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Simulating a natural fire regime on an Atlantic coast barrier island complex in Florida, USA

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ABSTRACT

The HFire fire regime model was used to simulate the natural fire regime (prior to European settlement) on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. Model simulations were run for 500 years and the model was parameterized using information generated from previously published empirical studies on these properties (e.g., lightning fire ignition frequencies and ignition seasonality). A mosaic pattern of frequent small fires dominated this fire regime with rare but extremely large fires occurring during dry La Niña periods. This simulated fire size distribution very closely matched the previously published fire size distribution for lightning ignitions on these properties. A sensitivity analysis was performed to establish which parameters were most influential and the range of variation surrounding empirically parameterized model output. Dead fuel moisture and wind speed had the largest influence on model outcome. A wide range of variance was observed surrounding the composite simulation with the least being 6% in total burn frequency and the greatest being 49% in total area burned. Because simulation modeling is the best option for fire regime reconstruction in many rapidly growing shrub dominated systems, these results will be of interest to scientists and fire managers for delineating the natural fire regime on these properties, the southeastern United States and other fire adapted shrub systems worldwide.

1. Introduction

The fire regime of a region is defined by its fire type, fire intensity, fire size, return interval, seasonality, and spatial pattern (Christensen, 1985; Agee, 1993). Humans have altered fire regimes by suppressing fires, shifting fire seasonality, fragmenting fuels, propagating non-native fuels, and permitting unnaturally high fuel loads. Understanding how anthropogenic influences have altered fire regimes is important when attempting to manage conservation areas for the survival of native fire-dependent species. A reference outlining the natural fire regime is useful to foster an understanding of the environment that native fire-dependent species have adapted to and coexisted in. Fire has been an active force on global ecosystems for millions of years (Bond and van Wilgen, 1996). A thorough knowledge of the difference between the natural fire regime and contemporary fire regimes is essential to effectively and efficiently manage habitat for fire-dependent species. Many fire-dependent species populations are declining in their native ecosystems with fire regime alteration being a large contributing factor (e.g., Noss and Cooperrider, 1994; Breininger and Carter, 2003; Quintana-Ascencio et al., 2003; Webb and Shine, 2008).

Florida is dominated by fire-adapted vegetative communities that have seen their composition and structure modified by fire regime alteration (Myers and Ewel, 1990; Duncan et al., 1999). The dominant terrestrial communities are pine flatwoods, dry prairies, Florida scrub, and high pine (Abrahamson and Hartnett, 1990; Myers and Ewel, 1990). These vegetation communities do not lend themselves to recording and preserving past fire history and present many problems for natural fire regime reconstructions. The prevailing regeneration strategy in the understory of these communities is through re-sprouting after being top killed by frequent fire. The relatively short-lived sand pine with thin bark (*Pinus clausa*) are easily killed by moderate to intense fires. The longer-lived slash pines (*P. elliotii* var. *elliottii*, *P. elliotii* var. *densa*) and longleaf pine (*P. palustris*) with their thick protective bark generally do not scar from low and moderate intensity fires but are killed by intense fire. This generally limits the utility of dendrochronologic techniques for historic fire regime reconstruction. However, with the convergence of particular circumstances, it is possible to use dendrochronology to reconstruct historic fire regimes in Florida (Huffman et al., 2004). The Huffman study was conducted on a protected barrier

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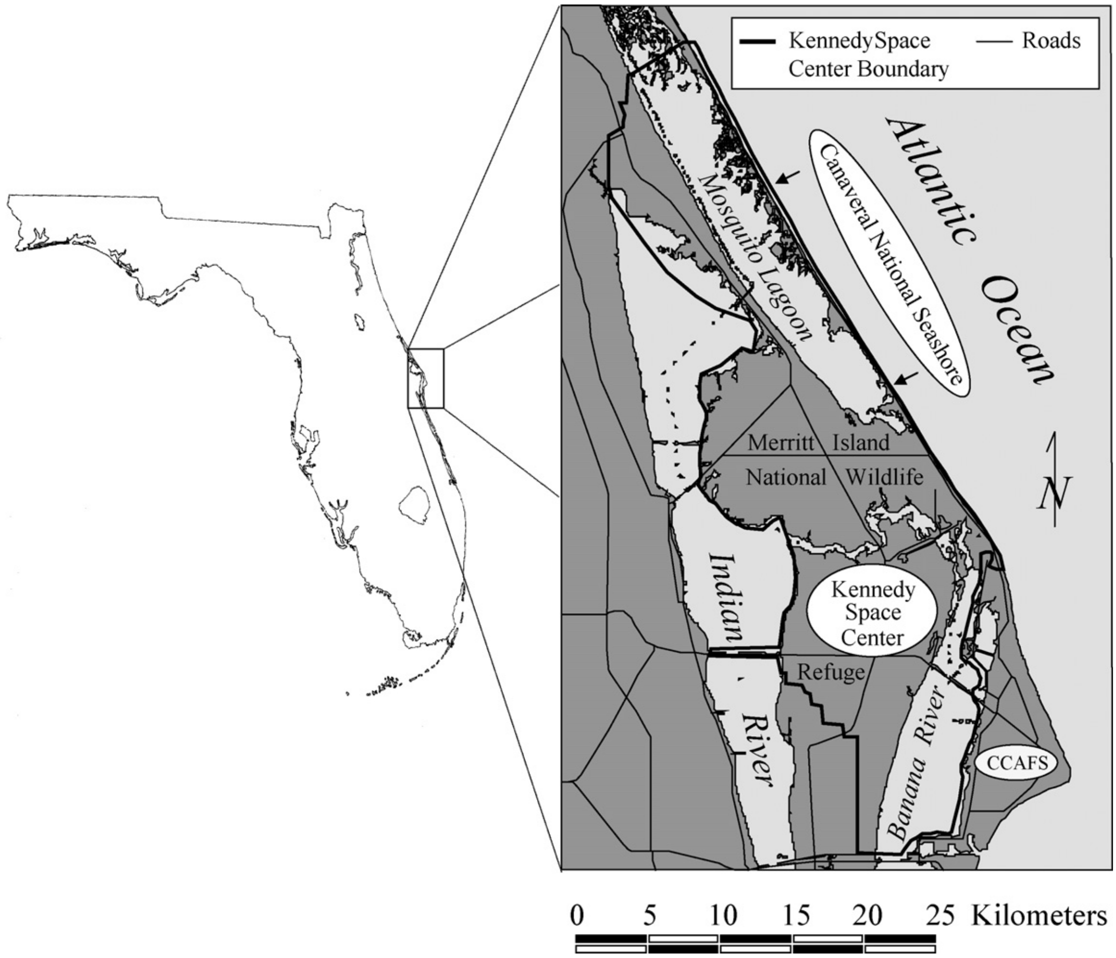

Fig. 1. The geographic locations of Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

island where past turpentining operations had stripped the protective bark from the pines allowing fires to scar the trees and facilitated fire scar dating. Stratographic varve dating has been used in Florida but has had limited success reconstructing historic fire dates (Shepherd, 2002). Remote sensing techniques have been used for reconstructing fire histories but are limited to recent time periods (Duncan et al., 2009).

Computer simulation is an alternative that has shown promise for reconstructing historic fire regimes in many ecosystems outside of Florida (Baker, 1992; Davis and Burrows, 1994; Li, 2000). There are at least 45 landscape fire succession models in use today (Keane et al., 2004). A few of the models have been successfully applied in shrubland systems that also share attributes of the Florida ecosystems and lack a natural record of fire history. The regional fire regime simulation model (REFIRES) was created to simulate prehistoric and modern fire regimes of the coastal California chaparral ecosystems (Davis and Burrows, 1994). The HFire simulation model has also been applied in the California chaparral ecosystem (Morais, 2001; Peterson et al., 2011). Both applications generated fire regime information such as maps of fire history, fire size distribution, fire recurrence interval, final patch size, and age distributions.

The cluster of federal properties known as Kennedy Space Center (KSC), Merritt Island National Wildlife Refuge (MINWR), Canaveral National Seashore (CNS), and Cape Canaveral Air Force Station (CCAFS) in Florida is the largest conservation area on the Atlantic coast of Florida. These properties have fire management programs that actively conduct prescribed burns to reduce/maintain fuel loads and to manage habitat for native fire-dependent species (Adrian and Farinetti, 1995). The goal of this work is to apply the HFire model (Morais, 2001) to simulate the natural fire regime (prior to European alteration) on KSC/MINWR/CNS/CCAFS. The model was parameterized with empirical information from previous studies and meteorological data. A sensitivity analysis was performed to determine the importance of each parameter and to establish a range of variation surrounding the empirical model. This approach offers an opportunity to apply an advanced fire regime model built on the best current fire simulation algorithms to estimate the natural fire regime in dynamic, fire-adapted ecosystem and provide a possible range of variation surrounding that estimate.

2. Methods

2.1. Study site and background

The United States federal government began acquiring land in the 1950s on Cape Canaveral and in 1962 on north Merritt Island, along the east coast of central Florida. KSC covers 57,000 ha of land and waters, which is primarily managed by the U.S. Fish and Wildlife Service as the Merritt Island National Wildlife Refuge with a smaller portion managed by the National Park Service as the Canaveral National Seashore (CNS). Cape Canaveral Air Force Station (CCAFS) is 6475 ha and occupies the Cape Canaveral barrier island (Fig. 1). When referring to these properties collectively we will use the first letter from each location and shorten the name from KSC/MINWR/CNS/CCAFS to KMCC.

KMCC is characterized by a warm, humid, climate with annual precipitation averaging around 130 cm (Mailander, 1990). Precipi-

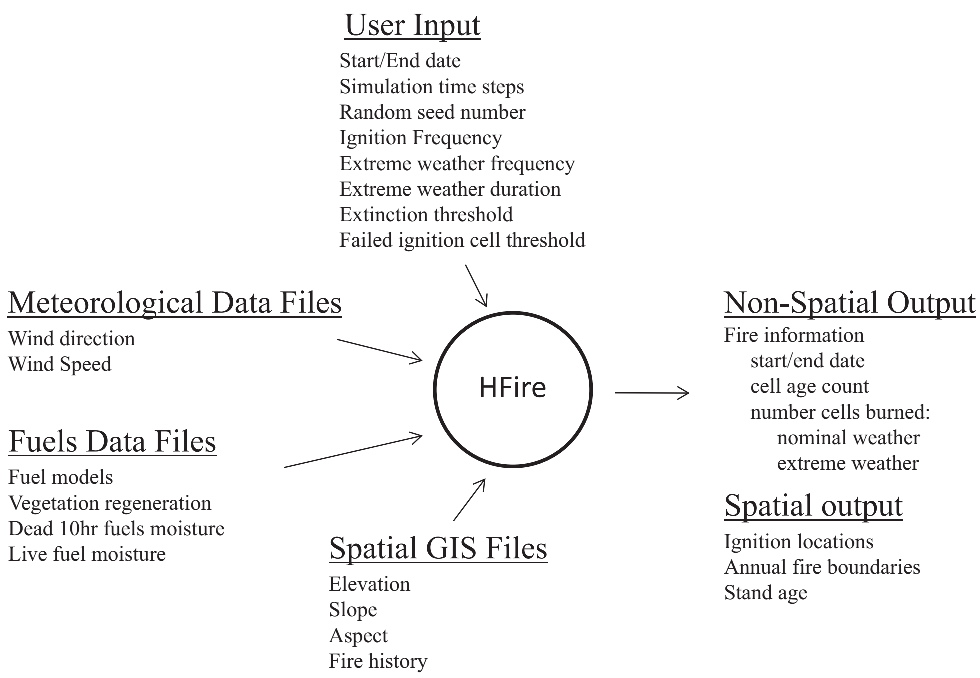

Fig. 2. HFire conceptual diagram of model input and output.

tation varies seasonally with a peak in rainfall between May and October from convective/tropical influences while the remainder of the year is relatively dry with winter cyclonic storms contributing to precipitation totals. Spring months are typically characterized by lack of precipitation and rising temperatures. Mean daily maximum temperatures are around 33.3 °C during summer and mean daily minimum temperatures 9.6 °C during the winter. Natural fires are ignited by lightning with frequent small fires occurring during the wet growing season and less frequent large fires occurring during the spring drought (Duncan et al., 2010). This fire pattern is enhanced by El Niño-Southern Oscillation (ENSO) events known to occur in Florida on a 3–7 years time cycle (Harrison and Meindl, 2001; Beckage et al., 2003). The El Niño cycle causes enhanced winter precipitation ultimately reducing flammability followed by the La Niña cycle which is typically hot and dry stimulating large, extreme fires (Brenner, 1991; Beckage et al., 2005; Goodrick and Hanley, 2009). The strength and timing of these cycle vary and have even been found to influence managed fire regimes in this region (Duncan et al., 2009).

KMCC occupies a barrier island complex covered with a diverse assemblage of fire-adapted terrestrial vegetative communities. Upland xeric sites are dominated by oak scrub vegetation (*Quercus* spp.), while mesic sites are dominated by flatwoods (e.g., saw palmetto (*Serenoa repens* (W. Bartram) Small), staggebrush (*Lyonia* Nutt. spp.), holly (*Ilex* L. spp.), and an overstory of slash pine (*Pinus elliotii* Engelm.)) (Schmalzer and Hinkle, 1992a, 1992b). Because the landscape is comprised of relict dunes forming ridge-swale topography, there are interleaving swale marshes and hammocks on hydric soils between the xeric ridges. The swales are dominated by cordgrass (*Spartina bakeri* Merr.) and bluestem (*Andropogon* L. spp.), while the hardwood hammocks are dominated by live oak (*Quercus virginiana* Mill.) and laurel oak (*Quercus laurifolia* Michx.) and have a structure that is much less flammable than surrounding communities. Coastal strand occurs just inland of the coastal dunes and is a shrub community with saw palmetto, sea grape (*Coccoloba uvifera* L.), and wax myrtle (*Myrica cerifera* L.) being dominant (Schmalzer et al., 1999).

2.2. HFire fire regime model

HFire (Highly Optimized Tolerance Fire Spread Model) is a spatially explicit raster-based model that can be used as a single event model or to simulate fire regimes over long time periods (Fig. 2). The model is based on the Rothermel fire spread equations (Rothermel, 1972) and can use standard (Anderson, 1982; Scott and Burgan, 2005) or custom fuel models. This model uses adaptive time steps and finite fractional distance techniques to solve the problem of distorted fire shapes that occur when using traditional raster fire spread models (Morais, 2001; Peterson et al., 2009). This model was used because it can be parameterized for Florida vegetation communities, is based on the robust Rothermel equations, it is computationally efficient, provides spatial output, and has been found to be reasonably accurate when simulating historic fire events (Peterson et al., 2009) and historic fire regimes (Peterson et al., 2011).

2.3. HFire parameterization

The parameters for the empirical HFire model run are shown in Table 1. The spatial resolution for the modeling was 30 meters, which was consistent with previous fire regime mapping work on these properties (Duncan et al., 2009) and is reasonable tradeoff between spatial detail and computing efficiency. Spatial resolution larger than 30 meters would reduce computation time but would have generalized the ridge-swale topography, misrepresenting the distribution of fuels on the KMCC landscape. To create a natural fuels map devoid of anthropogenic features (roads, railways, buildings, agricultural fields, etc.), these features were removed from a 1920 landcover map (Duncan et al., 2004) by using soils maps and soils vegetation relationships (Duncan et al., 2000). Each landcover type was converted to one of 13 standard fire behavior models (Anderson, 1982) with swale marshes assigned to the short grass fire behavior model 1. The tall grass model 3 could have been used in these marshes, as *Spartina bakeri* is prominant in many of these marshes. The problem with using the tall grass model is that it can cause unrealistically fast rates of fire spread in these marshes

Table 1
HFire configuration file parameters.

Variable	Entry type	Units/format	Empirical
Start date	User defined	Yr/mo/day/h	2000/3/1/0
End date	User defined	Yr/mo/day/h	2500/10/31/0
Simulation time step	User defined	s	3600
Ignition frequency	User defined	Number/yr	14
Random seed	User defined	Number	1260624655
Fire extinction thresholds	User defined	Hour/spread rate (m/s)	3/.05
Extreme fire weather frequency	User defined	Number/yr	0.8
Ellipse adjustment factor	User defined	Real number	0.66
Wind speed adjustment factor	User defined	Type	BHP
Failed ignition cell threshold	User defined	Number	1
Fuel models	File	Number	1,4,7,8
Vegetation regeneration	File	Number	File
Wind direction (hourly)[a]	File	°	File
Wind speed (hourly)[a]	File	km/h or mile/h	File
Dead 10hr fuel moisture (hourly)[a]	File	Percent	File
Live fuel moisture (hourly)[a]	File	Percent	File
Elevation (30 m)	Spatial file	m	File
Slope (30 m)	Spatial file	°	File
Aspect (30 m)	Spatial file	°	File
Fire history (30 m)	Spatial file	Age/yr	File
Export	Output files	.txt, .asc, .png, etc.	Files

[a] Parameterization needed for nominal and extreme weather conditions.

(Duncan and Schmalzer, 2004). Oak scrub was assigned to the chaparral model 4 and pine flatwoods was assigned to the southern rough fuel model 7. Hammocks and wetlands hardwoods were assigned to the fire behavior model 8. The elevation grid was given a uniform value of three meters and the slope and aspect grids were given values of zero. This barrier island landscape has very slight topographic relief of one to two meters. This small relief influences the distribution of fuels, which influences fire behavior. Despite the zero values in the slope and aspect grids, the most important aspects of topography are incorporated into the modeling through the fuels grid. Rather than starting with uniform fire history of zero age, the output from a previous model run of 300 years was used to help reduce effects of initial modeling conditions.

Vegetation regeneration with time since fire information was gathered by utilizing 25 years of vegetation monitoring data (Schmalzer, 2003) combined with expert opinion on specific transitions for each fuel type. Ignition frequency was derived from a previous study delineating the lightning ignition regime on KMCC (Duncan et al., 2010). Fires were simulated for March through October because natural winter fires rarely occur (Duncan et al., 2010).

The HFire model was originally written to simulate fire in the chaparral ecosystem of California, which experiences episodic extreme fire weather known as Santa Ana wind events. The model accommodates these extreme fire weather events, which here have been utilized to represent La Niña events that occur in Florida. Like Santa Ana events in California, La Niña events can have a profound influence on Florida fire dynamics (Brenner, 1991; Harrison and Meindl, 2001; Goodrick and Hanley, 2009). In the central Florida region, extreme fire years have occurred in the fire record on a rotation of 23 ± 5 years (Davison and Bratton, 1986). This corresponds to about every third or fourth La Niña event being truly extreme, such as the 1998 year. Setting the extreme fire event frequency in HFire to 0.8 events a year, led to an average of one extreme fire year every 23 years, mimicking the empirical records. In contrast to extreme La Niña events the term nominal is used in this manuscript to describe average weather conditions.

The fire extinction thresholds of 3 h and 0.05 m/s were used, i.e., if a fire did not spread outside of a single cell in 3 h or the rate of spread was less than 0.05 m/s for an hour the fire was extinguished by the model. The ellipse adjustment factor was set at 0.66 because that value was found to be the most realistic in relation to modeling historic fires (Peterson et al., 2009). Meteorological inputs were taken from the network of weather stations on KSC. These inputs totaled 30,000 hourly values for each meteorological input (wind speed, wind direction, and 10 h fuel moistures) organized in files by nominal vs. La Niña conditions and then by year, month, day, and hour. The model randomly selects data from these files appropriate for the time and season of fire being simulated. This is done on the simulated hour until a successful ignition occurs and then at least every minute, while an active fire is occurring. A wind speed adjustment factor is applied to wind speeds collected high on towers to adjust them to represent speeds at mid flame heights (usually eye-level). This saved time, reducing the effort required to calculate and enter the winds at mid flame heights initially. Live fuel moisture is typically less variable than dead fuel moisture, therefore the model randomly sampled daily values from the live fuel moisture herbaceous and woody input files. Fuel moistures were taken from data recorded by MINWR personnel and other unpublished fuel moisture data collected on KMCC (Duncan and Schmalzer, 2004).

2.4. HFire simulations

Ten model runs were conducted with the empirical parameter settings and different random seed numbers. These runs were averaged and are referred to as the composite simulation, which have a standard error associated with each measure. All simulations were run for 500 years.

A factor screening sensitivity analysis (Campolongo et al., 2000) was performed to determine the importance of each input variable with respect to the range of variability from the empirical model run. Model parameters were varied both positively and negatively by ten percent. The random number seed was held constant for most sensitivity model runs forcing the HFire model to be deterministic, isolating the influence of each input variable one at a time. The first empirical model run used the same random seed number as the sensitivity analysis runs. Nine other empirical model runs were performed using unique random seed numbers and were labeled empirical 2 through empirical 10. A total of ten empirical model runs were performed. A list of all model runs can found in Table 2.

2.5. HFire spatial output

The FRAGSTATS program (McGarigal and Marks, 1995) was used to quantify the spatial pattern of age polygons predicted by each model run. A subset of landscape metrics were selected to represent

Table 2
A complete list of HFire model simulations with corresponding total and maximum burned area and total burn frequency output on KMCC. Empirical 2–10 have unique random seed numbers, all other runs have the same random seed numbers to facilitate comparison within the sensitivity analysis. Empirical minimum values (light gray) and maximum values (dark gray) bound the empirical mean to form the envelop of empirical variability. Sensitivity analysis values below the envelope are underlined while values above are displayed in bold. Maximum variances above and below the empirical mean area displayed at the bottom of the table.

Model run	Total burn area (ha)	Max. individual fire area (ha)	Total burn frequency
Empirical	1,032,291	5866	6730
Empirical 2	1,068,640	5865	6756
Empirical 3	1,040,307	7720	6491
Empirical 4	1,017,558	6519	6826
Empirical 5	970,863	5289	6684
Empirical 6	983,539	7817	6721
Empirical 7	1,022,562	9153	6631
Empirical 8	1,015,630	7540	6758
Empirical 9	1,066,885	8092	6838
Empirical 10	1,019,247	8724	6826
Empirical mean	1,023,752	7258	6726
Annual ignition −10%	1,019,639	**10,320**	<u>6300</u>
Annual ignition +10%	**1,086,017**	6633	**7178**
Dead fuel moisture −10%	<u>761,110</u>	7237	6821
Dead fuel moisture +10%	<u>540,205</u>	8838	**6863**
Ellipse adjustment factor −10%	1,062,584	6539	6679
Ellipse adjustment factor +10%	986,404	7413	6755
Wind speed −10%	<u>897,010</u>	6189	6754
Wind speed +10%	**1,275,102**	7294	6674
La Niña annual frequency −10%	990,491	7960	6757
La Niña annual frequency +10%	1,050,416	6450	6736
La Niña dead fuel moisture −10%	1,058,339	8558	6748
La Niña dead fuel moisture +10%	1,067,532	**10,016**	6610
La Niña wind speed −10%	**1,076,376**	**9168**	6689
La Niña wind speed +10%	1,053,048	5664	6773
Nominal and La Niña dead fuel moist. −10%	<u>788,712</u>	**9543**	6811
Nominal and La Niña dead fuel moist. +10%	<u>519,993</u>	**9593**	**6934**
Nominal and La Niña wind speed −10%	<u>918,390</u>	8944	6740
Nominal and La Niña wind speed +10%	**1,292,625**	7528	6659
Maximum variance above empirical mean	21%	30%	6%
Maximum variance below empirical mean	49%	N/A	6%

Table 3
Select landscape metrics for the large magnitude sensitivity analysis model runs on KMCC. Empirical minimum values (light gray) and maximum values (dark gray) bound the empirical mean to form the envelop of empirical variability. Sensitivity analysis values below the envelope are underlined while values above are displayed in bold. Maximum variances above and below the empirical mean area displayed at the bottom of the table.

Model run	Number patches	Largest patch index	Mean patch area (ha)	Patch richness
Empirical	1079	32	64	189
Empirical 2	1107	57	62	203
Empirical 3	1075	59	64	193
Empirical 4	1159	32	60	225
Empirical 5	1217	30	57	220
Empirical 6	1261	58	55	234
Empirical 7	1123	58	62	216
Empirical 8	1037	60	67	204
Empirical 9	1001	31	69	178
Empirical 10	1136	30	61	222
Empirical mean	1120	45	62	208
Annual ignition −10%	1164	30	59	187
Annual ignition +10%	1129	60	61	179
Dead fuel moisture −10%	**1631**	58	<u>42</u>	**281**
Dead fuel moisture +10%	**1626**	60	<u>43</u>	**308**
Wind speed −10%	**1331**	31	<u>52</u>	215
Wind speed +10%	1095	**61**	63	189
Nominal and La Niña dead fuel moist. −10%	**1429**	30	<u>48</u>	**256**
Nominal and La Niña dead fuel moist. +10%	**1595**	31	<u>43</u>	**276**
La Niña wind speed −10%	1125	33	61	206
La Niña wind speed +10%	1151	60	60	227
Nominal and La Niña wind speed −10%	**1394**	31	<u>50</u>	202
Nominal and La Niña wind speed +10%	<u>965</u>	60	**72**	<u>152</u>
Maximum variance above empirical mean	31%	27%	14%	32%
Maximum variance below empirical mean	14%	N/A	32%	27%

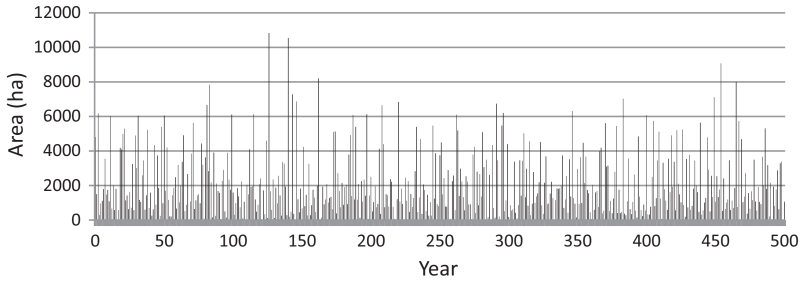

Fig. 3. Time series of annual area burned for the empirical HFire model run on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

the spatial distribution of polygons on the landscape (Table 3). Each of these metrics was selected based on their relevance to quantifying spatial pattern of burn age and their ease of interpretation.

3. Results

3.1. Fire size, area burned, and fire frequency

The composite simulation predicted that the mean fire size was 152 ha (standard error of 1.59), the median was 0.09 ha (standard error of 0.08), the minimum was 0.09 ha (standard error of <0.0001), and the maximum size was 9153 ha (standard error of 403.6) for the 500 years of simulation. The composite annual mean fire area was 2043 ha (standard error of 20.8), the median was 1518 ha (standard error of 27.1), the minimum was 0.18 ha (standard error of 0.53), and maximum was 15,060 ha (standard error of 527.5). The largest fires overall and annually were recorded during La Niña events. The amount of annual area burned followed a rising and falling cyclical pattern (Fig. 3) with significant negative autocorrelation at 1 ($r = -0.161$, $p < 0.001$) and 8 years ($r = -0.101$, $p < .0006$) and positive autocorrelation at 11 years ($r = 0.101$, $p < 0.003$) (Fig. 4). The majority of the fires predicted to burn in this system were very small (Fig. 5).

The model started an average of 6726 fires (standard error of 33.4) over 500 years. Many of those fires (average of 3417, standard error 18.1) or 51% failed to spread beyond a single cell. The composite mean of annual fires was 13.8, the median was 13.9, the minimum was 2.0, and the maximum was 29.0. The annual fire frequency increased and decreased through time (Fig. 6) but did not display a cyclical pattern or any significant autocorrelation.

The fire cycle is the number of years it takes to burn area equivalent to the study sites burnable area. The composite mean fire cycle was 14.4 years, the median was 14.2 years, the minimum was 7 years and the maximum was 21 years. The return interval was also calculated by dividing the burnable area (29,541 ha) by the annual average fire size (2043 ha), resulting in a return interval that matched the composite mean fire cycle value of 14.4 years.

3.2. Spatial pattern

The landscape age map displays a mosaic pattern of different age areas (Fig. 7). The landscape age pattern is dominated by smooth curved boundaries with the only unnatural straight edges cause by the federal land boundaries. The empirical model run had 1079 different age patches on it. The largest patch constituted 32 percent of the study area (largest patch index), a mean patch area of 64 ha, and 189 different age patches (patch richness). The average composite simulation area distribution by mapped age class shows a distribution that is skewed to the younger ages and peaks in the 8–10 years age class (Fig. 8). The standard error is the greatest in the 2 years age class and least in the 301–500 years age class.

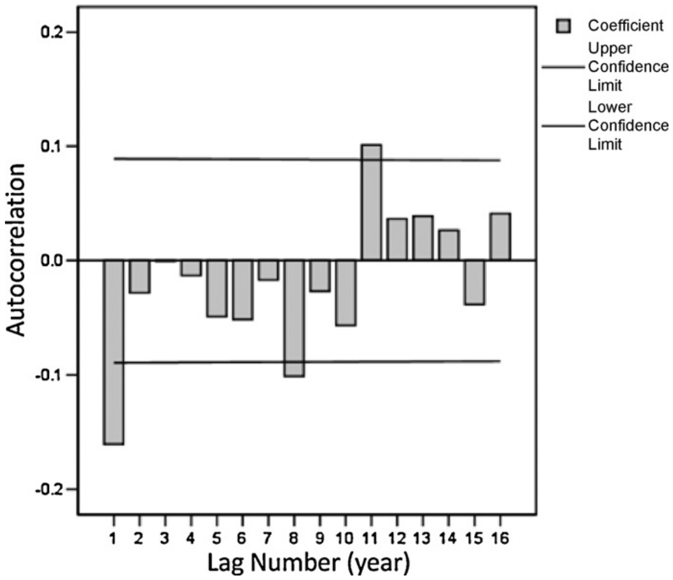

Fig. 4. Autocorrelation coefficient and 95% confidence limit values for the annual area burned time series generated using the HFire model on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

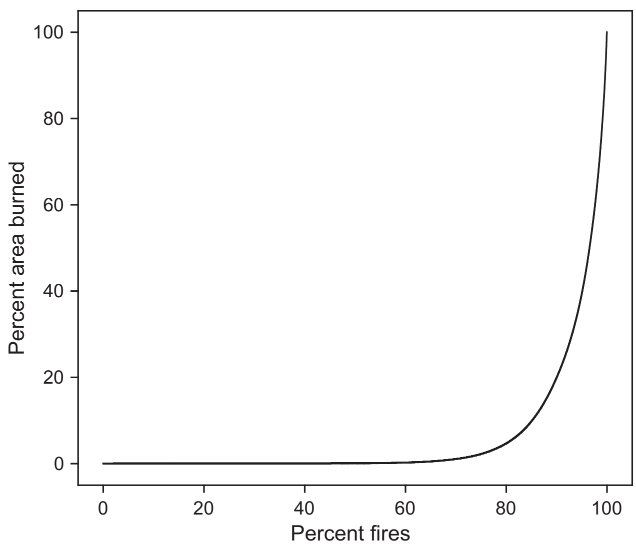

Fig. 5. The proportion of ranked fires (small to large) and the proportion of area burned during the empirical HFire model simulation on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

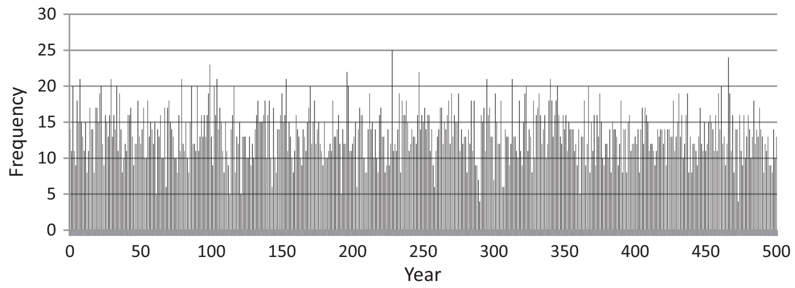

Fig. 6. Time series of annual fire frequency for the empirical HFire model run on Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida.

3.3. Sensitivity analysis and the natural range of variability

The sensitivity analysis revealed that there were six inputs that had a large influence on the output of the HFire model (Fig. 9). The combination of nominal and La Niña dead fuel moisture and nominal and La Niña wind speeds influence model outcome the most significantly.

3.3.1. Fire size, area burned, and fire frequency

There was a wide range of fire sizes that may serve as an indication of the potential range of variability in this system (Table 2). The mean total fire size for all 500 year simulations was 988,625 ha, the median was 1,021,100 ha, the minimum was 519,993 ha, and maximum was 1,292,625 ha. The difference between the minimum and maximum value was 40%. There was also a large range of varia-

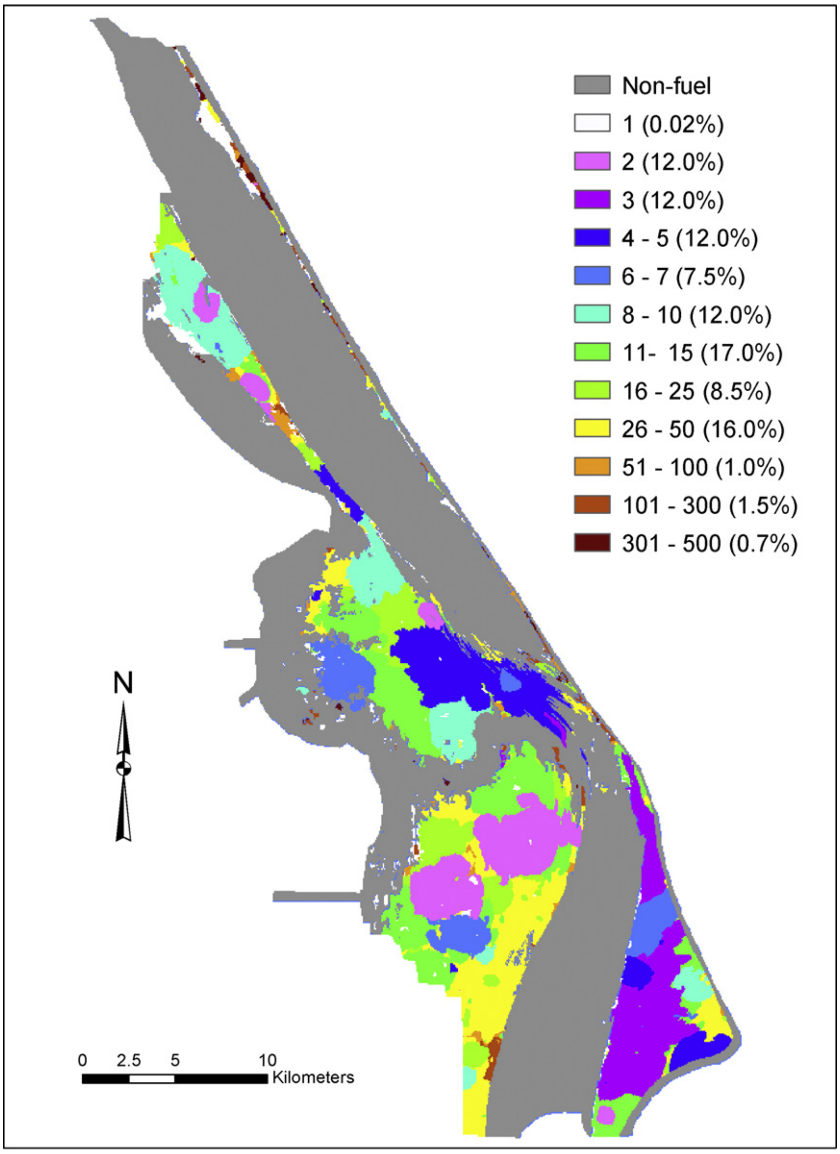

Fig. 7. Landscape age map produced by the empirical HFire simulation for Kennedy Space Center, Merritt Island National Wildlife Refuge, Canaveral National Seashore, and Cape Canaveral Air Force Station, Florida. Age is expressed in years and percentages in parenthesis are burnable study site proportions.

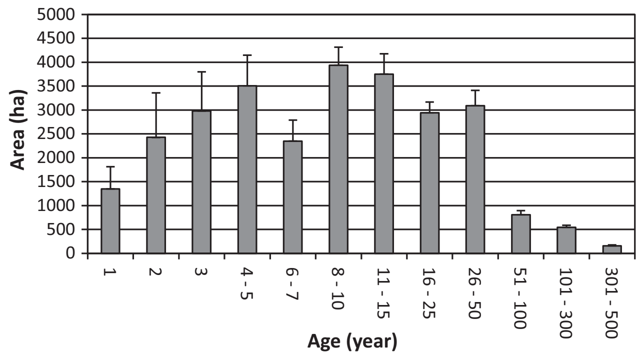

Fig. 8. Frequency distribution of the average composite simulation area by age class. Distribution was generated by averaging the ten empirical HFire model runs. Error bars represent standard error for each age class.

tion in the maximum individual fire sizes with a mean of 7731 ha, a median of 7630 ha, a minimum of 5289 ha, and a maximum of 10,320 ha. The difference between the minimum and maximum was 51%. Total fire frequencies displayed a bit tighter distribution with a mean of 6740, a median of 6751, a minimum of 6300, and maximum of 7178. This was only a difference of 12% between minimum and maximum fire frequencies.

To establish the range of variation from composite simulation values, each sensitivity analysis run was overlaid and compared to the envelope of minimum/maximum values derived from the composite simulation information (Tables 2 and 3). This was done for total area burned, total burn frequency, maximum individual fire size, number of patches, and parch richness. When comparing total area burned to the composite mean, the nominal and La Niña dead fuel moisture +10% model run displayed a difference of 49% less total area burned (Table 2, first column). Nominal and La Niña wind speed +10%, displayed 21% more total area burned than the composite mean value. When differencing the total burn frequencies from the composite average the annual ignition −10% was 6% below and the annual ignition +10% was 6% above (Table 2, third column). The comparison of maximum individual fire size with the composite mean value displayed that the annual ignition −10% model run was 30% greater (Table 2, second column).

3.3.2. Spatial pattern

The landscape metrics that were selected to diagnose the age structure predicted by the HFire model revealed a wide range of values (Table 3). The number of patches and the mean landscape patch area were normally distributed (Shapiro-Wilk test, $p = 0.253$, $p = 0.178$) and negatively correlated ($r = -0.99$, $p < 0.001$), while the number of patches and patch richness (number of age classes) were normally distributed (Shapiro-Wilk test, $p = 0.647$) and positively correlated ($r = 0.94$, $p < 0.001$).

More spatial variability was revealed by using all the sensitivity analysis runs and the FRAGSTATS program (Table 4). The relationship of the empirical model run (Table 3) can be compared to the distribution of landscape metric values from all sensitivity runs (Table 4). The number of patches, largest patch index, and patch richness for the empirical run was below the mean near the low end of the range; however, the mean patch area was above the overall mean and near the maximum value for those metrics. There was a difference of 41% between the smallest and largest number of patches, a difference of 51% in the largest patch index, a difference of 42% in the mean patch area, and a difference of 51% for patch richness. Comparing the mean number of patches from the composite simulation with the nominal dead fuel moisture −10 percent, revealed a difference of 31% more patches while the nominal and La Niña wind speed +10 percent model run had 14% fewer patches (Table 3, bottom two rows). Comparing patch richness to the mean average indicated that nominal dead fuel moisture −10 percent had 32% higher and nominal and La Niña wind speed +10 percent had 27% lower patch richness.

Table 4
The landscape metrics range of variability for all sensitivity analysis HFire model runs.

Statistic	Number patches	Largest patch index	Mean patch area (ha)	Patch richness
Mean	1349	44	53	230
Median	1394	32	50	215
Minimum	965	30	42	152
Maximum	1631	61	72	308

4. Discussion

4.1. Fire size, fire area, and fire frequency

The model predicted the majority of fires to be small. The cumulative fire size distribution generated by the model is very similar to a previously derived distribution for this site (Duncan et al., 2010). The modeled distribution has a higher percentage of medium sized fires than the previously derived distribution, presumably due to a lack of fire suppression efforts. Fire suppression is most effective within the medium size fires because the small fires are mostly undetected (Duncan et al., 2010), and the large fires burn under extreme meteorological conditions, making fires difficult to control or suppress in the contemporary managed fire regime. The largest individual fire was 9153 ha in size, which is much larger than both the largest lightning fire (1012 ha) and human ignited fire (1324 ha) that were previously documented (Duncan et al., 2009, 2010). The largest individual fire in this study was from a La Niña year. All the largest lightning fires on record for this site have burned during past La Niña events (Duncan et al., 2010). The smallest fires 0.09 ha were very similar in size to the other studies at 0.04 ha (Duncan et al., 2010). This information indicates that the predicted natural fire sizes were wide ranging and more variable than under the managed fire regime.

Grouping the fires in annual blocks reveals much the same pattern. The largest area burned annually was recorded during a La Niña year. The 15,060 ha maximum was much larger than the annual total recorded for the managed fire regime of 4078 ha (Duncan et al., 2009). The minimum burned annually within the managed fire regime was 603 ha. As with the individual fire sizes, the predicted range of annually grouped fire size is much greater.

Previous studies suggest that the largest fires in Florida occur during La Niña events (Brenner, 1991; Beckage et al., 2003; Duncan et al., 2009, 2010). There is evidence, however, that large fires do repeatedly occur during the spring dry periods (Beckage et al., 2005; Duncan et al., 2010). The model supports this as many very large fires occurred during non-La Niña years.

The time series of annual area burned predicted a cyclical pattern with fire area being the most dissimilar (negative autocorrelation) for 10 years and then switching to be similar (positive autocorrelation) at 11 years. There are two likely factors combining to create this pattern, fuel loadings and climate variability. The pattern is the most dissimilar in the first year following fire likely due to lack of fuels supporting fire. For the next 10 years the pattern of dissimilarity continues with a peak in the dissimilarity at 8 years. This may be climate driven with the ENSO cycle being around 7 years. The pattern switches to being one of similarity at 11 years and then generally repeats itself. As an example of this pattern, if the cycle starts during a year with lots of area burned then the point at which there is the smallest area burned is the following year (not much

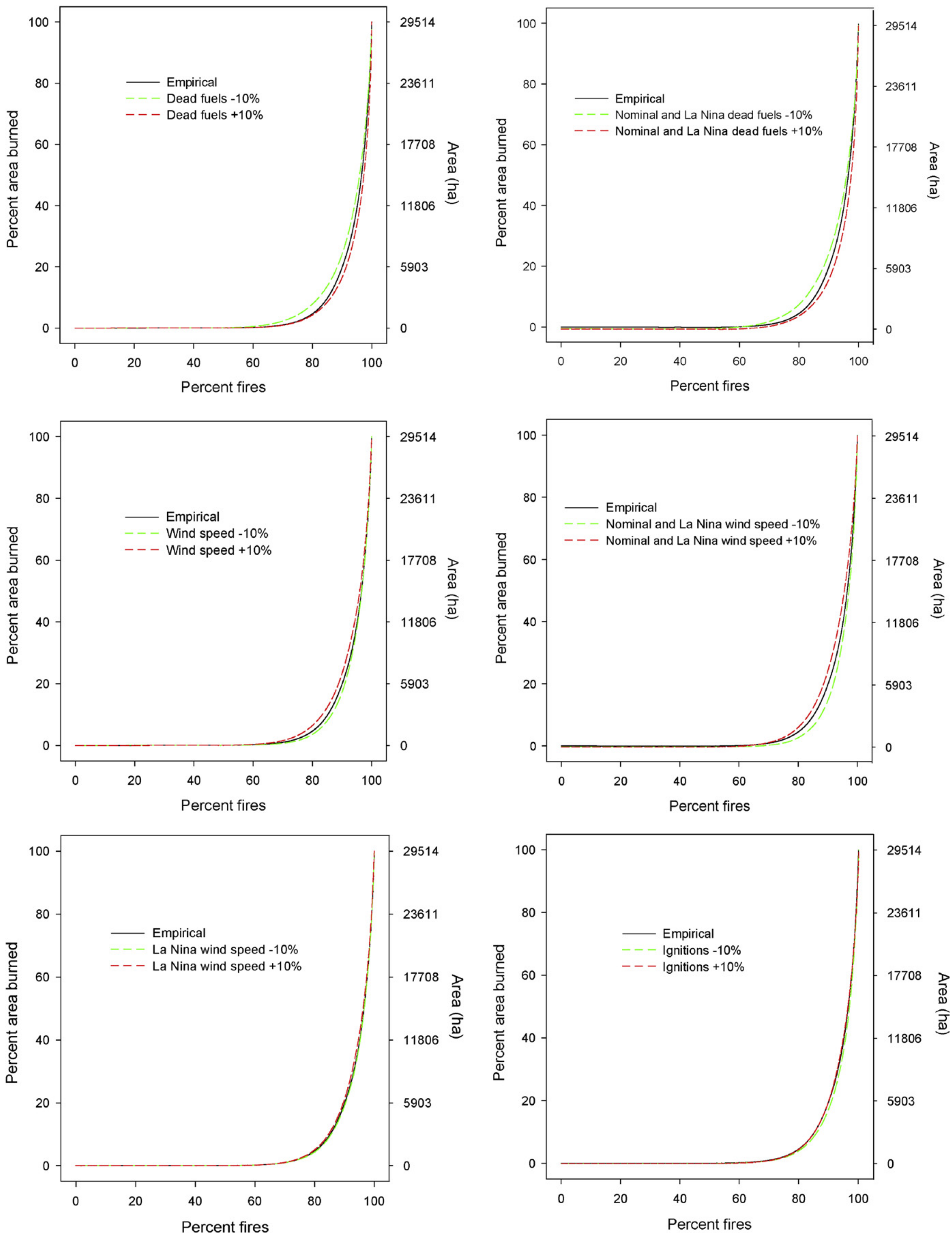

Fig. 9. HFire model sensitivity analysis results, comparing the six largest magnitude differences from the empirically parameterized model run. Random seed number was held constant for all sensitivity simulations isolating the influence of input parameter variation.

fuel left to burn) and then next, around 8 years followed at 11 years by another year with a large amount of area burned. The model is predicting this cycle which has a resemblance to the ENSO cycle at roughly an interval of 7 years that has been shown to influence area burned in Florida and the southeast (Brenner, 1991; Beckage et al., 2003). The eighth year could be explained by being a wet El Niño year followed by a dry event possibly a La Niña year at the eleventh year.

The HFire model builds a Poisson distribution around the mean fire frequency that is user entered through the configuration file. For this reason, the mean (13.8 ignitions per year) was very similar to the mean from the previous study (14 ignitions per year), the minimum was exactly the same with two, but the maximum (29) was smaller than the previous maximum (39) ignition frequency value (Duncan et al., 2010). The range in modeled ignition frequency values was less than was previously observed. Because the number of fires influences the distribution of fire on the landscape, the model was possibly underestimating both predicted area burned and the spatial pattern of fire.

4.2. Spatial pattern

Smooth curved boundaries dominated the pattern of modeled age classes on the landscape. The managed fire regime pattern on this same landscape has prominent straight edges from the human-made fire management unit boundaries and fire breaks (Duncan et al., 2009). The prominent fuel break crossing Merritt Island in an east-west direction is Banana Creek. This fuel break restricted fire spread across the center and widest part of the Merritt Island.

There was a mosaic of over a thousand different age patches on the landscape comprised of 189 different age patches at the end of the empirical model run. These may be conservative estimates because the model predicts the spread of a uniform burn pattern propagating from a single ignition point. Enclaves or islands of unburned fuels may not be realistically represented by this process. Spot fires that are secondary ignitions started by hot embers drifting aloft from an existing fire are common in this system (Duncan and Schmalzer, 2004), and are not represented by the model. The remote sensing process of mapping fires for the managed fire regime revealed a much finer/detailed pattern of both fire boundaries and within boundary pattern (Duncan et al., 2009). The absence of enclaves and spot fires undoubtedly influence the final pattern on the landscape.

The age distribution pattern in the empirical map has very little burned area in the 1 year old age class and a lot of 26–50 years old burned area. Comparing this to the composite simulation area by age distribution it appears that this is unusual. It appears that the empirical model run may have under predicted the amount of 1 year old burn area and over predicted the amount of 26–50 years old burn area. The large area mapped as 26–50 years old on the empirical map corresponds with very high cloud to ground lightning density and the area of highest lighting ignition density on these federal properties (Duncan et al., 2010). This area with its history of lightning activity and flammable pine flatwoods fuels, would have likely burned very frequently. Even the lower age threshold of 26 years seems unlikely for this particular area.

4.3. Sensitivity analysis and the natural range of variability

The sensitivity analysis revealed that there were several parameters that were more influential than others. Wind speed and dead fuel moisture consistently produced the largest magnitude differences. Because there was a different number of fires in each simulation, it was necessary to standardize using a cumulative percent scale. Displaying the data in this way is useful to identify model runs with high variance relative to the empirically derived model run. These curves show the similarity or difference in the small and medium sized fires effectively. There are limitations in the display of the data for the large area fires because the data are forced to conform to the cumulative percent scale and converge at 100 percent. Due to the steep trajectory of the curves in the large fires, it does not represent the actual magnitude of differences in the large fires effectively. For this reason the magnitude and range of variability was assessed for each sensitivity analysis model run in relation to the envelope of empirical variation.

4.3.1. Fire size, area burned, and fire frequency

The tables quantifying the range of variability indicated that the minimum highest variance was 6% with a maximum highest variance of 49%. In fact the largest reduction in total area burned was caused by varying both nominal and La Niña dead fuel moisture positively by 10%. It stands to reason that increasing fuel moisture would reduce the total area burned. More difficult to explain is how the reduction of fuel moisture also reduced the total amount of area burned, placing it outside of the empirical envelope of variability (Table 2, first column). The explanation is found by investigating the total burn frequency in Table 2. Ignition frequency is enhanced because dry fuels are more readily ignited, creating a mosaic of recently burned fuels on the landscape hindering fire spread through reduced fuel continuity. Combine this with the model predicting a dominance by small fires and previous studies showing the same (Duncan et al., 2010), and this becomes a plausible explanation. The model indicates that increasing wind speeds will cause fires to spread more rapidly, ultimately increasing total area burned.

4.3.2. Spatial pattern

The range of variability for the landscape metrics indicated that the largest number of patches was generated by reducing nominal dead fuel moisture by 10%. This again suggests that ignitions are enhanced by dryer fuels leading to a complex mosaic of different age patches across the landscape. The model suggests a second significant means of causing a high number of burn patches on the landscape, increasing fuel moisture. Presumably this reduces fire spread causing the fires to be smaller, creating many different age patches on the landscape. The model indicates that increasing nominal and La Niña wind speed by 10% would greatly decrease the number of patches. This makes sense, higher winds would lead to enhanced fire spread and cause fewer large fires. Clearly the dynamics of fuel moisture and wind speed have a profound impact on landscape burn mosaic structure.

By using the sensitivity analysis model runs, the model predicted that there was an inverse relationship between the number of patches and the mean fire size on the landscape. It also indicated a direct relationship between patch richness and patch number. Ecologically this means that spatial landscape pattern, specifically patch richness and mean fire size vary through time, both seasonally, with wet and dry seasons (small and large fires respectively) and on a longer time frame, with climatic variations such as El Niño and La Niña (small and large fires respectively).

The range of fire size variation indicated that some very large fires are expected to occur on these federal properties. The model indicates that the largest fires would occur if there were fewer fires. An explanation for this may be that over many years, fewer fires on the landscape would increase the continuity between fuels capable of carrying fire, creating a more even-aged fuel bed. With more fires, a fuel mosaic is created with a patchwork of different age/fuel loadings. The younger areas have less fuel and may not burn as well, acting as a fuel break. The total area burned and total frequency show the cumulative effect of altering each input parameter over long time periods. The model indicates that there can be large variation in area but less variation in total burn frequency.

The landscape metrics for the large magnitude sensitivity analysis runs summarized the spatial distribution of age classes on the landscape (Tables 3 and 4). The empirical model results are generally at the lower end of the range of variability. Reducing fuel moisture increased the number of landscape patches to the highest number in the study and caused the smallest mean patch area. The model suggests that there is a negative relationship between the two (number of patches and mean patch area). The smallest landscape patch (largest patch index) value was caused by reducing nominal and La Niña fuel moisture, reinforcing the previous finding. Increasing the wind speed caused there to be the fewest patches, the largest landscape patch mean area, and smallest patch richness. The model suggests that the higher winds cause fires to spread and become larger than would otherwise occur, reducing the number of different age patches on the landscape. This is reinforced by the largest patch index, because the largest value was caused by increasing the wind speed. The highest patch richness was caused by increasing fuel moisture values. The model predicts that higher fuel moistures cause increased resistance to burn; so more patches of different ages are ultimately left unburned.

4.4. General observations and model limitations

The Banana Creek feature running in an east-west direction limited individual fire sizes. Fire sizes would undoubtedly be larger if this non-flammable feature was not on this landscape. A Monte Carlo model structure may be necessary to accurately quantify the true range of variation. It is likely that the approach used here covered the major variability but an even larger number of simulations exploring all possible parameter value combinations would help make certain that all subtleties were covered. The standard errors derived by the composite simulation were generally small, indicating that the predicted stochastic range of variation for the empirical run was limited and generally captured in the modeling structure used here.

The sensitivity analysis used in this study was a one at a time screening technique (Campolongo et al., 2000). This technique was used because it is a simple, efficient, and effective way to identify influential variables and, for our purposes here, to estimate the range of variability about the empirical model. In nature it is unlikely that each variable would vary independently. The main limitation of this sensitivity technique is the inability to consider interactions among variables. More advanced sensitivity analysis techniques have been developed to incorporate interactions (Saltelli et al., 2000). In this initial modeling study however, principally designed to estimate the natural fire regime and to develop an estimate of variation about that prediction, the screening technique represented the most straight forward and parsimonious rout to the required information.

The HFire model was designed to model fires in the chaparral system. The vegetation regeneration/succession routine in this model is restricted to 30 years post-fire. In a chaparral system fuel accumulation may cease to differ significantly after this time frame but the flammability will increase. In the southeast and especially on KMCC within the oak scrub community, flammability can actually decrease with time since fire. Long fire suppression periods can cause the structure of oak scrub to become xeric hammock reducing flammability (Schmalzer and Hinkle, 1992b; Duncan et al., 1999). This is less critical for simulations under natural conditions but could be important for simulations on the contemporary landscape. The model currently does well to predict fire size, return interval, and spatial distribution of ages on the landscape.

The season and month of fires can be tracked but this information is of limited use. The model does not incorporate information on the seasonal/monthly distribution of ignition and then use this information to randomly sample the meteorological data by season/month. The distribution of fires by season and month were plotted but showed little useful information. For these reasons, a year is the minimum temporal unit that should be quantified using this version of the fire regime model. If seasonal and monthly trends could be predicted, this would add to the utility of the model. This would likely require more input data but could extend the models usefulness to predicting all elements of a fire regime.

Increasing model reality could possibly be aided by representing areas of higher than average ignition frequency. Modern lightning detection networks are helping to make this information more available (Manry and Knight, 1986; Nash and Johnson, 1996; Wierzchowski et al., 2002; Duncan et al., 2010). Evaluating the appropriateness of such information would need to take place given the possibility of modern anthropogenic influences on this information relative to a natural modeling scenario.

It may also be useful to allow specific distribution values to be input through the parameter files. Currently the mean is the only value entered. The full distribution of values may be available in some locations, and the model should take advantage of that information. As an example in this experiment, minimum and maximum ignition frequencies are available but not utilized. The result is that the model output may not be as informative and realistic as possible. The absolute effect of this was not explored in this study but would be useful to explore in the future.

5. Conclusion

Fire regime modeling can be useful in the absence of a traditional means of reconstructing fire regimes such as dendrochronology. The raster based HFire model represents the latest in fire regime models, it improves efficiency and accuracy from previous models, it is based on the robust Rothermel equations, and has been benchmarked and evaluated (Peterson et al., 2009). The Hfire fire regime model does well to predict fire size, return intervals, and spatial distributions of age classes. Other fire regime elements such as intensity and seasonality are not directly supported by this model.

The model was parameterized primarily using empirically derived values from studies conducted on these federal properties. The model predicted that the natural fire regime was dominated by a mosaic of quickly recycling small fires, with fewer medium and large fires on the landscape. Large fires were common during La Niña ENSO events but also occurred during nominal weather conditions. The largest variance from the empirical-derived output values obtained from varying input parameters by ten percent in the sensitivity analysis was from varying fuel moistures and wind speeds. The variance in some parameters may be as high as 50% over many years or as little as 6%. This information may especially be relevant in a climate changes scenario where it is possible for a small change in an environmental variable to causes a much larger change in long term fire regime response.

The information generated in this study may be directly useful to land managers who have an interest in mimicking the natural fire regime for purposes of managing habitat for native fire dependent species. Many of the findings in this study reinforce results gathered by empirical means and others may be new and warrant further study. This study represents only one of many steps in a quest to quantify the natural fire regime in a region that has been shaped and maintained by fire. Mimicking aspects or the results of the natural fire regime and adapting them on the contemporary landscape within the boundaries of conservation areas may be one of the best hopes for conserving many native fire-dependent species in this region. This will take more information generated by studies including empirical and modeling techniques, then applying this knowledge through bold and innovative land management.

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