase wildfire activity. This result shows that prescribed fire and land management can play an important role in managing drought and fire risks in the present day and under future climate change. Moreover, it suggests that prescribed fires are successfully helping to mitigate the extent and damages of wildfires during drought.

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