

Complex burn prioritization models as a decision-support tool for managing prescribed fires in large, heterogeneous landscapes: an example from Everglades National Park, Florida, USA

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Abstract

Background

Prescribed fire is an essential strategy employed by natural resource managers to serve ecological objectives of fire management. However, limited operational resources, environmental conditions, and competing goals result in a finite number of burn days, which need to be allocated towards maximizing the overall benefits attainable with fire management. We developed a decision-support framework and a burn prioritization model for wetlands and wildland-urban interfaces in Everglades National Park (Florida, USA). The model included criteria relative to the conservation of plant communities, the protection of endangered faunal species, the protection of human life, the protection of cultural, archeological, and recreational resources, and the control of invasive plant species. A geographic information system was used to integrate the multiple factors affecting fire management into a single spatially and temporally explicit management model, which provided a quantitative computations-alternative to decision making that is usually based on qualitative assessments.

Results

The model outputs were 50-meter grid maps showing prioritization scores for the pixels which are targets of prescribed fire. During the 50 years of simulated prescribed fires run for model validation, the mean burned surface corresponded to $716 \pm 501 \text{ km}^2 \text{ y}^{-1}$. Mean fire return intervals, simulated for marshes, prairies, and pine rocklands were 9.9 ± 1.7 , 7.3 ± 1.9 , 4.0 ± 0.7 years, respectively. Mean fire return intervals, simulated within the *A. maritimus mirabilis*, *A. troglodyta floridalis* and *S. acis bartrami* butterflies, and *E. floridanus* critical habitats were 7.4 ± 1.5 , 3.9 ± 0.2 , 6.5 ± 2.9 years, respectively.

Conclusions

By performing fine-scale spatial computations, the model supported diverse fire regimes across the wetland landscape, based on spatial variability of ecosystem types and species habitats, while satisfying the need to protect human life, cultural heritage, and infrastructure. Employment of the burn prioritization model will allow the achievement of optimal or near-optimal fire return intervals for the higher-priority conservation objectives, by applying a quantitative methodology to fire management planning. We recommend using decision-support frameworks and models for managing fire return intervals, while also accounting for finer-scale fire characteristics, such as patchiness, seasonality, severity, and intensity.

Background

Fire is a fundamental driver of ecological processes that coevolves with biotic communities and that is changing under direct and indirect anthropogenic impacts (McLauchlan et al., 2020; Shuman et al., 2022; Turner et al., 2022). The interplay between fire and humans has been going on for hundreds of thousands

of years (Roebroeks and Villa, 2011). This long history makes it impossible to separate anthropogenic effects from natural background fire regimes (Bowman et al., 2011). When and how did anthropogenic fires depart from the natural cycles of planet Earth? We have no clear answer. Nonetheless, the human populations are altering fire regimes worldwide, by clearing forests and shifting land use, dispersing plants, altering ignition patterns, and actively suppressing fires (Bowman et al., 2011; Parisien et al., 2016; McLauchlan et al. 2020), with important consequences for fire-adapted ecosystems and the species inhabiting them. Fire suppression and shifts in fire return intervals (FRIs) have caused habitat degradation (Van Lear et al., 2005), woody encroachment into grasslands (Twidwell et al., 2013), and decline or extinction of fauna populations (Woinarski et al., 2015). Model simulations have predicted that the complete exclusion of fire from Planet Earth would result in a global transfiguration of biomes (Bond et al., 2005).

Hence, to serve biological conservation objectives, natural resource managers employ prescribed fire, supplementing the modified wildfire regimes. Often, by applying prescribed fire, natural resource managers try to mimic as best as possible the natural conditions that were occurring before the human technologic eras (Frost, 1998; Conedera et al., 2009). However, although knowledge of historical fire regimes is important, understanding contemporary fire-biota interactions across trophic levels, functional groups, spatial scales, and management contexts is also critical (Freeman et al., 2017) for an effective fire management that accounts for the evolving feedbacks between ecosystems and fire regimes (i.e., pyrodiversity; Bowman et al., 2016). Overall, the concept of pyrodiversity, defined as variable fire regimes in relation to the spatial variability of trophic levels and ecological processes (Bowman et al., 2016), seems to be extensively supported across disciplines such as ecosystem ecology, forest management, and conservation biology (Martin and Sapsis, 1992; Williams and Baker, 2012; Kelly et al., 2012; Mason and Lashley, 2021).

Management of prescribed fire is complicated by the need to consider the protection of human life and infrastructure, and the provision of ecosystem services (Bowman et al., 2013). The presence of human infrastructure affects the ability of natural resource managers to achieve conservation objectives through fire management. For example, densely populated areas rarely support high pyrodiversity, largely because of fire suppression (Steel et al., 2021). Moreover, habitat loss and fragmentation may interact with fire regimes in ways that are not totally predictable, with the risk of even causing unintended local extinctions with fire management (Driscoll et al., 2021).

Since prescribed fire management is restricted by a combination of limited operational resources, environmental conditions, and competing ecological objectives, opportunities to perform a prescribed fire can be considered a “zero-sum game”: there are a finite number of burn days, and decisions on where and when to burn necessarily involve difficult tradeoffs. The problem becomes acute in large, complex landscapes that include wildland-urban interfaces (WUIs), where optimizing prescribed fire decision-making would substantially enhance efficiency, promote better resource management outcomes, and protect the health and safety of adjacent human populations.

Fire science as a field is challenged by rapidly changing fire regimes, climate change, and growing human populations in WUIs. A recent synthesis of these challenges (Shuman et al. 2022) identified a need to integrate across disciplines, co-produce knowledge, utilize big data, and develop models with human and natural dimensions. Spatial modeling using geographic information systems (GIS) offers a quantitative approach for resolving biological conservation and landscape management issues (Hiers et al., 2003; Kandel et al., 2015). It provides a mechanism by which spatially explicit quantitative and qualitative data can be integrated to analyze and model landscape level processes at different spatial scales. For example, GIS can be used to integrate multiple determinant factors affecting fire management across a landscape into a single spatially and temporally explicit management model that informs and drives management decisions. By displaying the different factors influencing fire management planning in a spatially explicit fashion, contrasting issues within the landscape can be modeled in their granularity by assigning numerical, standardized scores based on expert opinion and published research.

Fire-related decision-support tools should be employed to manage ecosystems that experience variation in fire regimes at large spatial scales. For example, wetlands of the Florida Everglades vary in hydrology (e.g., days of water inundation or hydroperiod, as well as flooding and drought cycles) and fire return intervals, and therefore need to be managed differently for short- and long-term hydroperiod wetlands (Lockwood et al. 2003). Further, the combined effects of fire and changing hydroperiod influence post-fire recovery and vegetation composition (Ruiz et al. 2013, Kominoski et al. 2022, Nocentini et al. 2024) and are therefore important for habitats structure. In 1958, after recognizing the role of fire in maintaining pine rocklands, Everglades National Park (ENP) ignited the first prescribed fire in National Park Service history (National Park Service, 2023). Since then, prescribed fire has been used as an important conservation tool for fire-prone biomes of ENP: marshes, prairies, and pine rocklands. Fire management planning in ENP is nonetheless a complex matter, as it must address a variety of competing ecological and logistical goals (National Park Service, 2015; Nocentini et al., 2021a). For example, the time window for carrying out a prescribed fire in certain areas of ENP is often constrained by the need to burn with the appropriate hydrologic conditions while also burning outside of the nesting season of endangered species. Although ENP fire management plans are carefully considered and built through expert opinion, which are also based on current conditions observed during helicopter surveys of the landscape, they are mostly based on qualitative rather than quantitative assessments.

Here, we developed a decision-support framework (Fig. 1) and a burn prioritization model that, through fine-scale spatial computations, supported diverse fire regimes across ENP wetland landscape, based on spatial variability of ecosystem types and species habitats, while satisfying the need to protect human life, cultural heritage, and infrastructure. Burn prioritization tools allow natural resource managers to compute FRIs (i.e., fire frequency), and to plan fire management in the medium to long term with high efficiency (Hiers et al., 2003). Fire frequency is particularly critical as it shapes vegetation structure and composition, and subsequently maintains faunal habitats (Griffiths et al., 2015).

Methods

Study region

Everglades National Park comprises about 4,000 km² in South Florida, mostly freshwater wetlands. Topographic variation dictates surface water depth and inundation duration, resulting in ecosystem types characterized by different soil types, variable biogeochemistry, and distinct vegetation communities, which provide habitat for distinct faunal communities as well. The dominant ecosystem types within ENP are mangrove forests, freshwater marshes, marl prairies, and pine rocklands (Fig. 2). Coastal mangrove forests were not considered in this study as they are not a target for prescribed fires. Freshwater marshes are characterized by extended inundation, and by the presence of herbaceous plant species typical of both ridges (higher soil elevation and shallower surface water), such as sawgrass (*Cladium jamaicense* Crantz), and sloughs (lower soil elevation and deeper surface water), such as spikerush (*Eleocharis cellulosa* Torr.) and American white waterlily (*Nymphaea odorata* Aiton). Prairies are characterized by short inundation, and by the presence of herbaceous plant species such as sawgrass and gulf hairawn muhly [*Muhlenbergia capillaris* (Lam.) Trin. Var. *filipes* (M. A. Curtis) Chapm. ex Beal]. In both marsh and prairie environments, high elevation patches of land, characterized by short inundation periods and high tree cover, called “tree islands”, are common. Tree islands are characterized by a mixed-species assemblage of both temperate and tropical species, ranging from swamp forests to well-drained upland tropical hardwood hammock communities (Ross et al., 2022). Pine rocklands are characterized by dry conditions, and are dominated by an open canopy of South Florida slash pine (*Pinus elliottii* var. *densa*) with a patchy subcanopy of palms and shrubs; tree islands composed of tropical hardwood hammock species are also embedded within the pine rockland fire-adapted community. Wetland hydrologic regimes control not only plant species composition but also plant aboveground biomass (Childers et al., 2006), and therefore have a strong effect on fuel loads available for wildfires.

Everglades National Park hosts abundant wildlife as well. A total of 23 faunal species occur in ENP that are federally listed as threatened or endangered or are candidates for listing under the Endangered Species Act of 1973 (National Park Service, 2021). Within this group, there are several species that have critical habitat designation within ENP. These species include the Cape Sable seaside sparrow (*Ammodramus maritimus mirabilis*) and the Florida leafwing butterfly (*Anaea troglodyta floridae*), whose habitats are known to depend on certain FRIs (Possley et al., 2016; Benscoter et al., 2019; Benscoter and Románach, 2022; Henry et al., 2022). In addition, there are other endangered species that can occur within ENP boundaries but that also occur in other regions, such as the Florida bonneted bat (*Eumops floridanus*) and the Bartram's scrub hairstreak butterfly (*Strymon acis bartrami*), whose habitats also depend on the application of prescribed fire (Possley et al., 2016; Braun de Torrez et al., 2018a and 2018b; Henry et al., 2022), or such as the snail kite (*Rostrhamus sociabilis plumbeus*) and eastern black rail (*Laterallus jamaicensis*), whose habitats can benefit from the application of prescribed fire (Miller et al., 1998; Lawson et al. 2022; Johnson and Lehman, 2021).

Fire is a critical component of the Everglades ecosystems, as it helps to maintain landscape heterogeneity (Ruiz et al. 2013), drives nutrient cycling and productivity (Carter and Foster 2004, Nocentini et al., 2022), and slows the natural successional processes which drive plant communities

toward increased woody plant dominance (Robertson 1953, Duever 1984, White 1994). The composition and structure of the vegetation communities maintained by fire also serve as critical habitats for the fauna (Miller et al., 1998; Benscoter et al., 2019; Henry et al., 2022). Optimal FRIs vary among ENP ecosystem types, based on the need to preserve the vegetation and faunal communities supported by each ecosystem type (Noss, 2018). Fire is an essential driver of wetland biogeochemical cycling as well (Bodí et al., 2014; Nocentini et al., 2022). Prescribed fire has been applied in ENP since 1958, and its use has increased in recent decades (Smith III et al., 2015; Nocentini et al., 2021b).

While the southern and western boundaries of ENP adjoin Florida Bay and the Gulf of Mexico, the northern and eastern boundaries are in proximity of urban areas. The proximity of ENP to urban areas poses challenges in terms of using fire to preserve and restore, since the protection of urban and suburban communities is a priority. Prescribed fires are conducted in these areas to reduce vegetation biomass which, if left to grow, could fuel hazardous wildfires (Nocentini et al., 2021a). Similarly, within ENP boundaries, there is a series of anthropogenic landscape features around which prescribed fire is applied to control fuel loads. These are cultural and archeological resources (Stutts, 2014), recreational resources such as campgrounds and trails, paved roads, and buildings with various designations (e.g., management, scientific research, lodging).

The presence of native and exotic invasive plant species is another factor affecting ENP fire management. Prescribed fire is employed, in some cases after herbicide applications or mechanical treatments, to remove both invasive woody plants, like coastal plain willow (*Salix caroliniana* Michx.), broad-leaved paperbark (*Melaleuca quinquenervia* Cav. S. T. Blake), and Australian pine (*Casuarina equisetifolia* L. ex J. R. & G. Forst), and herbaceous plant species like old world climbing fern (*Lygodium microphyllum* Cav. R. Br.) and cattail (*Typha* spp.)].

Modeling approach, and criteria selection, ranking, and value scoring

To develop a spatially explicit burn prioritization model, we followed the methodology described in Hiers et al. (2003). The spatial model was built on ArcGIS Pro 3.0.3 (ESRI, California, USA). The ArcGIS Pro software was chosen because it allowed for all spatial data processing and, later, directly integrate the outputs into the built-in Model Builder (Fig. S1).

The selection of criteria critical for prioritizing burns was done by incorporating the experience of ENP fire managers and by reviewing ENP Fire Management Plan (National Park Service, 2015). Criteria were ranked according to Fire Management Plan guidance and through discussions with ENP fire managers. Based on the ranking, criteria were assigned a different weight that reflected their importance to overall burn prioritization (Table 1). For example, “time since last fire” had the highest influence on the model output, accounting for 30% of the total final score calculated for each individual pixel. Then, a value weighting factor was also used according to the specific values that each criterion could assume (Table 1). So, while the “overall model influence” corresponded to the maximum score that each individual criterion could contribute to the overall prioritization score, the value “weight” dictated the

proportion of the maximum score that each criterion actually contributed to the overall prioritization score during a single model run, for a specific land unit.

Table 1

List of input criteria for the burn prioritization model of Everglades National Park (ENP). Overall model influence represents the importance of each criterion in the model and reflects how criteria were ranked; the overall model influence also corresponds to the maximum score that each individual criterion can contribute to the overall prioritization score (the maximum potential overall prioritization score for a pixel equals 100). The values assumed by each criterion then dictate the proportion (i.e., weight) of the maximum potential score that is computed during a model run. TSLF = Time Since Last Fire.

<i>Input criteria</i>	<i>Overall model influence (%)</i>	<i>Value</i>	<i>Weight (%)</i>
TSLF in prairie ecotype (years)	30	1	0
		2	10
		3	20
		4	30
		5	40
		6	50
		7	60
		8	70
		9–10	80
		> 10	100
TSLF in marsh ecotype (years)	30	1–2	0
		3–4	10
		5	20
		6	30
		7	40
		8	50
		9	60
		10	70
		11–12	80
		> 12	100
TSLF in pine rocklands ecotype (years)	30	1	0
		2	10
		3	40
		4	60

<i>Input criteria</i>	<i>Overall model influence (%)</i>	<i>Value</i>	<i>Weight (%)</i>
		5	80
		6–7	90
		> 8	100
Wildland-urban interface (WUI)	10	no WUI	0
		WUI	100
Protection of cultural and archeological resources	6	no presence	0
		presence	100
Protection of recreational resources	5	no presence	0
		presence	100
Protection of endangered fauna species: Cape Sable seaside sparrow (<i>Ammodramus maritimus mirabilis</i>)	8	no CSSS site	0
		CSSS site with TSLF = 1	-50
		CSSS site with TSLF = 2	0
		CSSS site with TSLF = 3	20
		CSSS site with TSLF = 4	40
		CSSS site with TSLF 5–6	60
		CSSS site with TSLF 7–8	80
		CSSS site with TSLF > 8	100
Protection of endangered fauna species: Florida leafwing butterfly (<i>Anaea troglodyta floridalis</i>) and Bartram's scrub-hairstreak (<i>Strymon acis bartrami</i>)	8	no butterfly site	0
		butterfly site with TSLF = 1	-50
		butterfly site with TSLF = 2	0
		butterfly site with TSLF = 3	20
		butterfly site with TSLF = 4	40

<i>Input criteria</i>	<i>Overall model influence (%)</i>	<i>Value</i>	<i>Weight (%)</i>
		butterfly site with TSLF = 5	60
		butterfly site with TSLF = 6	80
		butterfly site with TSLF > 6	100
Protection of endangered fauna species: Florida bonneted bat (<i>Eumops floridanus</i>)	6	no bonneted bat site	0
		bonneted bat site with TSLF 0–2	0
		bonneted bat site with TSLF 3–4	40
		bonneted bat site with TSLF 5–6	80
		bonneted bat site with TSLF > 6	100
Protection of endangered fauna species: black rail (<i>Laterallus jamaicensis</i>)	2	no black rail site	0
		black rail site with TSLF = 1	0
		black rail site with TSLF = 2	40
		black rail site with TSLF 3–5	80
		black rail site with TSLF > 5	100
Protection of endangered fauna species: snail kite (<i>Rostrhamus sociabilis plumbeus</i>)	2	no snail kite site	0
		snail kite site with TSLF = 1	0
		snail kite site with TSLF = 2	40
		snail kite site with TSLF 3–5	80
		snail kite site with TSLF > 5	100
Control of invasive plant species: old world climbing fern (<i>Lygodium microphyllum</i>)	4	no presence	0

<i>Input criteria</i>	<i>Overall model influence (%)</i>	<i>Value</i>	<i>Weight (%)</i>
		presence with TSLF = 1	30
		presence with TSLF = 2	60
		presence with TSLF > 2	100
Control of invasive plant species: willow (<i>Salix caroliniana</i>)	4	no presence	0
		presence	100
Control of invasive plant species: paperbark tree (<i>Melaleuca quinquenervia</i>)	2	no presence	0
		presence	100
Control of invasive plant species: australian pine (<i>Casuarina equisetifolia</i>)	2	no presence	0
		presence	100
Control of invasive plant species: cattail (<i>Typha latifolia</i>)	2	no presence	0
		presence	100
Hydrologic conditions	4	wet	0
		intermediate	50
		dry	100
Oligotrophic status	1	soil TP $\geq 200 \mu\text{g g}^{-1}$	0
		soil TP $< 200 \mu\text{g g}^{-1}$	100
Size of burn unit	2	small ($< 10 \text{ km}^2$)	0
		medium ($10\text{--}100 \text{ km}^2$)	50
		large ($> 100 \text{ km}^2$)	100
Complexity of burn unit	2	complex	0
		moderate	50
		easy	100

Data sources and data processing

We collected spatial data representative of each criterion from public repositories: ENP vegetation cover (Ruiz et al., 2021); ENP fire perimeters (Malone, 2019); faunal species critical habitats (U.S. Fish & Wildlife Service, 2023); ENP buildings, roads, trails, and campsite perimeters (Barrow and National Park Service Southeast Region Geospatial Resources, 2022); ENP cultural and archeological resources (Stutts, 2014); digital elevation model (U.S. Geological Survey, 2019); ENP gage surface water stages (South Florida Water Management District, 2023). Due to the sensitivity of the information, the locations of some of the cultural and archeological resources within ENP are not publicly available and were directly provided to us by the National Register of Historic Places. Moreover, all tropical hardwood hammocks characterizing tree islands, identified through the ENP vegetation cover map, were considered archeological sites. This assumption derives from the fact that, potentially, any tropical hardwood hammock could have hosted indigenous people and could therefore potentially contain archeological artifacts (Fradkin, 2016).

Fire perimeters recorded within ENP from 1948 to 2022 (Smith III et al., 2015; Malone, 2019; fire data for the most recent years were unpublished and were provided to us by ENP's fire managers) were used to calculate time since last fire (TSLF). For each land unit, TSLF was expressed as the number of years elapsed between the last fire event and the year for which the model was simulating burn prioritization scores (Fig. 3).

The wildland-urban interface (WUI) criterion was conceived with the scope of managing fuel loads in proximity of landscape features characterized by the presence of human life, to minimize the risk of hazardous wildfires. To correctly represent the WUI criterion in our model, we created a buffer of 2.5 km around all roads and buildings, in agreement with the practices described in the ENP Fire Management Plan (National Park Service, 2015). With the same intent, a buffer of 200 m was created around trails and campsite perimeters to represent the criterion related to the protection of recreational resources. Similarly, to represent the criterion related to the protection of cultural and archeological resources, 2.5 km and 200 m buffers were created, differentiating between buildings of cultural relevance and archeological sites within the perimeter of tree islands, respectively.

The hydrologic conditions criterion was conceived with the scope of assigning additional burn prioritization points to areas characterized by dry conditions. This is justified by the need to maintain lower fuel levels in drier areas where severe wildfires, which spread more rapidly, are more likely to burn organic soils (Turetsky et al., 2015) and may threaten the safety of urban and suburban communities. To represent this criterion in the model, we used surface water stage data (National Geodetic Vertical Datum of 1929), collected between the years 2019 and 2022 from 69 stations located within and around ENP boundary (South Florida Water Management District, 2023), together with the data from a high-resolution LIDAR digital elevation model (U.S. Geological Survey, 2019), and we calculated mean surface water depths of the last three years. Empirical Bayesian kriging, a strong prediction method for complex data (Krivoruchko and Gribov, 2019), was used to generate a surface water stage map covering the entire ENP area. Next, the values from the digital elevation model were subtracted from the values of the surface water stage map to generate a surface water depth map. Areas characterized by mean water

depths below 0, between 0 and 50, and above 50 cm were considered dry, intermediate, and wet, respectively.

The oligotrophic status criterion was conceived with the scope of assigning additional burn prioritization points to areas characterized by more oligotrophic conditions, where the periodical return of fire is essential for nutrient recycling (Nocentini et al., 2021b; Nocentini et al., 2022). Oligotrophic conditions in ENP are exhaustively represented by soil phosphorus (P) concentrations, since ENP is a naturally P-limited region (Davis and Ogden, 1994). Using data collected at $n = 899$ sites during different projects (Scheidt et al., 2021; Nocentini et al., 2021b; Nocentini and Kominoski, 2021), empirical Bayesian kriging was used to generate a soil P concentration map covering the entire ENP area.

The burn unit size and complexity criteria were conceived with the scope of assigning additional burn prioritization points to areas that did not pose any particular logistical challenge and that helped maximize the burned surface in any one given year. In the model, the burn unit size corresponded to the total surface target of prescribed fire (i.e., marshes, prairies, and pine rocklands) present within each unit, while the burn unit complexity reflected a qualitative characterization of the ease of burning. The characterization of the ease of burning was performed by ENP fire managers.

All spatial data were converted to 50-meter grid raster layers. To allow their use together in the model, all maps were aligned by selecting the same spatial extent during conversion to raster file format.

Model validation

Model validation was performed by simulating 50 years (2023 to 2072) of fire management following the priorities suggested by the burn prioritization model. Two distinct scenarios were simulated, S1 and S2. Every year, by running the model, mean burn prioritization scores were calculated for each burn unit. Next, based on the mean scores, units were selected to be treated with prescribed fire. We set two rules in the selection of the units to burn: i) only units that scored 30 points or more (S1), or units that scored 25 points or more (S2), could be selected, and ii) no additional units could be selected once a threshold of 400 km² of treated land (National Park Service, 2023) was passed. These rules were set to satisfy the conditions that ENP fire managers would not apply fire more often than natural and historic FRIs, and that the amount of land treated every year would not exceed ENP resource capabilities. After generating the fire perimeters for the simulated year, we re-calculated TSLF for the following year. With the TSLF calculated for the following year, the model was run again, and new prioritization scores were calculated for that year.

At the end of the validation period, we had generated 50 years of simulated fire perimeters that were used to calculate FRIs for the different ecotypes and fauna critical habitats. The simulated FRIs were then compared with the target FRIs gathered from the literature, and the goodness of fit was evaluated with Pearson's correlation.

Results

The model outputs were a 50-meter grid map, showing prioritization scores only for the pixels occupied by ecotypes which are a target of prescribed fire (i.e., marshes, prairies, and pine rocklands; Fig. 4A), and a map where the prioritization scores were averaged and scaled to the burn unit polygons (Fig. 4B).

During the 50 years (2023 to 2072) of simulated prescribed fires based on the calculated prioritization scores run for model validation, the mean burned surface corresponded to 607 ± 510 and $716 \pm 501 \text{ km}^2 \text{ y}^{-1}$, in S1 and S2, respectively.

Based on the validation results, the model achieved FRIs appropriate to maintaining ENP conservation priorities. Scenario S2 produced the best results. Mean FRIs, simulated for marshes, prairies, and pine rocklands during S2 model validation, were 9.9 ± 1.7 , 7.3 ± 1.9 , 4.0 ± 0.7 years, respectively (Table 2). Mean FRIs, simulated within the *A. maritimus mirabilis*, *A. troglodyta floridalis* and *S. acis bartrami* butterflies, and *E. floridanus* critical habitats during S2 model validation, were 7.4 ± 1.5 , 3.9 ± 0.2 , 6.5 ± 2.9 years, respectively (Table 2). There was good agreement between the target and simulated mean FRIs by ecotype and by fauna species critical habitat in both S1 ($r^2 = 0.88$; RMSE = 1.79; $p = 0.02$) and S2 ($r^2 = 0.88$; RMSE = 1.11; $p = 0.02$; Fig. 5).

Table 2

Summary of model validation results for both scenarios S1 (more conservative approach by burning units that scored 30 points or more) and S2 (more aggressive approach by burning units that scored 25 points or more). Simulated mean fire return intervals (FRI) and simulated FRI ranges are shown by ecotype and critical habitat of fauna species known to benefit from certain fire regimes [i.e., “sparrow” = Cape Sable seaside sparrow (*Ammodramus maritimus mirabilis*); “butterflies” = Florida leafwing and Bartram's scrub hairstreak (*Anaea troglodyta floridalis* and *Strymon acis bartrami*); “bat” = Florida bonneted bat (*Eumops floridanus*)]. Target FRI were estimated using optimal ranges and values previously published. These targets are not necessarily the targets set by Everglades National Park (ENP) in every circumstance.

<i>Ecotype or habitat</i>	<i>Scenario</i>	<i>Simulated mean FRI (± SD)</i>	<i>Simulated FRI range</i>	<i>Target FRI</i>	<i>Optimal FRI range</i>	<i>References</i>
<i>years</i>						
Marsh ecotype	S1	11.0 ± 1.4	2.9–12.5	9.0	3.0–25.0; 3.0–12.0	Hendrickson (1972); Ogden et al. (2005); National Park Service (2015)
	S2	9.9 ± 1.7	2.6–12.5			
Prairie ecotype	S1	8.4 ± 2.0	2.5–12.5	7.5	5.0–10.0; 3.0–12.0; 4.0–11.0	Kushlan et al. (1982); National Park Service (2015); Benscoter and Romañach (2022)
	S2	7.3 ± 1.9	2.6–12.5			
Pine rockland ecotype	S1	4.4 ± 0.9	2.8–12.5	4.5	3.0–5.0; 3.0–7.0	Duever (2005); National Park Service (2015)
	S2	4.0 ± 0.7	2.5–12.5			
Sparrow habitat	S1	8.7 ± 1.8	2.9–10.0	7.0	5.0–8.0; 5.0–10.0	Benscoter et al. (2019); Benscoter and Romañach (2022)
	S2	7.4 ± 1.5	2.9–8.3			
Butterflies habitat	S1	4.1 ± 0.3	3.8–10.0	4.0	3.0–5.0	Henry et al. (2022)
	S2	3.9 ± 0.2	3.1–8.3			
Bat habitat	S1	7.3 ± 3.5	2.5–12.5	4.0	3.0–5.0	Braun de Torrez et al. (2018b); Tallie et al. (2021)
	S2	6.5 ± 2.9	2.5–10.0			

Discussion

Our decision-support framework and burn prioritization model illustrate how diverse fire regimes across a landscape can be managed while considering multiple climatic, ecological, and human criteria. By providing a transparent and objective framework during fire management planning, employment of the burn prioritization model presented here would allow managers to achieve optimal or near-optimal FRI for their higher-priority conservation objectives. In fact, our model addresses competing management goals, without focusing fire management on individual endangered species or single management priorities and promotes the most efficient allocation of management effort. Using two different

scenarios for burn prioritization in ENP, we simulated optimal mean fire return intervals for different wetland ecosystems (ranging from ~ 4 to 10 years FRI) and endangered species needs (ranging from ~ 4 to 7 years FRI).

We demonstrated that full achievement of conservation objectives will also depend on resource availability, as more resources will translate into the ability to target more burn units, therefore providing the possibility of achieving shorter FRIs where needed. However, the model's purpose is to make the most of limited resources. In our simulation we used a restrictive criterion in terms of the maximum land surface that could be targeted with prescribed fire in any one year (i.e., limited resources). Nonetheless, we simulated near-optimal FRIs for the conservation of vegetation communities and of the fire-dependent fauna populations. Applying a threshold to the total surface burned by prescribed fires every year resulted in a reduced number of treated burn units, especially in those years where a large unit was prioritized. As a side benefit of such strategy, the reduced number of burn units treated in such years would allow ENP natural resource managers to focus on addressing sub-unit issues, as, for example, the avoidance of burning specific landscape patches (e.g., to support nesting of endangered species). For such applications, the 50-meter grid map produced by the model may become extremely useful, particularly when complemented with field observations.

Although the model simulated near-optimal mean FRIs towards ecological goals, the simulated maximum FRIs consistently corresponded to 12.5 years across ecotypes, and ranged between 8.3 and 12.5 years across habitats. This is a result of the prioritization score being averaged across large burn units, which included multiple ecotypes and parts of endangered species habitats. Unit size therefore had a large effect on simulated maximum as well as mean FRIs. Had we unrealistically applied fire during validation at the pixel scale, we would have observed an even better fit between the target and simulated mean FRIs. But, as a management support tool, the model needs to reflect the reality of fire management in ENP. Nonetheless, ENP fire managers will have the ability to target sub-units to achieve shorter local FRIs. One example of a sub-unit that might require such treatment are patches of prairie vegetation or of *A. maritimus mirabilis* habitat embedded within large burn units dominated by the marsh ecotype, which is characterized by the longest target FRI among the fire-dependent habitats identified in this study. Regardless, according to model predictions, even with limited resources, ENP fire managers could potentially achieve $\text{FRIs} \leq 12.5$ across the whole ENP surface target of prescribed fires. This FRI corresponds to the upper limit of the optimal range of FRIs recommended for a high proportion of ENP landscape (National Park Service, 2015).

There seems to be wide consensus on the optimal FRI ranges for the prairie and pine rockland ecotypes (Kushlan et al., 1982; Duever, 2005; National Park Service, 2015; Nocentini et al., 2021b; Benscoter and Romañach, 2022). Further confirmation of this is that, for example, the target FRI used here for marl prairies, which we estimated from the literature, corresponded to 7.5 years, which almost coincided with the 8-years FRI indicated in ENP fire management plan for prairies outside of the WUI zone (National Park Service, 2015); 8 years is also the time needed by prairie vegetation to fully recover (Sah et al., 2007). In contrast, almost no information is available on the optimal FRI for the marsh ecotype.

Therefore, it seems that the marsh ecotype, although it benefits from the application of fire (Ogden et al., 2005), depends on FRIs less than the other ENP ecotypes analyzed in this study.

It is important to note that the optimal FRI ranges indicated in the literature for the conservation of endangered fauna species aim at maintaining vegetation composition and structure ideal for nesting and the reproductive cycle of said species. For vegetation communities to be maintained and conservation goals to be achieved, prudent fire management needs to be complemented by prudent hydrologic management (Lockwood et al., 2003). Our simulated mean FRI within the *A. maritimus mirabilis*'s habitat was towards the high end of the optimal FRI range reported by some authors (Benscoter et al., 2019). Although the mean FRI simulated for the *A. maritimus mirabilis*'s habitat would be still short enough for maintaining habitat structure (La Puma, 2010), allocation of more resources to fire management of ENP, complemented by the right amounts and timing of water deliveries, would constitute a solid foundation for the prosperity of *A. maritimus mirabilis* (Haider et al., 2021; Benscoter and Romañach, 2022). The mean simulated FRI for *A. troglodyta floridalis* and *S. acis bartramii*'s habitat was extremely close to the optimal FRI recommended by Henry et al. (2022). In the case of *E. floridanus*'s habitat, the simulated mean FRI was higher than the recommended target FRI, and even higher than the optimal range. However, differently from habitats inside ENP for which there's agreement in the scientific literature on their dependance on certain FRIs (i.e., *A. maritimus mirabilis*'s, *A. troglodyta floridalis* and *S. acis bartramii*'s habitats), it seems that the effect of fire management on *E. floridanus*'s activity is confounded by other important factors such as vegetation type and conditions (Tallie et al., 2021). For this reason, the maximum score that the protection of *E. floridanus*'s habitat contributed to the model (6 points) was slightly lower than the maximum score attainable for the protection of *A. maritimus mirabilis*'s, *A. troglodyta floridalis* and *S. acis bartramii*'s habitats (8 points). Moreover, a high portion of the *E. floridanus*'s habitat within ENP surface target of prescribed fire was characterized by the marsh ecotype (42%; 65.7 km²), which is the ecotype with the highest target FRI. Overall, the variability simulated in fire regimes by our model among landscape patches within the *E. floridanus*'s habitat may reflect an acceptable fire management towards this ecological goal (Tallie et al., 2021).

Our model offers flexibility and can be easily updated by and for fire scientists and natural resource managers. This dynamism fits the adaptive management approach adopted by ENP and other collaborating agencies in the context of Everglades restoration (Gunderson and Light, 2006). As management priorities or landscape conditions may change, new spatial layers may be added, or existing spatial layers may be replaced with current conditions. Similarly, if new information becomes available through scientific literature or technical reports, model parameters may be re-calibrated. Another advantage of a spatial model such as the one we presented here is that it can be understood and manipulated by a variety of professionals within the agency, and transferred to other agencies in south Florida that manage prescribed fires in natural areas north of ENP, but characterized by similar environmental conditions, and by the same endangered species to protect, or invasive species to control (Ogden et al., 2005; Duever, 2005).

While we believe in the efficacy of the burn prioritization model in enhancing the ability of ENP fire managers to achieve conservation objectives through an objective, process-based tool, we also recognize its limitations. First, our model does not consider the occurrence of wildfires when employed during natural resource planning for future years; presently, the contribution of wildfires to total area burned within ENP is below 30% (Nocentini et al., 2021b). Second, we did not simulate burn of sub-units and assumed in every case that the whole unit is treated. In practice, because of a variety of issues, such as differing hydrologic conditions and differences in fuel loads (plant biomass) or vegetation communities throughout the unit, or the observation of nesting of endangered species in specific areas of a burn unit, sub-units might be targeted. Third, the model can be used to simulate fire occurrence, but not other fire characteristics. We recognize that other fire characteristics, such as patchiness, seasonality, and severity, are important controls of ecosystem processes and interactions and, in order to fulfill pyrodiversity's principles, they need to be as well addressed during planning and when applying prescribed fires (Noss, 2018).

Conclusions

Prescribed fire is an essential strategy of natural resource managers in many regions worldwide and spatial, numerical models built for prescribed fire prioritization have the potential to support efficient decision making and resource allocation towards biological conservation, especially in large, heterogeneous landscapes.

Although prescribed fire is essential to maintaining fire-adapted species and native habitats, changes in both climate and fire regimes are likely changing the role of fire as a driver of ecosystem structure and function (Lockwood et al. 2003, Johnstone et al. 2016, Shuman et al., 2022). Increases in global temperatures and shifts in precipitation patterns with climate change are transforming the frequency, severity, and intensity of fires worldwide (Shuman et al. 2022), with important consequences for vegetation structure and productivity (Wardle et al. 2004, Krawchuk et al. 2009, Turner et al. 2022). It is critical to better understand how both altered climate and hydrology and subsequent changes in wildfires will influence fire management needs among ecosystems, especially in WUIs. Our decision framework and prioritization modeling are broadly applicable to ecosystems that range in habitat types and hydrology, where FRIs need to be forecast and managed to achieve enhanced pyrodiversity (Bowman et al. 2016).

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Data Availability

All data used in the study are already published and publicly available from a variety of sources, which are cited in the main text and reported in the reference list (Ruiz et al., 2021; Malone, 2019; U.S. Fish & Wildlife Service, 2023; Barrow and National Park Service Southeast Region Geospatial Resources, 2022; Stutts, 2014; U.S. Geological Survey, 2019; South Florida Water Management District, 2023).

Competing interests

The authors declare that they have no competing interests.

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Authors' contribution

AN, PR, JO'B, and MR conceived the study. AN and JK designed the general decision-support framework for burn prioritization. AN, MG, PR, and MT selected criteria, assigned overall model influences, and value scoring. AN, TM, CA, and PR collected and processed the spatial data, and built the model. AN and TM performed model validation. All authors contributed to manuscript preparation.

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Figures

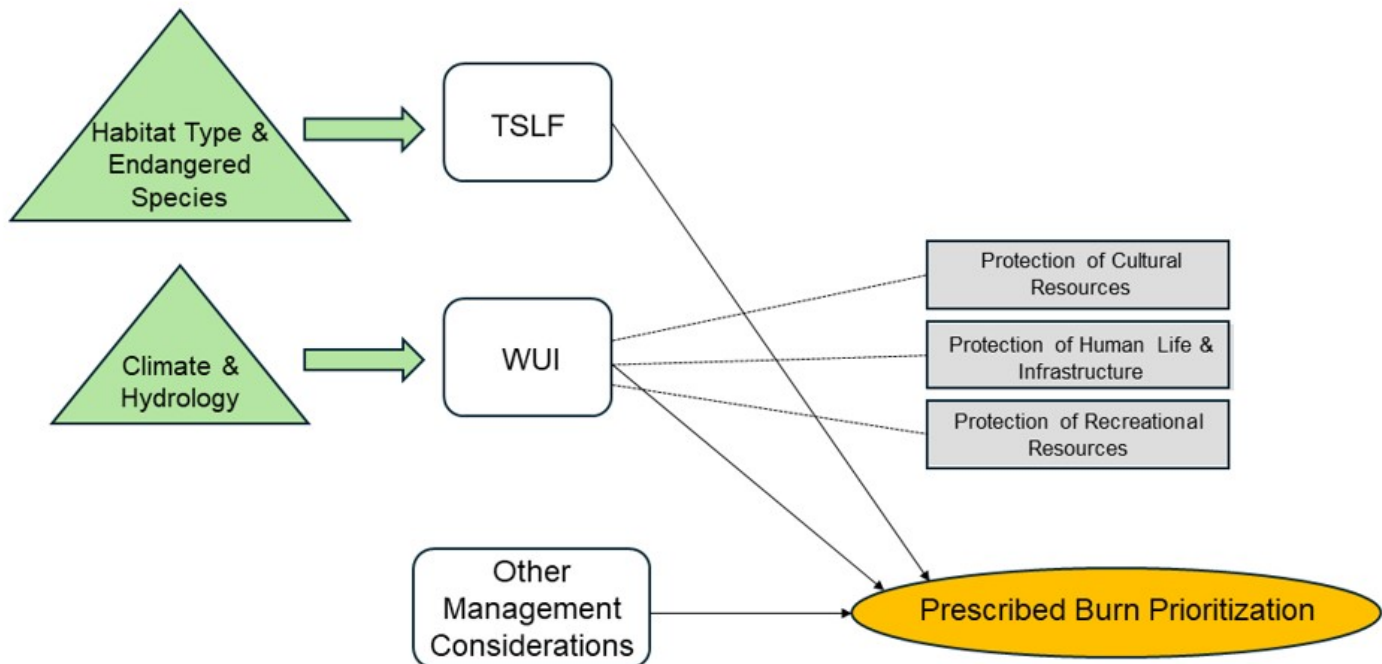


Figure 1

Decision-support framework for burn prioritization among diverse ecosystems within large, heterogeneous landscapes. Criteria categories are within white boxes, while green triangles indicate factors conditioning the relative importance of the criteria. Habitats and organisms are adapted to certain ranges of fire return interval and therefore affect the importance of time since last fire (TSLF) towards prescribed burn prioritization. Climate and hydrology drive fuel accumulation and fuel flammability and therefore affect the level of vigilance of fire managers at the wildland-urban interface (WUI). Other management considerations, such as control of invasive species, nutrient management, support of recreational activities, and burn logistics, may be taken into account towards prescribed burn prioritization. Assessing the conditions of the distinct criteria categories within patches of a landscape can be translated into differences in prescribed burn prioritization.

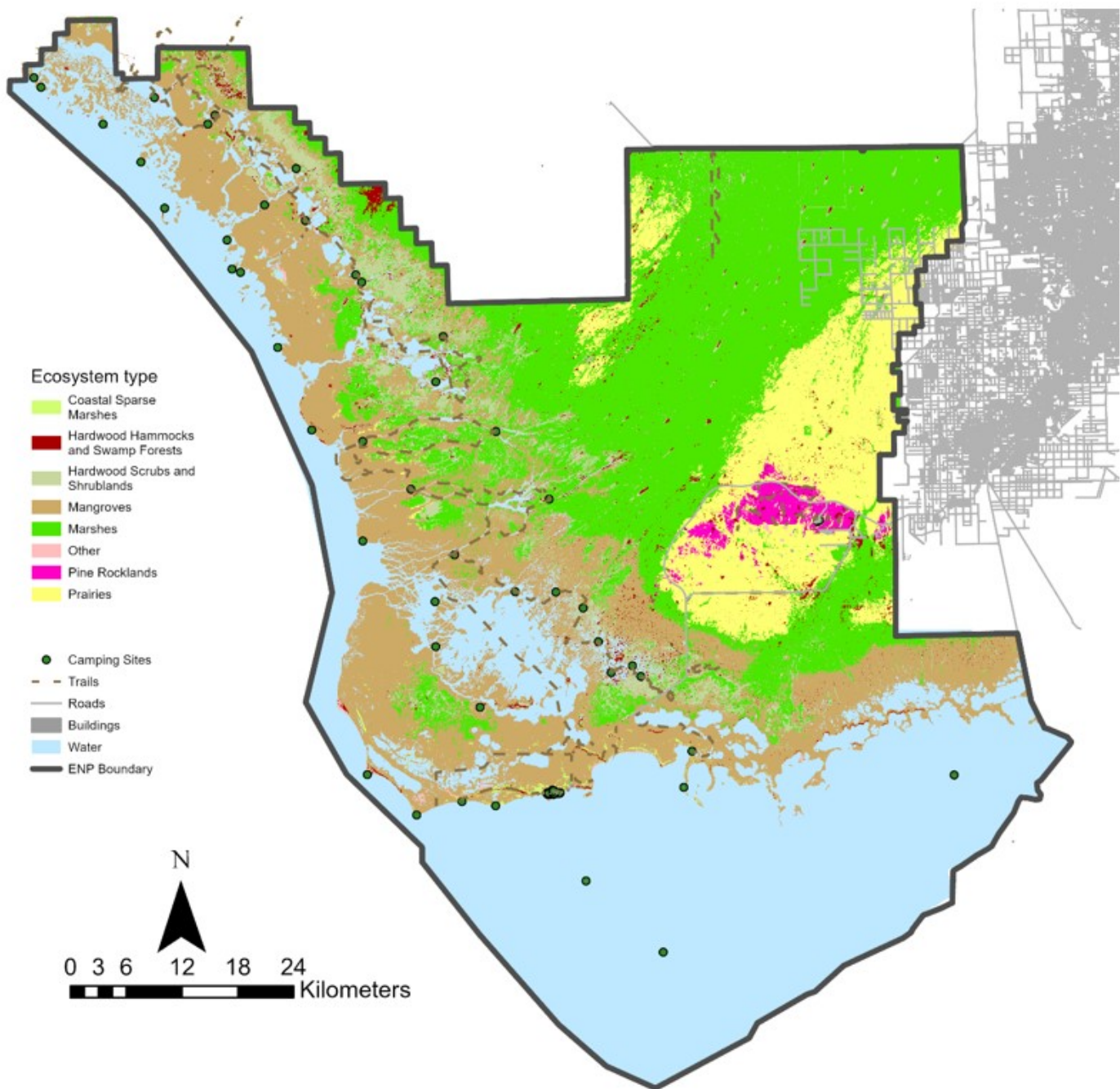


Figure 2

Main ecosystem types, roads, buildings, trails, and camping sites within Everglades National Park (ENP) boundaries. Ecosystem types were derived from recent ENP vegetation maps (Ruiz et al., 2021). Mangrove forests, freshwater and saltwater marshes, marl prairies, hardwood scrubs and shrublands, hardwood hammocks and swamp forests, and pine rocklands are the ecosystem types characterizing ENP and cover about 34, 40, 14, 6, 2, and 1 %, respectively, of the 3963 km² of land within ENP. “Other” includes dunes, barren salt flats, tidal flats, beaches, and canals and levees. These spatial data layers were used to represent criteria in the prioritization model.

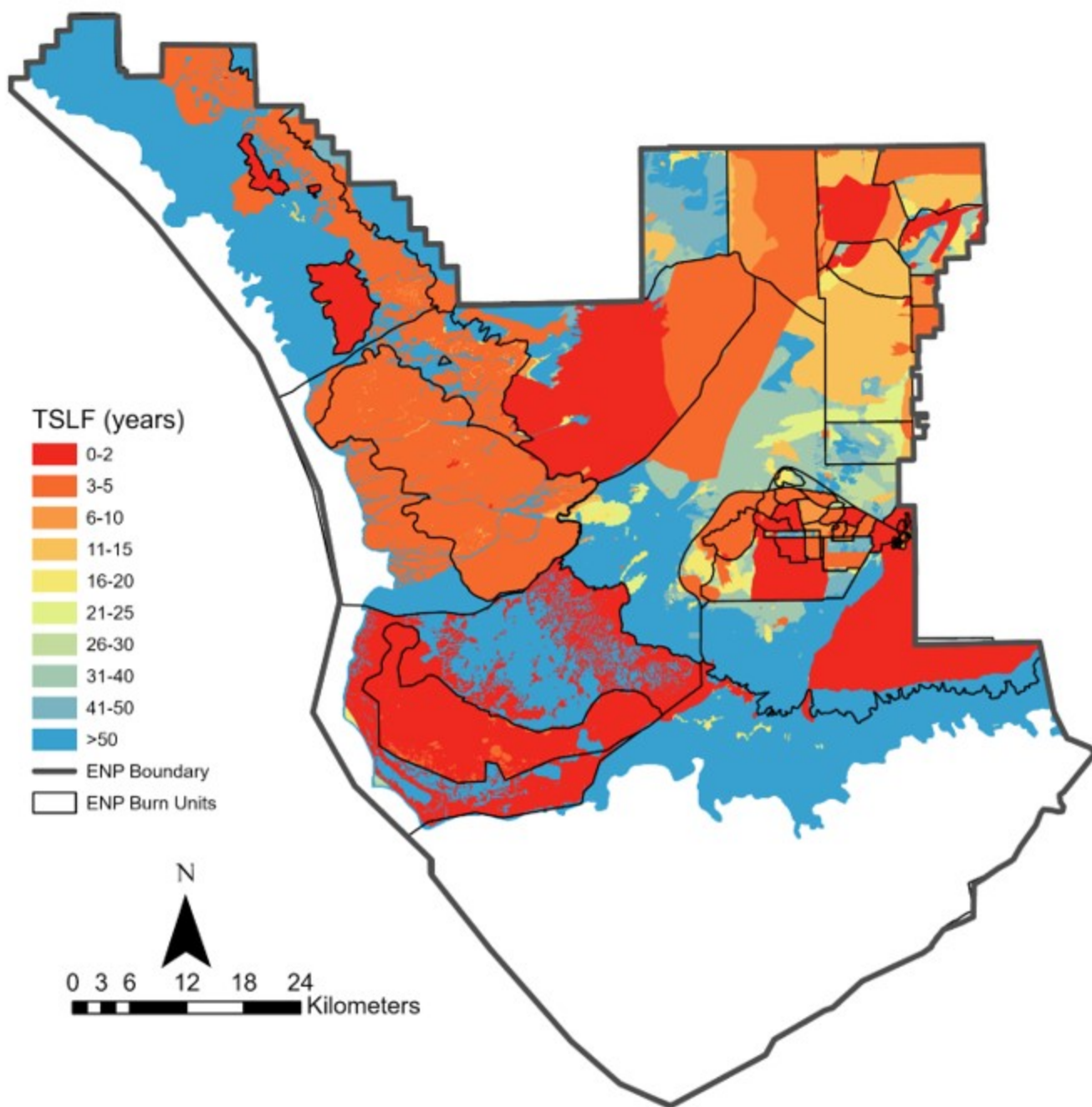


Figure 3

Time since last fire (TSLF) at the end of calendar year 2022, calculated for each 50 ´ 50 m pixel within each burn unit of Everglades National Park (ENP). Fire perimeters from both wild and prescribed fires, collected from 1948 to 2022, were used in the calculation of TSLF. This is one of the spatial data layers used to inform criteria in the prioritization model.

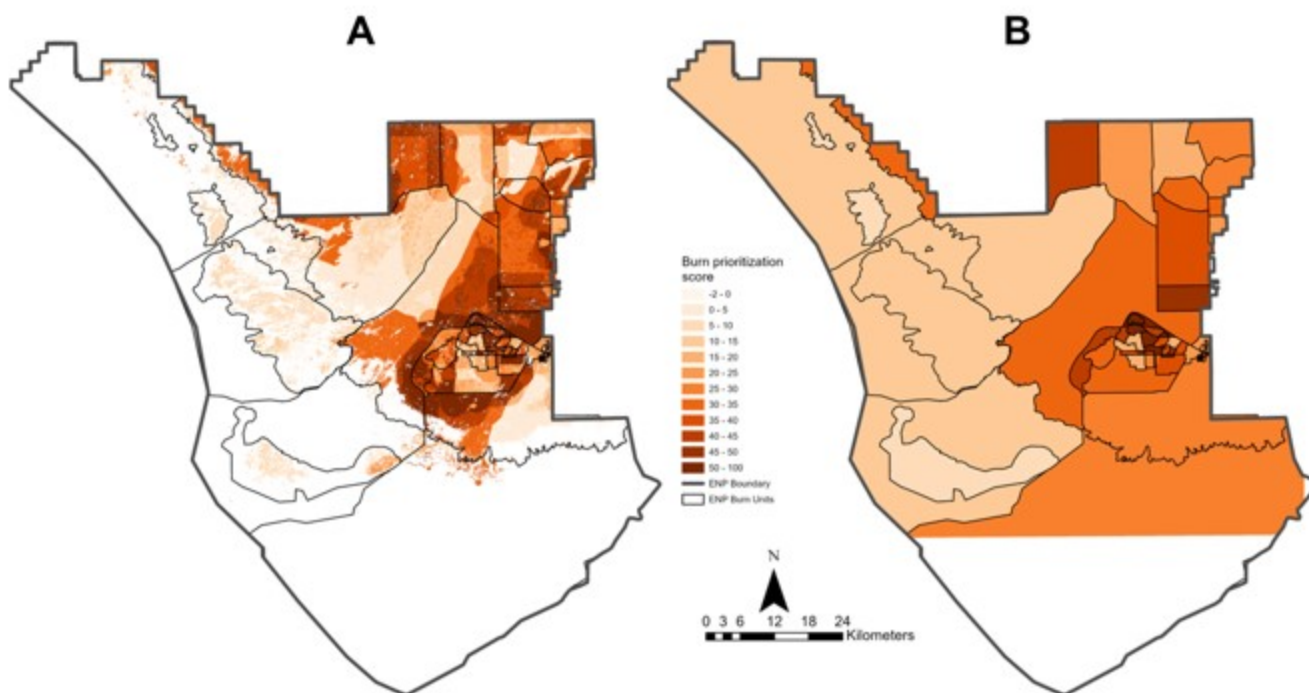


Figure 4

Burn prioritization scores modeled for Everglades National Park (ENP) and scaled to management-relevant units: 50-meter grid (A) and burn units (B). High values correspond to high priority for treatment with prescribed fire. Prioritization scores were modeled only for those pixels (50 ´ 50 m) characterized by ecosystem types that are target of prescribed fires (i.e., marsh, prairie, and pine rocklands). In these ecosystem types, the application of prescribed fire is considered ecologically beneficial. These prioritization scores were the outputs of the simulation to support decision-making in 2023 and varied between 0 and 71 (A) or between 6 and 62 (B).

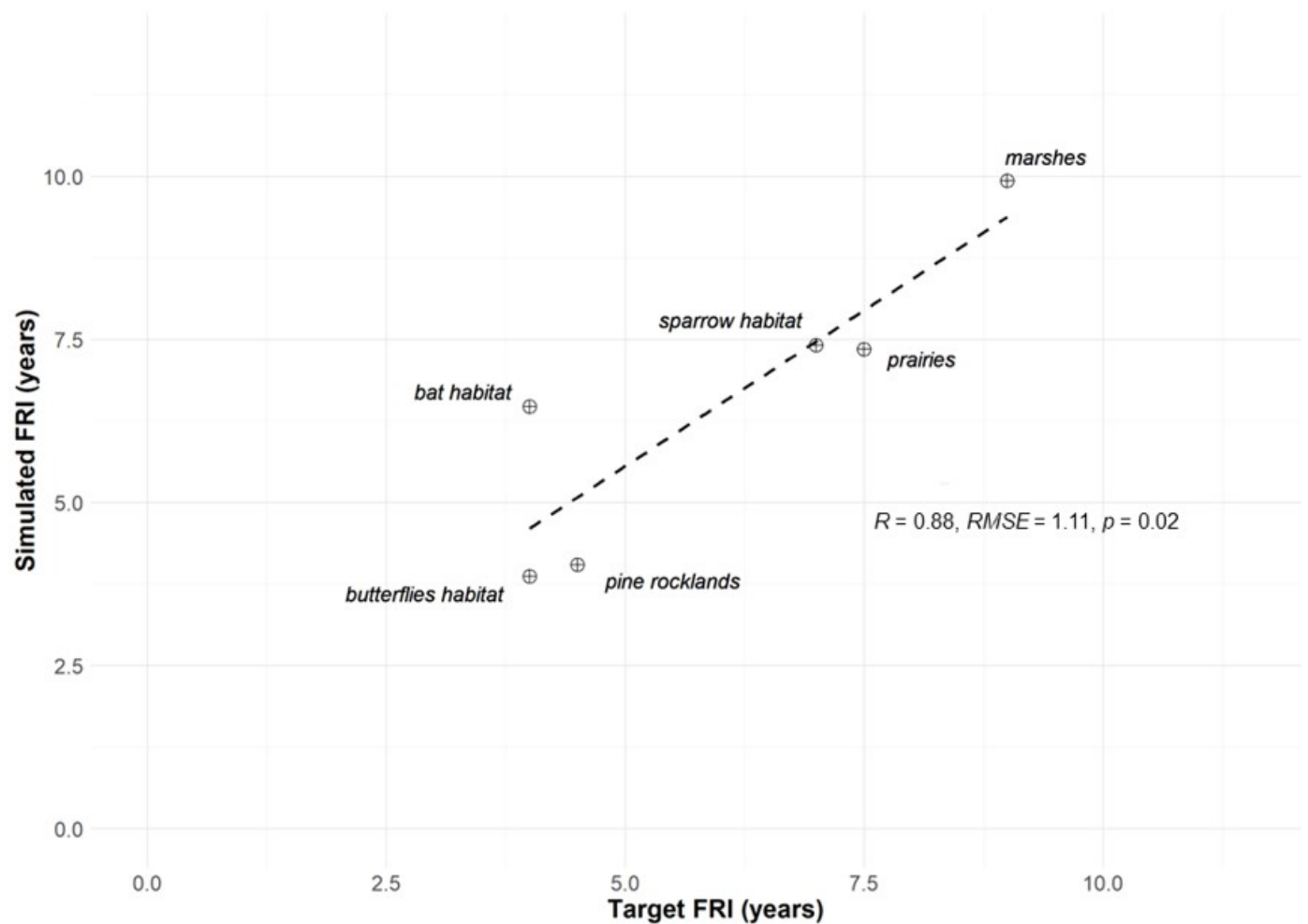


Figure 5

Target versus simulated mean fire return intervals (FRIs). Simulated mean FRIs were calculated over a period of 50 years (2023-2072) during which, based on the simulated prioritization scores, future fire perimeters were generated every year and time since last fire was iteratively updated. Two distinct scenarios were simulated, S1 and S2 (see Table 2 for details). This figure shows the results from scenario S2, which produced the best fit between target and simulated FRIs. Target and simulated mean FRIs were compared by ecotype (i.e., marshes, prairies, and pine rocklands), and by critical habitat of fauna species known to benefit from certain fire regimes [i.e., “sparrow” = Cape Sable seaside sparrow (*Ammodramus maritimus mirabilis*); “butterflies” = Florida leafwing and Bartram's scrub hairstreak (*Anaea troglodyta floridalis* and *Strymon acis bartrami*); “bat” = Florida bonneted bat (*Eumops floridanus*)].

Supplementary Files

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