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Current Distribution and Long-Term Changes in Mesomammal Communities of Big Cypress National Preserve

Eastern Spotted Skunk image was captured in Big Cypress National Preserve during 2025 field season.
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Current Distribution and Long-Term Changes in Mesomammal Communities of Big Cypress National Preserve

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Abstract

Vertebrates, especially mammals, are declining rapidly across the globe. One of the leading causes of this decline is invasive species. Few regions demonstrate species declines from invasive species more dramatically than the Greater Everglades Ecosystem (GEE), where widespread reductions in native mammals have been linked to the invasive Burmese python (*Python bivittatus*). Prior research has suggested that portions of the western GEE served as a refuge from pythons; however, it is not clear if this is still true. It is also unclear how environmental variation might facilitate or mitigate the impact of pythons on mammal populations. To address this gap, we used camera trap surveys and an occupancy modeling framework to quantify temporal changes in mammal occurrence and evaluate the influence of environmental variation on mammal occupancy in protected areas of the western GEE. Between 2014 and 2025, mammal occurrence was generally lower in areas where pythons had been established for longer periods, particularly for medium-sized mammals such as white-tailed deer, raccoons, marsh rabbits, and bobcats. Environmental factors, including inundation periods and fire history, also influenced species occurrence, indicating that mammal distributions are shaped by interactions between invasive predators and ecosystem properties. Collectively, these findings indicate that protected areas once considered refugia are now experiencing mammal declines as pythons expand across the landscape.

Acknowledgments

We would like to thank Matthew McCollister (Big Cypress National Preserve), Mark Danaher (Florida Panther National Wildlife Refuge), and Karen Rogers (Florida State Parks) for providing fire history datasets used in this study. Their assistance was instrumental in the completion of this project. Matthew McCollister provided substantial logistical support, including housing and equipment, and facilitated field coordination through BICY biologist Travis Mangione. This support was critical to the successful completion of sampling.

We are also grateful for the hard work and dedication of our field technicians, Marcellus Murray, Emilio Pedroza, and Joe White, whose efforts in the field made this research possible.

Introduction

Vertebrates, especially mammals, are declining precipitously across the globe (Ceballos et al. 2015). Although charismatic large mammals are often the focus of conservation efforts (Albert et al. 2018), mesomammals (mid-sized mammal species weighing between 1 and 25 kg) are also declining due to overharvesting, habitat loss, and invasive species (Bowyer et al. 2019). Mesomammals provide critical ecological functions, and their loss is likely to lead to changes that radiate across ecosystems (Roemer et al. 2009). Few places have seen sharper declines in mesomammals than the Greater Everglades Ecosystem (GEE) in Florida. Starting in the early 21st Century, native mesomammals, including Virginia opossums (*Didelphis virginiana*), raccoons (*Procyon lotor*), bobcats (*Lynx rufus*), rabbits (*Sylvilagus palustris; Sylvilagus floridanus*) and foxes (*Urocyon cinereoargenteus*; *Vulpes vulpes*), declined precipitously in the southern GEE, likely as a result of the establishment and spread of invasive Burmese pythons (*Python bivittatus*) (Dorcas et al. 2012; Guzy et al. 2023; McCleery et al. 2015; Taillie et al. 2021). However, this system is highly modified, and these same species are also likely to be impacted by alteration of water flow through the system, altered disturbance regimes, and variation in vegetation types (Light and Dineen 1994; Mitsch and Hernandez 2013).

Nonetheless, we know surprisingly little about the mesomammal communities in one of the GEE's two nationally designated areas, Big Cypress National Preserve (BICY), which encompasses 295,000 ha. Limited survey efforts in BICY suggest that previously common mesomammals like marsh rabbits, raccoons, Virginia opossum and bobcat may have a limited distribution, particularly in the southern and eastern extents of BICY (Burkett-Cadena et al. 2021; Reichert et al. 2017; Sovie et al. 2016; Taillie et al. 2021). The most extensive of these surveys was conducted in 2014 by Reichert et al. (2017). They sampled all mammals at 113 sites throughout the GEE. They sampled mammals larger than a rabbit using randomly placed 30 m × 30 m plots with two independent dung surveys and two unbaited trail cameras collecting data for 14 days. However, with only limited sampling (n = 25) in BICY, these efforts do not provide BICY with the information needed to address critical management issues. Specifically, we do not know 1) if mesomammal populations have changed over time, 2) the current distribution and factors influencing the presence of common mesomammals, and 3) the best approaches for monitoring mesomammals within BICY. This information is critical for BICY management to help them adjust hunting regulations, implement fire management practices, mitigate or eradicate invasive species like the python, and to maintain mammalian diversity.

Project Goal

The goal of this project was to estimate current distribution of common mid-sized mammals in BICY and provide recommendations for future monitoring.

Specific Project Objectives

The specific project objectives included:

1. Determine the changes in marsh rabbit abundance over 11 years by comparing results from this study to data collected in 2014 (Reichert et al. 2017; Sovie et al. 2016; Taillie et al. 2021).
2. Determine the factors currently influencing the distribution of Virginia opossum, marsh rabbit, raccoon, coyote, and bobcat, as well as factors associated with their distributional changes over 11 years.
3. Compare the detection rates of common mammals with baited and unbaited camera traps.
4. Establish methods and sites that can be sampled for the future monitoring of mesomammal species in BICY.

Approach and Methods

Site Selection / Study Area

To study the spatial and temporal variation in mesomammals in BICY, we used both game cameras and scat surveys. We sampled throughout the extent of BICY to capture its spatial and habitat gradients. These habitats represent a gradient from open, herbaceous wetlands (freshwater marsh and prairie) to transitional woody shrublands (scrub and forested swamp) to upland-associated closed-canopy communities (woodland and hammock), reflecting differences in hydrology, vegetation structure, and species composition across the landscape. To examine the changes over time, we leveraged and expanded upon 25 mesomammal camera trapping and scat surveys conducted in BICY in 2014 (Reichert et al. 2017). These surveys were conducted on randomly selected 30 × 30 m sites located within 2 km of a road or ATV accessible trail.

To compliment these 25 historic sites, we established 15 additional sites for a total of 40 sites; the maximum number that can be sampled by one field crew during one dry season. To add these 15 sites, we identified terrestrial habitats and areas of BICY that were underrepresented in the historical samples. Then we randomly selected 15 areas from this subset. To be consistent with the 2014 survey, we constrained samples to within 2 km of a road or ATV accessible trail (Figure 1). Additionally, we used funding from the USGS to re-sample 11 more sites that were adjacent to BICY and also sampled in 2014. Combined, we had a total of 51 sites selected to capture the temporal and spatial variation of mesomammals in the greater BICY system.

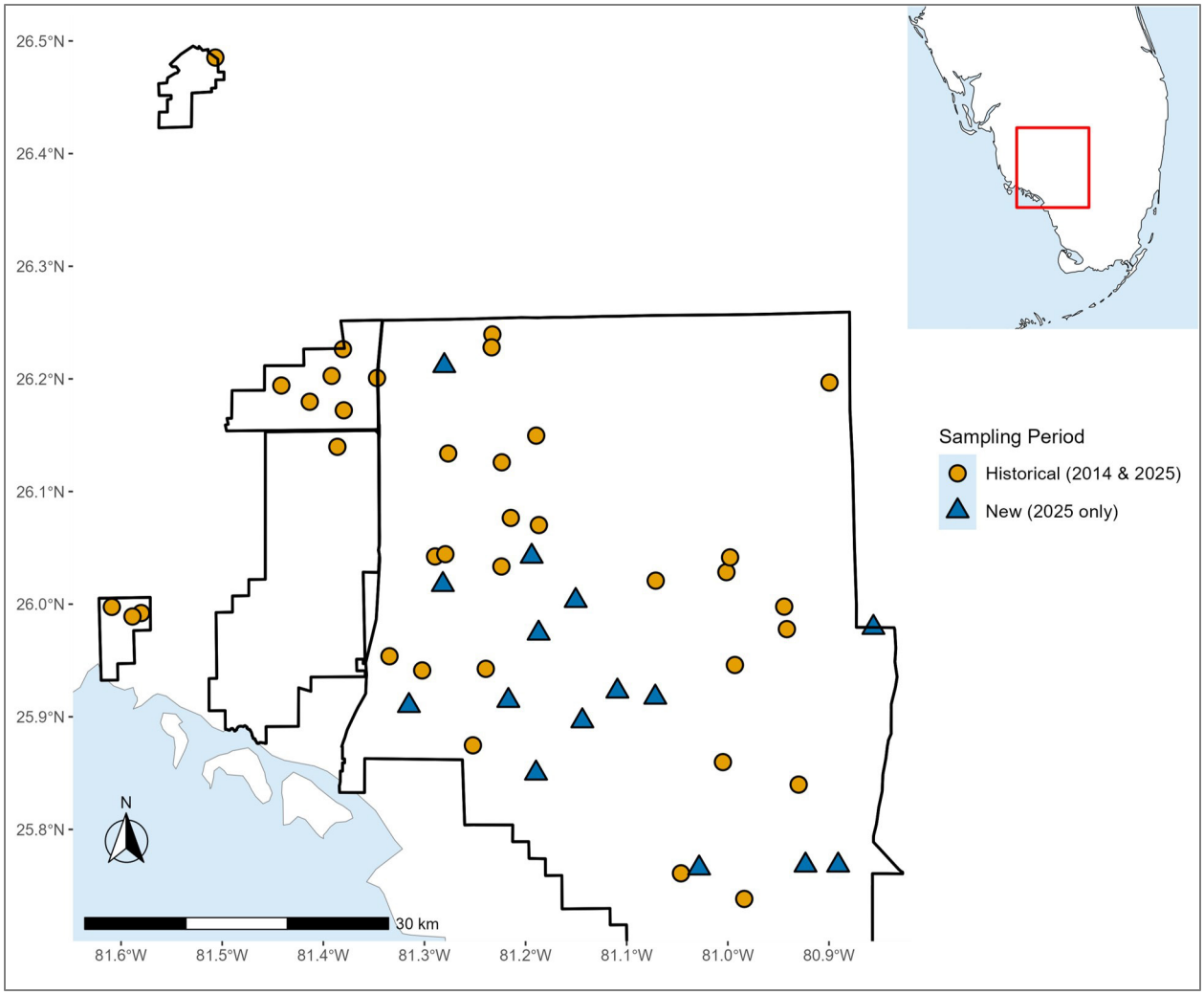

Figure 1. Map of sampling locations. Yellow circles represent sites surveyed in both 2014 and 2025, whereas blue triangles represent newly established sites surveyed in 2025 only.
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Field Methods

For field surveys, each site consisted of two plots placed 200 m apart. The first plot was unbaited to allow direct comparison with historic efforts from 2014. The second plot was placed 200 m away in a random direction. This plot was baited with sardines (Avrin et al. 2021) to determine if baiting increased detection of target animals.

In keeping with historic surveys, we created and sampled 30 × 30 m areas on each plot. Using belt transects which were spaced 2 m apart, two observers independently surveyed the plots for scat (Figure 2). They recorded the number of pellets for marsh rabbit, and species of scat observed for other species. This was particularly important for marsh rabbits, as pellet counts are closely related with density (Schmidt et al. 2011) and we had pellet count data from 36 historic sites (25 in BICY, 11 adjacent to BICY) from 2014 (Sovie et al. 2016). In addition to scat surveys, we installed two trail cameras within each plot. We placed cameras 45 cm above the ground in areas that maximized

mesomammal detections (e.g., game trails and openings). We removed vegetation that interfered with mammal detections from within 10 m in front of the cameras' cones of detection and set them to motion trigger. We collected the cameras after 14 days in the field.

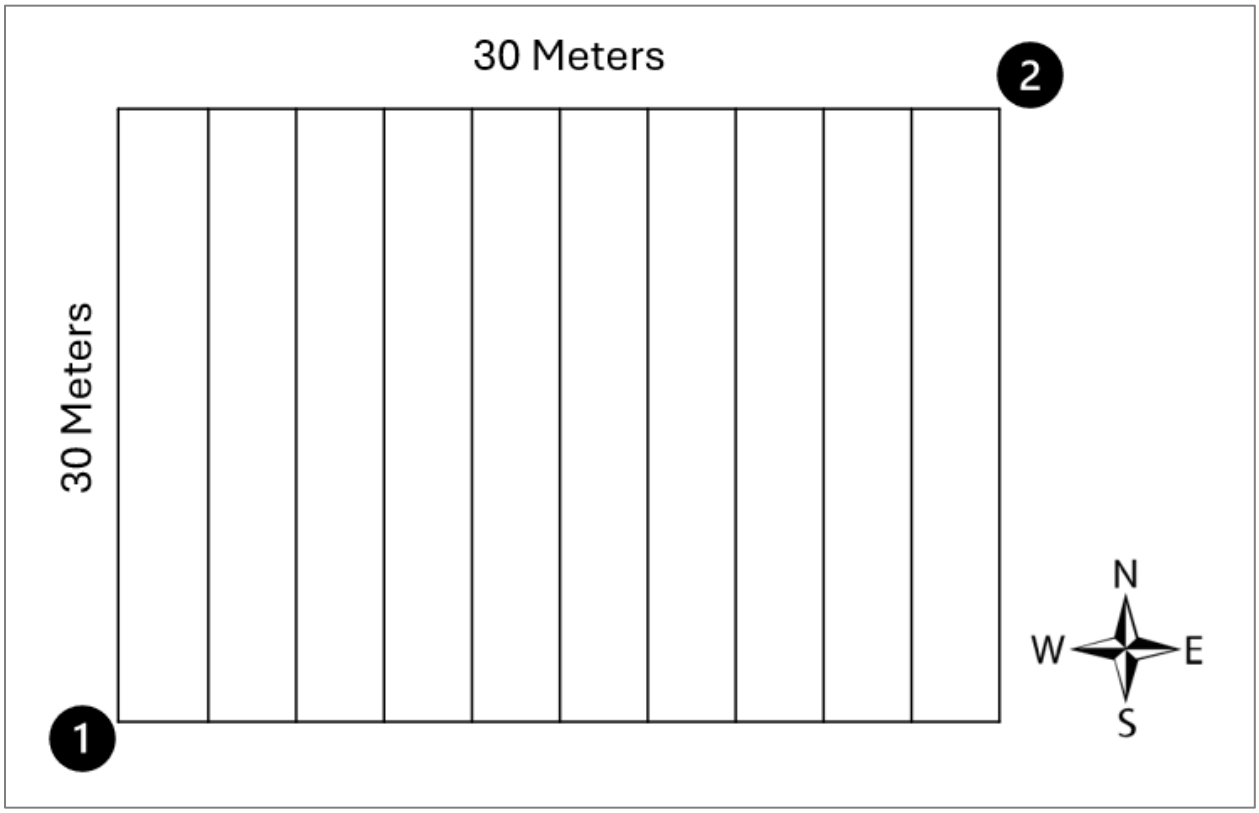

Figure 2. Survey design for each 30 × 30 m plot. Vertical lines represent parallel transects running north to south. Two independent observers, beginning at opposite corners (indicated by the numbers 1 and 2), traversed the plot along transects to reduce overlap and improve detection coverage.
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Environmental Data

Hydrology

Following Reichert et al. (2017), we modeled the potential effects of local hydrology on mesomammal occurrence. To do this, we estimated the hydroperiod (average days of continuous inundation) (Figure 3) and mean water depth for five years prior to our survey (Figure 4). Both hydrology metrics were based on water-level data from DBHYDRO (DbhydroInsightsData 2025).

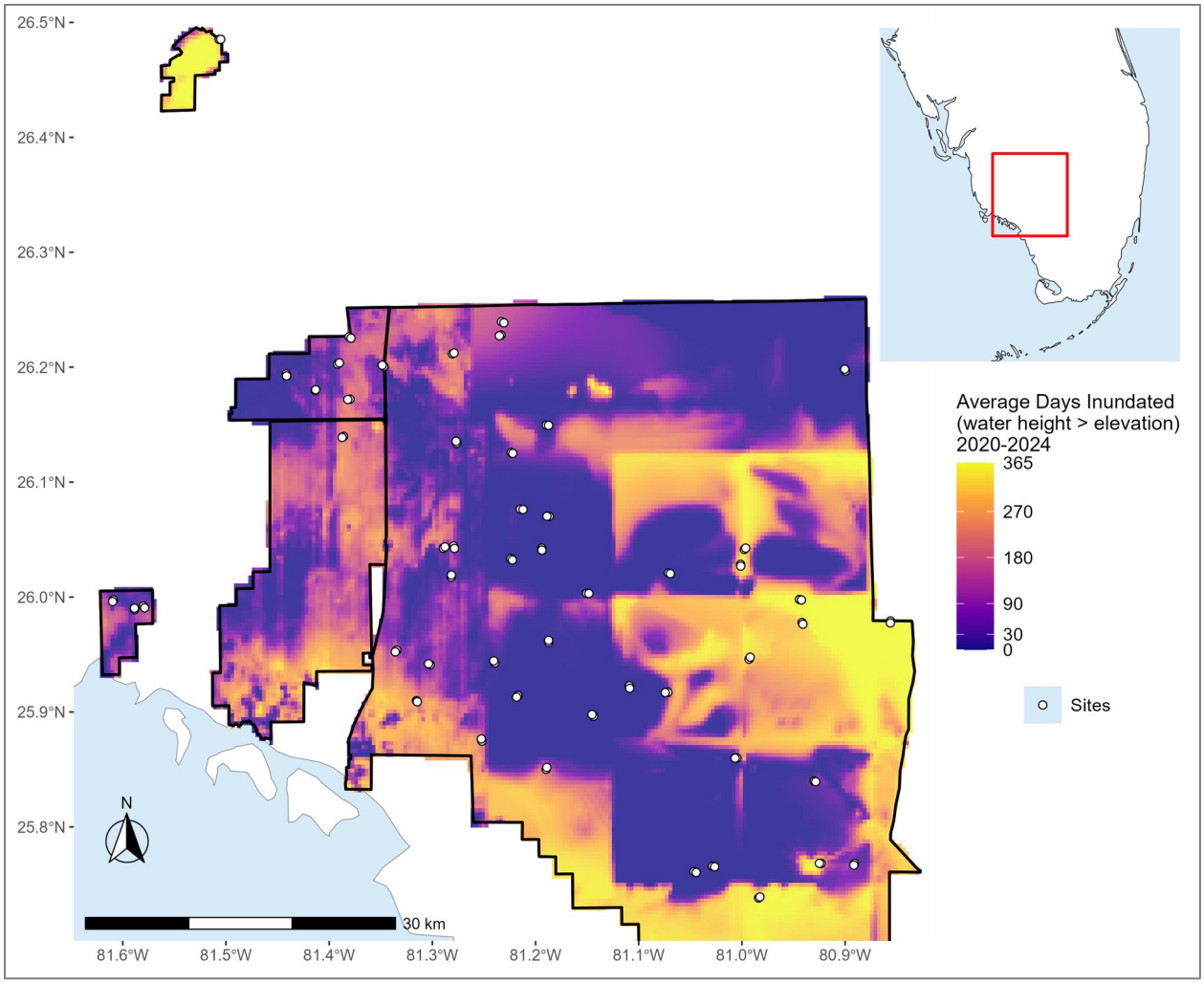

Figure 3. Map of average days inundated from 2020 to 2024 with sampling sites overlaid on map for reference. Values represent the average number of days in which water height exceeded ground elevation.

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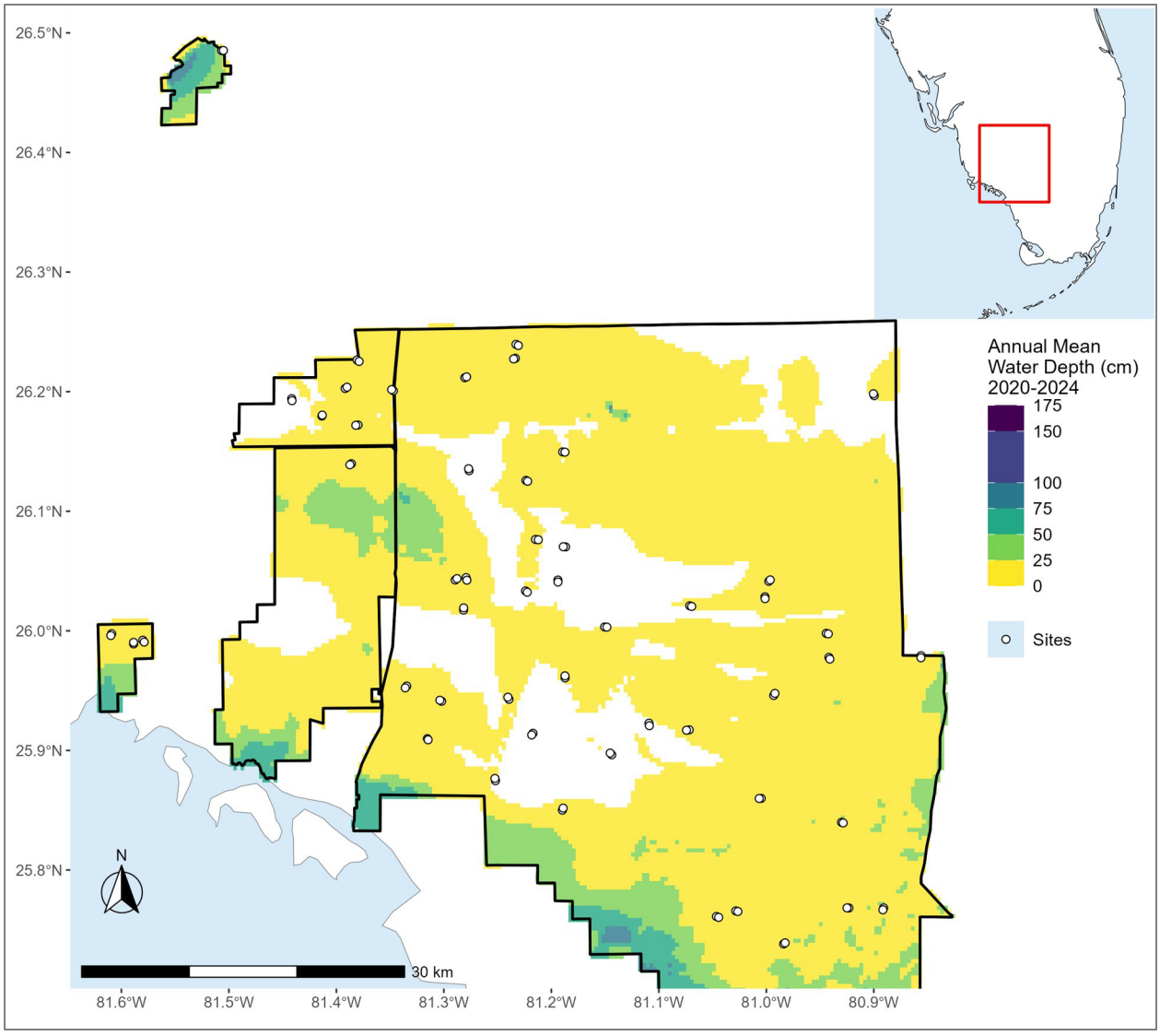

Figure 4. Map of average water depth from 2020 to 2024. Color gradients represent variation in mean water depth across the study area, with sampling sites overlaid on the map for reference.
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Habitat Type

We classified each site into one of three broad habitat types (Figure 5) based on Florida Natural Areas Inventory FNAI classification (FNAI 2025) and current vegetation and water data. Classifications included freshwater marsh-prairie, scrub and forested swamp, and woodland and hammock. These three habitat types were broader classifications of 15 vegetation communities identified previously by Sovie et al. (2016) and determined based on species composition, structure, and inundation period (Reichert et al. 2017).

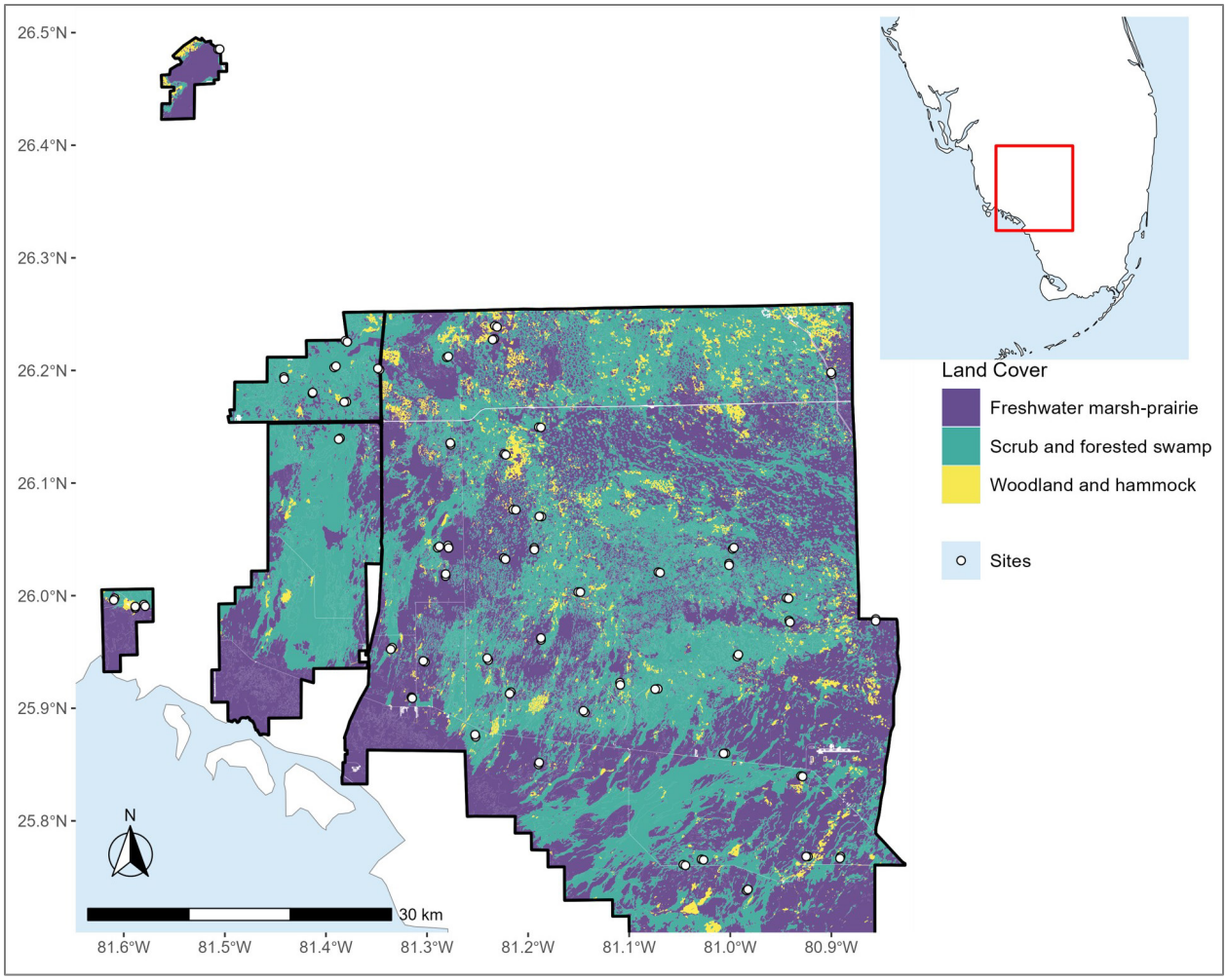

Figure 5. Three broad habitat categories in this study area: freshwater marsh-prairie, scrub and forested swamp, and woodland and hammock. Categories were consolidated from 15 vegetation communities based on composition, structure, and hydroperiod.

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Fire

To determine the potential influence of fire on mesomammals, we collected fire data from BICY (Matthew McCollister, personal communication, 2025), Florida Panther National Wildlife Refuge (Mark Danaher, personal communication, 2025), and Florida State Parks (Karen Rogers, personal communication, 2025). First, we used these data to calculate the number of fires (wildfires or prescribed burns) that occurred at each survey site over the previous 20 years (Figure 6). Fires could only be counted once per season (i.e., a multi-day burn was considered one fire). From this we generated two metrics of fire; fire count (number of burns in 20 years) and time since last burn (number of years since the last burn) (Figure 7).

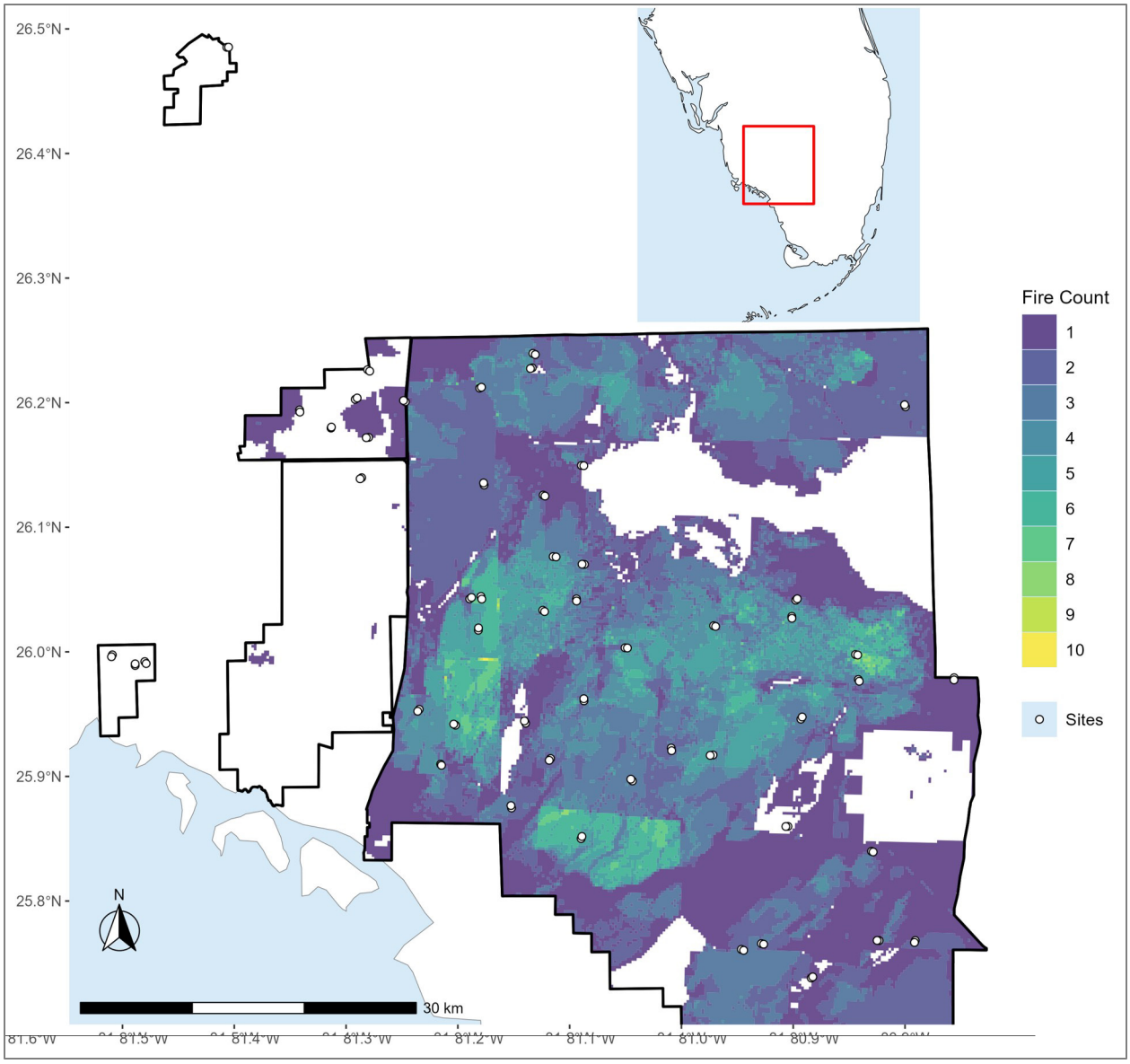

Figure 6. Number of fires recorded from 2005 to 2024 across the study area. Color gradients represent fire count (total number of fires during the 20-year period), with sampling sites overlaid for reference.
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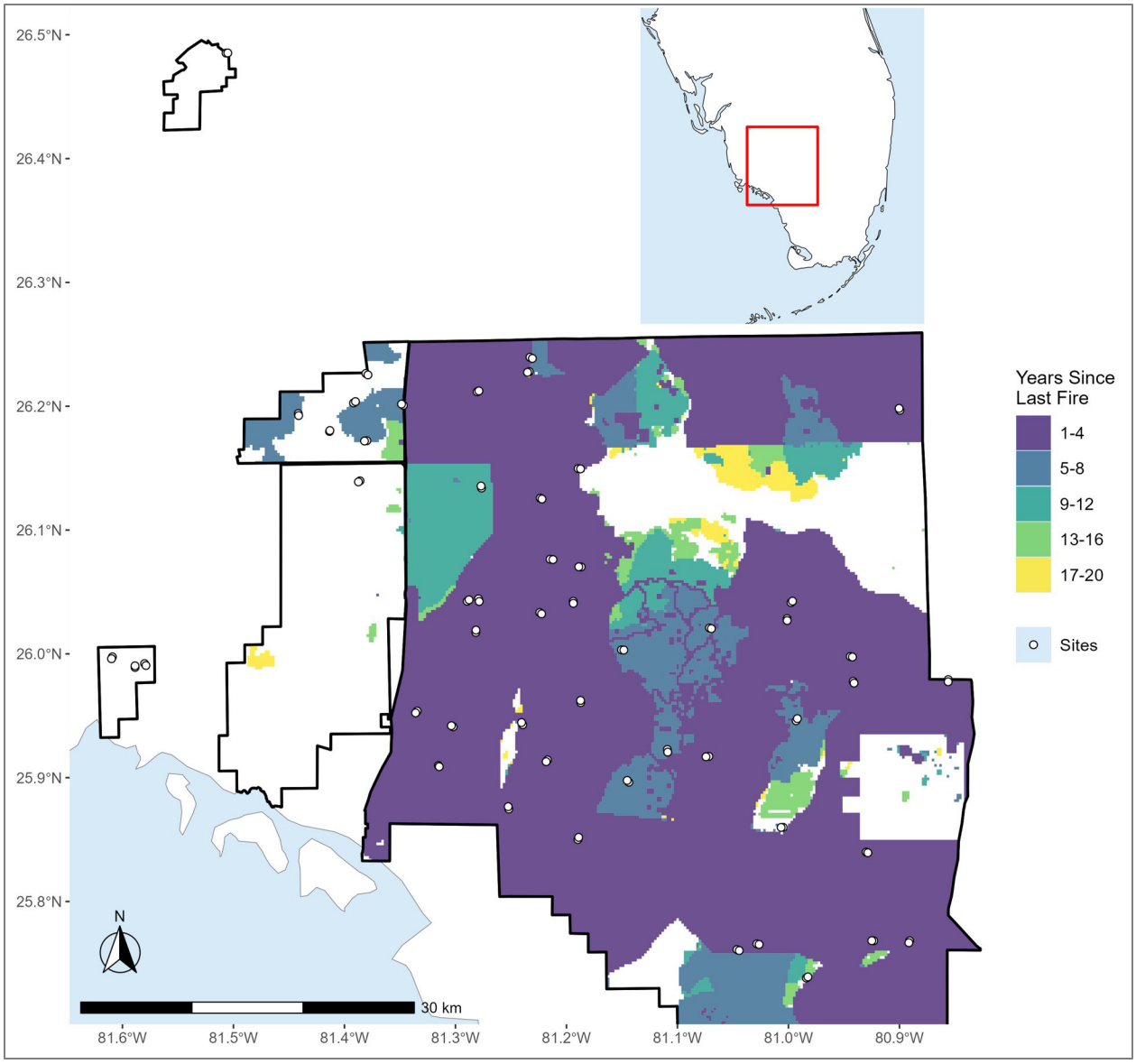

Figure 7. Years since the last fire (2025 baseline), calculated by intersecting fire perimeters with grid cells and identifying the most recent fire year within each cell. Values represent the difference between 2025 and the last observed fire year per grid cell.

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Change in Pythons

While it is currently not possible to generate precise measures of python occurrence or abundance (Guzy et al. 2023), we can use measures of change in detections as a proxy for the python invasion (Taillie et al. 2021). First, we will use the python invasion front delineated from python observations between 2000 and 2006 (Guzy et al. 2023) to serve as a baseline for areas colonized by pythons early in the invasion. Conversely, we considered areas outside of the line to be colonized by pythons later in the invasion (Figure 8).

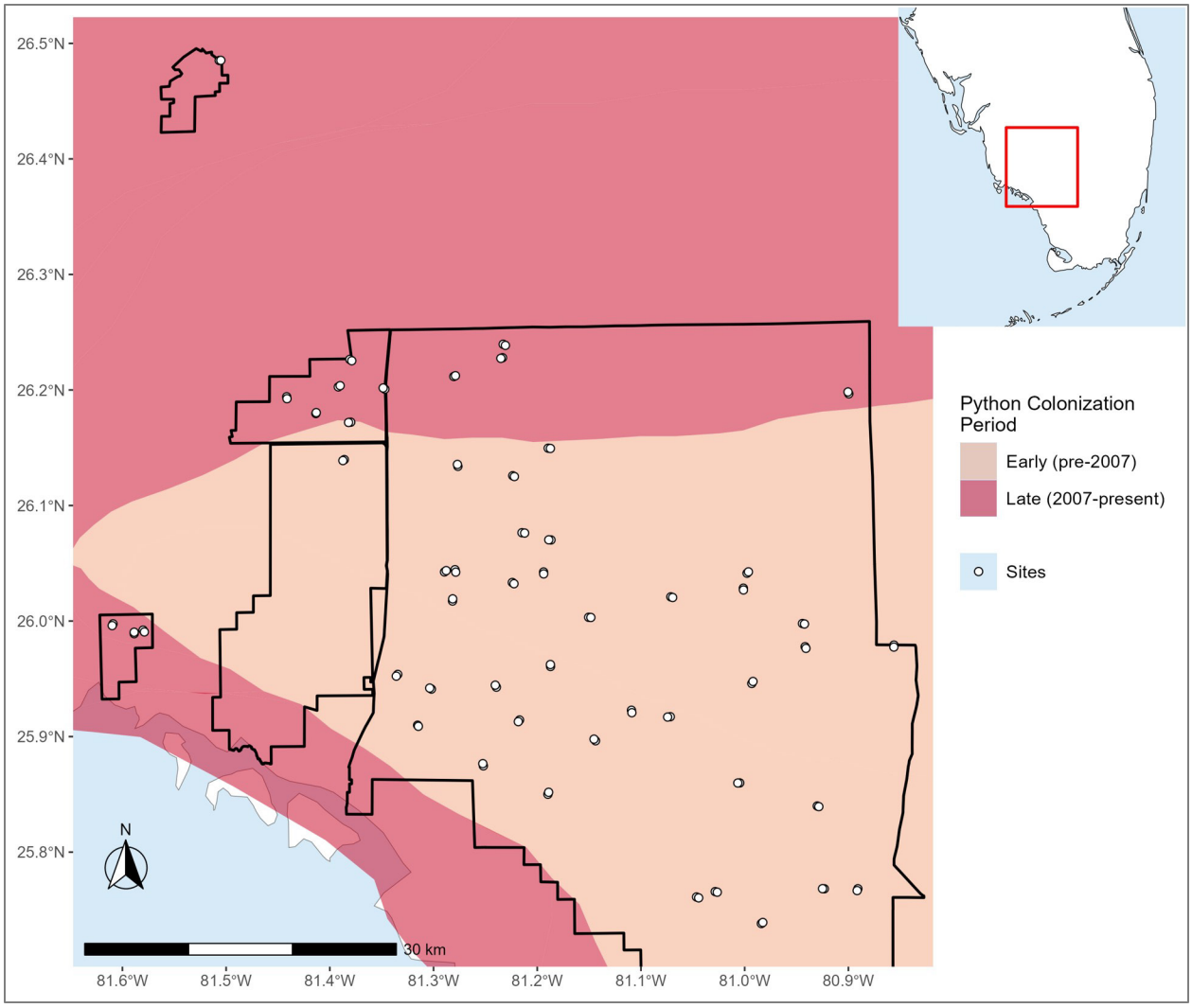

Figure 8. Python expansion map showing areas colonized before 2007 (early invasion) from those colonized after 2007 (late invasion).

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Analytical Methods

Objective 1

To quantify changes in rabbit pellet abundance between the 2014 and 2025 surveys, we modeled pellet counts for each sampling by fitting a generalized linear mixed model to a negative binomial error distribution and log link using the glmmTMB package. We treated survey period (Time; levels T1 = 2014, T2 = 2025) as a fixed effect and included random intercepts for each observer (n = 4, 2 during each period) and site to account for non-independence of repeated counts by the same observer and at the same sampling location. From this model, we obtained estimated marginal means (predicted mean pellet counts) for each survey period using the *emmeans* package, and back-transformed them to the original count scale. We then contrasted T2 against T1 to estimate the T2/T1 rate ratio, which we interpreted as the fold-change in mean pellet counts between 2014 and 2025. We computed tests and confidence intervals for this contrast on the log scale and reported them on the

response scale, allowing us to express the magnitude of decline in terms of both absolute predicted counts and the proportional reduction (e.g., T2 as a percentage of T1).

To estimate marsh rabbit abundance from pellet counts, we applied the relationship developed by Schmidt et al. (2011): rabbits/ha = 0.947 × pellets/m². Schmidt et al. derived this equation from sites where marsh rabbits were known to occur, so we used it only for occupied habitat. Because we detected marsh rabbit pellets at only a subset of sampling plots, we applied the equation only to plots where pellets were present and calculated pellet density using the occupied area only. To standardize the sampled area and account for detection limitations, we included only the area within 1 m of either side of each transect. This sampling area totaled 540 m² per 30 × 30 m plot (30 m × 2 m × 9 transects).

Objectives 2 and 3

To understand changes in distributions over time, the factors influencing the current distribution (Objective 2), and the influence of bait (Objective 3) on detecting mesomammals, we used an occupancy modeling approach that accounts for imperfect detection (MacKenzie et al. 2017). This approach allowed us to estimate changes in distributions over time. Prior to fitting a model for each species, we used the observations of mesomammals to build a detection history for each species at each site. We did this by manually reviewing all camera trap photos to identify the mammal species observed and using AddaxAI which uses MegaDetector to annotate images with animal classifications which can then be imported into Timelaspe (Greenberg 2025). For marsh rabbits, we used scat data because of the elevated number of detections using this method.

To evaluate changes in occupancy over time and quantify the influence of bait on detection, we used single-season Bayesian hierarchical occupancy models implemented in the ubms package, which fits occupancy models in a fully Bayesian framework (Kellner et al. 2022). This approach allowed us to model detection and occupancy as separate latent processes, incorporate random effects for paired sites (e.g., bait vs. unbaited) and model species with modest sample sizes. For all models we ran four MCMC chains with 1,000 iterations of warmup and 4,000 iterations of sampling. We used weakly informative (normal distribution, mean = 0, standard deviation = 2) priors for occupancy and detection coefficients to stabilize estimation while following recommendations for logistic-scale regression parameters (Lemoine 2019). We summarized uncertainty using 90% credible intervals, commonly used in Bayesian ecological analyses because they avoid overconfidence in datasets with modest sample sizes (Kéry and Schaub 2012).

First, we used occupancy modeling to examine changes in mesomammal distributions over time (Objective 2). We restricted the analysis to the 36 unbaited plots that were surveyed in both 2014 and 2025. For each focal species, we used the camera-trap data to construct binary nightly detection histories and fit a single-season occupancy model in which occupancy was modeled as a function of year with detection held constant across years. We used posterior draws of the occupancy intercept and year effect to generate posterior distributions of 2014 and 2025 occupancy probabilities and the resulting change in occupancy, an approach consistent with Bayesian propagation of uncertainty in derived parameters (Kéry and Schaub 2012):

$$\Delta\psi = \Psi_{2025} - \Psi_{2014}$$

where

$\Delta\psi$ = change in occupancy

Ψ = occupancy probability

From these posterior distributions, we summarized results using posterior means, 90% credible intervals, and species-specific posterior density plots of $\Delta\psi$ to compare the strength of evidence for declines among species.

Next, we evaluated whether baiting cameras with sardines altered either the probability of detection or the probability of occupancy at our plots (Objective 3). Increased detection probability would indicate that animals present at the site were more frequently detected, whereas an increase in occupancy would suggest that bait attracted animals that would not have occurred otherwise on the site or appeared in front of the camera. To assess these two distinct mechanisms, we leveraged the experimental design of 51 paired plots, each consisting of unbaited camera traps directly paired with baited cameras 200 m away.

For each species, we constructed two Bayesian single-season occupancy models, each incorporating a random intercept for plot pair to account for shared site-level conditions. The first model tested whether baiting affected detection, specifying detection probability as a function of a survey-level bait covariate ($p \sim bait$) while holding occupancy constant across pairs. The second model tested whether baiting influenced occupancy, modeling ψ as a function of the bait treatment applied at the site level while keeping detection constant ($p \sim 1$). We then used posterior draws to estimate detection and occupancy for baited and unbaited sites, their differences (Δp, $\Delta\psi$), and the posterior probability that baiting increased detection or occupancy. Under the standard camera-trap occupancy framework, ψ is interpreted as the probability that a camera site is used at least once during the sampling period (MacKenzie et al. 2017; Sollmann 2018). When attractants alter animal movements around cameras, they can therefore influence not only detection but also the probability that animals use the immediate vicinity of the camera. By contrasting ψ at baited and unbaited stations, we estimate how bait changes this probability of site use, while parallel models with bait as a detection covariate isolate its effect on detection alone.

After identifying the best-supported detection model for each species (i.e., whether detection p was constant or varied with vegetation thickness measured with a Robel), we evaluated a candidate set of occupancy models in which occupancy (ψ) was modeled as a function of fire history (fire count; years since most recent fire), hydrology (inundation duration; mean water depth), habitat group (three-level habitat class), and python colonization timing (early vs. late) (Table 1). We compared these models using approximate leave-one-out cross-validation. Specifically, we used difference in Leave-One-Out Information Criterion (ΔLOOIC) and considered models ≤ 2 relative to the best model as competitively supported. For inference and plotting, we evaluated the simplest competitive model that retained essentially equivalent predictive fit to the top-ranked alternative.

Table 1. Occupancy models for all species.

Model name	Occupancy (ψ) predictors
null	ψ ~ 1 (no environmental or habitat modifiers)
fire_only	ψ ~ number of fires at site
time_only	ψ ~ years since most recent fire
inund_only	ψ ~ total number of days inundated
water_only	ψ ~ mean surface-water depth
group_only	ψ ~ habitat class (prairies/water, conifer/cypress wetlands, hardwood forests)
PCearly_only	ψ ~ early python colonization indicator (1 = early python arrival, 0 = later)
inund_time_2var	ψ ~ total days inundated + years since most recent fire
inund_PCearly_2var	ψ ~ total days inundated + early python colonization indicator
fire_water_group	ψ ~ number of fires + years since most recent fire + total days inundated + water depth + habitat class
fire_water	ψ ~ number of fires + years since most recent fire + total days inundated + water depth
fire_time_inund	ψ ~ years since most recent fire + total days inundated
fire_time_water_group	ψ ~ years since most recent fire + total days inundated + water depth + habitat class
fire_water_PCearly	ψ ~ years since most recent fire + total days inundated + early python colonization indicator
All_variable_noG	ψ ~ years since most recent fire + number of fires + total days inundated + water depth + early python colonization indicator

Objective 4

We evaluated the covariates that influenced detection estimation in Objective 2 and used them to determine the optimal survey approach for mesomammals, in terms of method (baited, camera, scat), duration, and sampling locations. We coupled this information with detailed logistical information (e.g., time to get to each site) on each sampling site to establish methods and sites to be used in the future monitoring of mesomammal species at BICY. Additionally, we will provide annotated code and an instructional video to facilitate analysis of future efforts.

Results

Sampling Effort

Our effort yielded over 2,240 nights of camera trapping within BICY. From this effort we acquired a total of 86,087 images from BICY, 748 of which were of mammals. Including the 11 adjacent sites, we compiled a total of 1,919 images of mammals. Specifically, we detected black bear, bobcat, coyote, white-tailed deer, eastern gray squirrel, eastern spotted skunk, Big Cypress fox squirrel, Eurasian wild pig, marsh rabbit, Virginia opossum, and raccoon (Table 2). For our additional 11 sites adjacent to BICY we also detected armadillo and otter. We did not detect either species of fox, stripped skunk (*Mephitis mephitis*), everglades mink (*Neovision vison evergladensis*) or long tailed weasel (*Neogale frenata*) in our study. For scat counts we detected eight species (Table 3), all of which had been detected on cameras. Notably, we detected considerably more otters and marsh rabbits using scat surveys.

Table 2. Comparison of raw species site occupancy counts from camera trapping on baited and unbaited sites in and adjacent to Big Cypress National Preserve (BICY) and across 36 non-baited sites sampled in 2014 and 2025.

	Non-baited				Baited	
Species	**BICY 2025 (n = 40)**	**Adjacent 2025 (n = 11)**	**2014 (n = 36)**	**2025 (n = 36)**	**BICY 2025 (n = 40)**	**Adjacent 2025 (n = 11)**
Armadillo	0	1	1	1	0	2
Black bear	0	0	2	0	2	2
Bobcat	2	4	4	3	3	5
Coyote	0	0	0	0	1	0
White-tailed deer	11	5	19	13	10	5
Eastern gray squirrel	6	4	2	9	8	3
Eastern spotted skunk	2	0	1	1	1	0
Big Cypress fox squirrel	2	0	1	0	4	1
Eurasian wild pig	0	1	0	1	1	1
Marsh rabbit	1	1	2	2	0	1
Virginia opossum	1	4	10	5	8	8
Otter	0	1	0	1	0	0
Panther	0	0	0	0	0	1
Raccoon	2	3	7	4	4	8

Table 3. Comparison of raw species site occupancy counts from scat detection on baited and unbaited sites in and adjacent to Big Cypress National Preserve (BICY) and across 36 non-baited sites sampled in 2014 and 2025.

	Non-baited				Baited	
Species	BICY 2025 (n = 40)	Adjacent 2025 (n = 11)	2014 (n = 36)	2025 (n = 36)	BICY 2025 (n = 40)	Adjacent 2025 (n = 11)
Armadillo	0	0	0	0	0	0
Black bear	1	0	0	1	0	0
Bobcat	0	1	0	1	0	0
Coyote	0	0	0	0	0	0
White-tailed deer	3	3	6	5	2	2
Eastern gray squirrel	9	4	0	11	7	3
Eastern spotted skunk	0	0	1	0	0	0
Big Cypress fox squirrel	0	0	1	0	0	0
Eurasian wild pig	0	0	0	0	0	0
Marsh rabbit	1	2	16	3	0	1
Virginia opossum	2	0	1	1	3	0
Otter	8	3	0	6	8	0
Panther	0	1	1	1	0	0
Raccoon	0	0	0	0	0	1

Objective 1

We saw a dramatic decline in rabbit pellets over the 11-year period. In 2014, we detected pellets at 16 of 36 sites (44%), whereas in 2025 we found pellets at only 3 of 36 sites (8%). The estimated marginal means from our model also suggested that predicted pellet counts declined from 0.45 pellets per plot in 2014 (95% CI: 0.03–6.91) to 0.002 in 2025 (95% CI: 0.00–0.04). The 2025-to-2014 rate ratio was 0.004 (SE = 0.003, $z = -6.45$, $p < 0.001$), indicating that 2025 pellet counts averaged only about 0.4% of 2014 levels (≈ 250-fold reduction).

To provide a direct comparison between survey periods, we estimated abundance using only the three sites where we detected marsh rabbit pellets in 2025 and used pellet data from those same sites in 2014. Within these matched sites, pellet totals declined from 604 in 2014 to 16 in 2025. Applying the Schmidt et al. (2011) pellet-density relationship to the occupied sampling area, we estimated marsh rabbit abundance at 0.35 rabbits/ha in 2014 and 0.009 rabbits/ha in 2025. This matched-site decline in estimated abundance closely paralleled the reductions in occupancy and pellet counts, providing additional evidence of a substantial population decline over the 11-year period.

Objectives 2 and 3

Change Over Time

Our estimates from the two-season Bayesian occupancy models indicated clear patterns of declines for most mesomammal species between 2014 and 2025 (Figure 9; Tables 4–5). For four of the six species examined, the posterior distributions of $\Delta\psi$ were centered below zero, with high posterior (>83%) probabilities of a decline. Marsh rabbit, opossums, and deer exhibited the strongest evidence for reduced occupancy. Using repeated pellet counts, mean marsh rabbit occupancy declined from 0.46 (90% CRI: 0.31–0.61) in 2014 to 0.13 (0.05–0.23) in 2025, with a 99.9% posterior probability of a decline (Table 4). Opossum occupancy also declined from 0.39 (90% CRI: 0.22–0.61) in 2014 to 0.21 (0.09–0.38) in 2025, with a 92.5% posterior probability of a decline (Table 4). Deer showed a similar magnitude of reduction, declining from 0.61 (90% CRI: 0.45–0.77) to 0.43 (90% CRI: 0.28–0.59), with a 92.1% probability that ψ decreased. Raccoons also demonstrated downward shifts, though with more posterior uncertainty. Raccoon occupancy dropped from 0.26 (90% CRI: 0.13–0.42) to 0.15 (90% CRI: 0.06–0.28) with an 85% probability of a decline. Bobcats showed less directional change, with a posterior mean $\Delta\psi$ of -0.061 and wide 90% CRI (-0.316 to 0.175), indicating substantial uncertainty and only a 68% chance of a decline. Gray squirrels were the only species exhibiting a positive shift with a posterior mean $\Delta\psi$ of +0.161 (90% CRI: 0.034–0.298) and only a 2% chance of decline. This pattern contrasts strongly with the consistent declines inferred for the other mesomammals. Across all species, MCMC diagnostics indicated adequate convergence (all $\hat{R} \approx 1.00$, large effective sample sizes), supporting confidence in the posterior summaries.

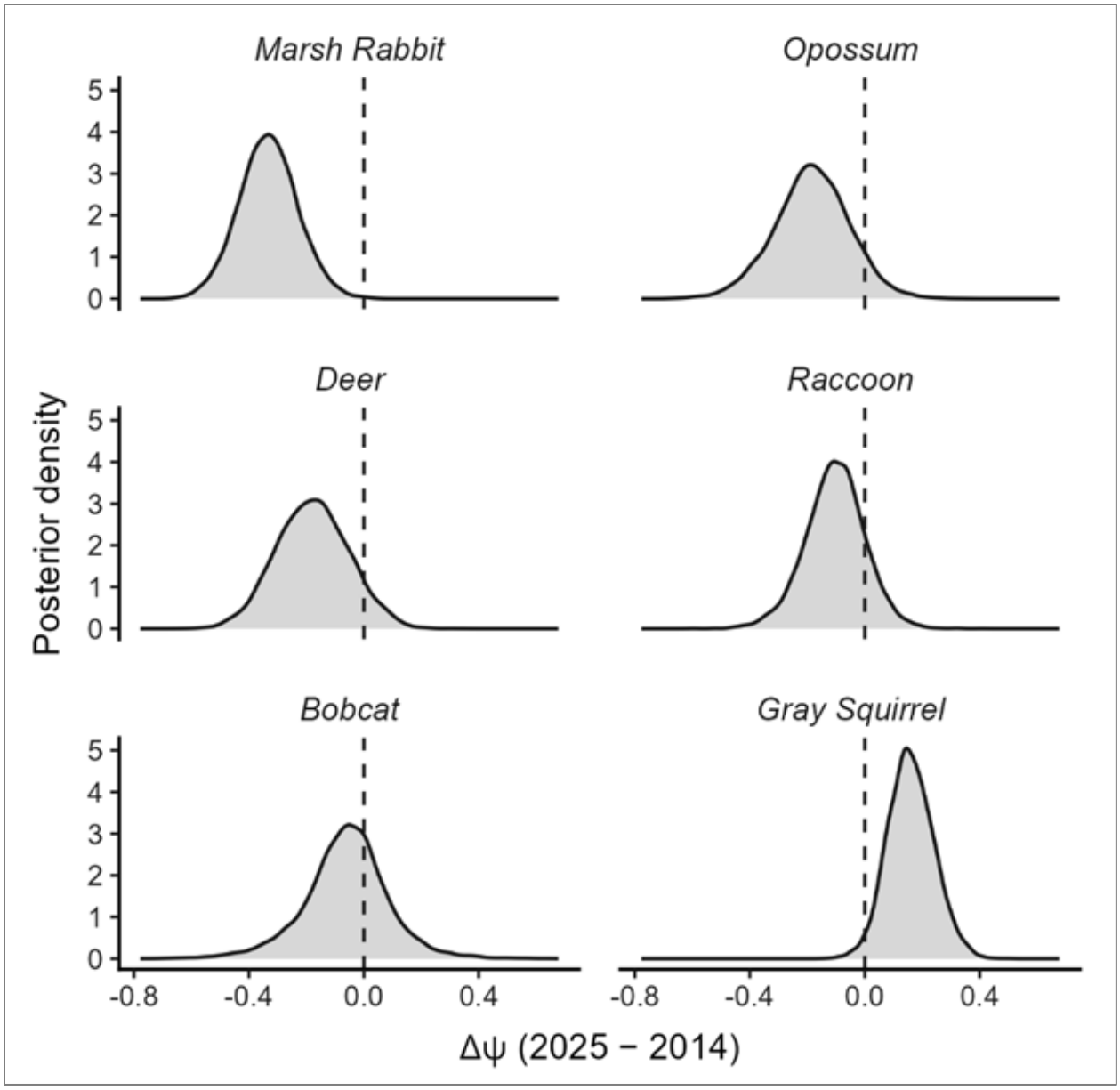

Figure 9. Posterior distributions of the change in occupancy ($\Delta\psi = \psi_{2025} - \psi_{2014}$) for each mesomammal species. The vertical dashed line at $\Delta\psi = 0$ indicates no change in occupancy; curves concentrated left of zero indicate posterior support for declines, whereas curves centered near or right of zero indicate little evidence for change or possible increases.

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Table 4. Posterior means and 90% credible intervals (LCI = 5th percentile, UCI = 95th percentile) of the probability of occupancy (ψ) in 2014 and 2025.

Species	Year	Mean ψ	90% LCI	90% UCI
Opossum	2014	0.39	0.22	0.61
Opossum	2025	0.21	0.09	0.38
Deer	2014	0.61	0.45	0.77
Deer	2025	0.43	0.28	0.59
Raccoon	2014	0.26	0.13	0.42
Raccoon	2025	0.15	0.06	0.28
Marsh rabbit	2014	0.46	0.31	0.61
Marsh rabbit	2025	0.13	0.05	0.23
Gray squirrel	2014	0.08	0.03	0.16
Gray squirrel	2025	0.25	0.14	0.37

Table 5. Posterior means and 90% credible intervals (LCI = 5th percentile, UCI = 95th percentile) of the probability of decline in occupancy (ψ) from 2014 to 2025.

Species	Mean Δψ	90% LCI	90% UCI	P(Δψ < 0)
Opossum	−0.183	−0.401	0.025	0.925
Deer	−0.178	−0.381	0.031	0.921
Raccoon	−0.104	−0.277	0.064	0.852
Marsh rabbit	−0.332	−0.500	0.162	0.999
Bobcat	−0.061	−0.316	0.175	0.679
Gray squirrel	0.161	0.034	0.298	0.021

Influence of Baiting

Across species, bait had relatively weak effects on probability of detection for most mesomammals (Table 6). Mean detection probabilities at unbaited vs. baited cameras were similar for deer, marsh rabbit, raccoon, bobcat, and gray squirrel, with Δp distributions centered near zero and low support for higher detection with bait ($P(\Delta p > 0) \leq 0.63$). In contrast, opossums showed a strong positive response, with p increasing from 0.16 (90 % CRI: 0.08–0.27) at unbaited cameras to 0.31 (90% CRI: 0.25–0.37) at baited cameras.

Table 6. Posterior detection probability (p) at unbaited and baited cameras for each species. Values are means with 90% credible intervals in brackets. Δp is the posterior mean difference, and P(Δp > 0) is the posterior probability that detection is higher at baited cameras.

Species	p unbaited	p baited	Δp (p_bait − p_no_bait)	P(Δp > 0)
Deer	0.184 [0.131, 0.242]	0.136 [0.091, 0.188]	−0.048 [−0.123, 0.025]	0.095
Marsh rabbit	0.109 [0.019, 0.254]	0.043 [0.002, 0.177]	−0.066 [−0.209, 0.058]	0.100
Raccoon	0.117 [0.046, 0.219]	0.081 [0.040, 0.139]	−0.035 [−0.140, 0.046]	0.224
Bobcat	0.045 [0.011, 0.121]	0.051 [0.017, 0.104]	0.005 [−0.064, 0.058]	0.630
Opossum	0.163 [0.075, 0.274]	0.309 [0.251, 0.371]	0.183 [0.036, 0.334]	0.992
Gray squirrel	0.269 [0.198, 0.347]	0.220 [0.154, 0.292]	−0.049 [−0.150, 0.049]	0.167

Across species, the effect of bait on occupancy was highly variable (Table 7). Herbivores such as deer, gray squirrel, and marsh rabbits showed little evidence that bait increased their probability of site use, and posterior probabilities of a positive bait effect were low ($P(\Delta\psi > 0) \approx 0.18–0.56$). In contrast, the three omnivorous or carnivorous species—raccoon, bobcat, and opossum—showed stronger indications that bait elevated occupancy. For raccoons and bobcats, mean baited–unbaited differences were imprecise but high ($P \approx 0.83$), suggesting the possibility of increased occupancy. Opossums exhibited the clearest response, increasing from 0.05 (90% CRI: 0.01–0.12) at unbaited sites to 0.22 (90% CRI: 0.08–0.38) at baited sites, with a high posterior probability of a positive effect ($P = 0.998$). This pattern indicates that bait may influence species with carnivorous and omnivorous diets, potentially increasing their likelihood of site use.

Table 7. Posterior mean of occupancy probability (ψ) at unbaited and baited cameras for each species. Values are means with 90% credible intervals in brackets. Δ ψ is the posterior mean difference, and P(Δ ψ > 0) is the posterior probability that detection is higher at baited cameras.

Species	ψ_no_bait (90% CRI)	ψ_bait (90% CRI)	Δψ (90% CRI)	P(Δψ > 0)
Deer	0.210 [0.057, 0.409]	0.198 [0.048, 0.398]	−0.013 [−0.198, 0.168]	0.449
Marsh rabbit	0.077 [0.013, 0.215]	0.038 [0.004, 0.110]	−0.039 [−0.156, 0.032]	0.177
Raccoon	0.096 [0.016, 0.229]	0.170 [0.033, 0.373]	0.074 [−0.054, 0.248]	0.826
Bobcat	0.187 [0.028, 0.539]	0.319 [0.062, 0.778]	0.132 [−0.095, 0.442]	0.829
Opossum	0.049 [0.007, 0.120]	0.222 [0.079, 0.377]	0.173 [0.054, 0.317]	0.998
Gray squirrel	0.130 [0.042, 0.246]	0.139 [0.043, 0.262]	0.009 [−0.093, 0.116]	0.555

Response to Environmental Predictors

For deer, model support centered on python colonization timing (Table 8). The top-ranked model included only python colonization timing (PCearly_only; ΔLOOIC = 0) and was clearly favored over all alternatives. The only model ≤2 ΔLOOIC was the best model with the addition of inundation, which did not improve the model. Models incorporating hydrology or fire history received substantially less support, indicating limited additional explanatory value once python colonization timing was included. Under the best-supported model, deer occupancy was markedly lower at sites

colonized earlier by Burmese pythons compared to later or uncolonized sites (β = −1.71, 90% CRI: −3.04 to −0.38), corresponding to a pronounced reduction in occupancy probability. These results suggest that current spatial variation in deer occurrence was most strongly associated with the duration of python colonization, with little evidence that fire history or inundation meaningfully improved predictive performance.

Table 8. Ranking of candidate models based on difference in Leave-One-Out Information Criterion (ΔLOOIC).

Model	Deer	Marsh rabbit	Squirrel	Bobcat	Opossum	Raccoon
PCearly_only	**0.00** [A]	0.61	3.90	2.64	5.06	**0.00** [A]
fire_time_water_group	15.01	8.63	8.02	18.43	5.47	18.93
water_only	6.59	0.09	3.05	18.20	15.73	25.42
group_only	8.08	2.98	1.38	14.84	4.29	15.30
fire_water_PCearly	3.92	5.77	4.28	**0.00** [A]	1.58	1.37
All_variable_noG	9.02	7.37	9.58	3.10	6.20	3.39
inund_PCearly_2var	1.31	1.33	3.93	4.35	**0.00** [A]	0.63
fire_water_group	20.45	9.76	10.19	17.68	6.78	21.38
fire_only	6.91	**0.00** [A]	6.88	20.91	17.09	25.92
time_only	6.67	3.14	1.53	17.39	13.88	24.11
Null	3.67	0.29	2.09	17.14	14.28	23.54
inund_only	5.93	0.97	**0.00** [A]	18.41	10.94	25.56
fire_water	14.24	3.89	8.05	20.74	13.92	29.85
fire_time_inund	8.69	4.23	0.89	18.58	11.15	26.71

[A] Models with the lowest score are in bold and are the most parsimonious.

For marsh rabbits, two competing models were ranked above the null model. One model incorporated water depth, and the other, time since the last fire (Table 8). While there were trends of increasing occupation with both water depth (β = 0.70, 90% CRI: −0.02 to 1.42) and the time since the last fire (β = 0.58, 90% CRI: −0.09 to 1.25), the 90% credible intervals of both variables included zero, suggesting that they did little to explain the variation in rabbit occurrence across our study areas. However, it is important to note that modeling the current distribution of marsh rabbits was limited by number of current detections (n = 5).

The top-supported occupancy model for raccoons included only python colonization as a predictor (PC_early; ΔLOOIC = 0). Two slightly more complex models that also incorporated inundation and fire metrics were competitive but did not meaningfully improve predictive performance. All remaining models, including those with fire history, water depth, or habitat grouping, were substantially less supported. In the best-supported model, raccoon occupancy was strongly and negatively associated with early python colonization (β = −4.50, 90% CRI: −6.39 to −2.62). Mean occupancy declined sharply from 0.76 (90% CRI: 0.53–0.96) at sites colonized later by pythons to

0.06 (90% CRI: 0.00–0.14) at early-colonized sites (Figure 10). Together, these results indicate a pronounced reduction in raccoon occurrence corresponding with the duration of python presence, with little additional explanatory value from fire or hydrologic variables.

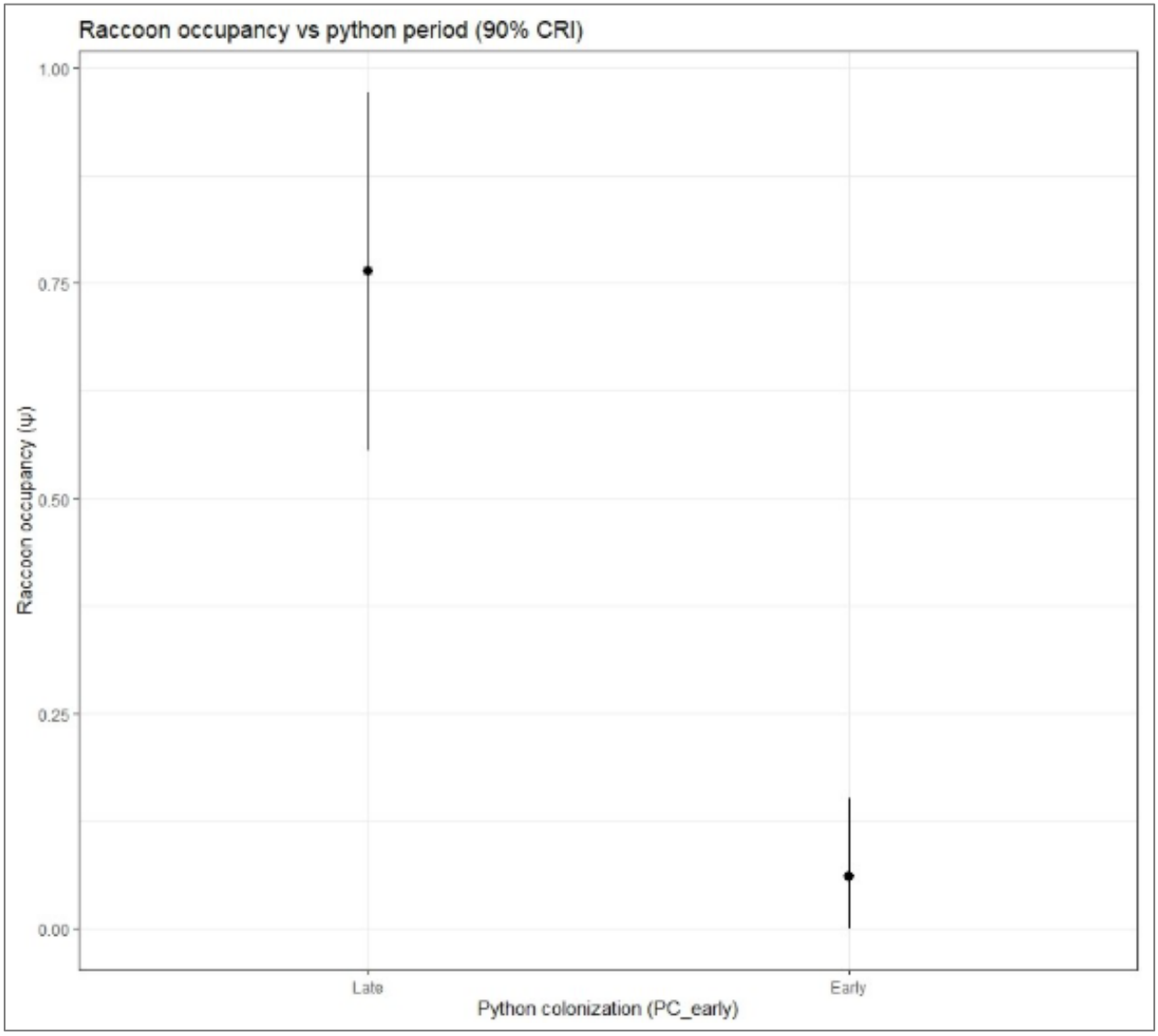

Figure 10. Predicted raccoon occupancy (ψ) and 90% CRI as a function of python colonization period (late and early).
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Bobcat occupancy was best supported by models combining fire history, hydrology, and python colonization timing (Table 8). The top-ranked model included time since fire, fire count, water depth, inundation, and python colonization timing (fire_water_PCearly; ΔLOOIC = 0). All remaining candidate models were substantially less supported (ΔLOOIC ≥ 2.1). Within the best-supported model, bobcat occupancy showed a strong negative association with early python colonization (β = −3.30, 90% CRI: −6.23 to −2.12), indicating considerably lower occurrence at sites colonized earlier by pythons. There was also a positive significant relation with time since fire (β = 1.52, 90% CRI:

0.24 to 2.79), with bobcat occurrence increasing with more time since the last fire (i.e., less fire = greater occurrence). The effects of fire history (i.e., fire count) and hydrology were comparatively weaker and less certain, with 90% credible intervals overlapping zero. Together, these results suggest that while bobcat occupancy is plausibly influenced by multiple environmental factors, python colonization timing emerges as the strongest predictor of spatial variation in occurrence (Figure 11).

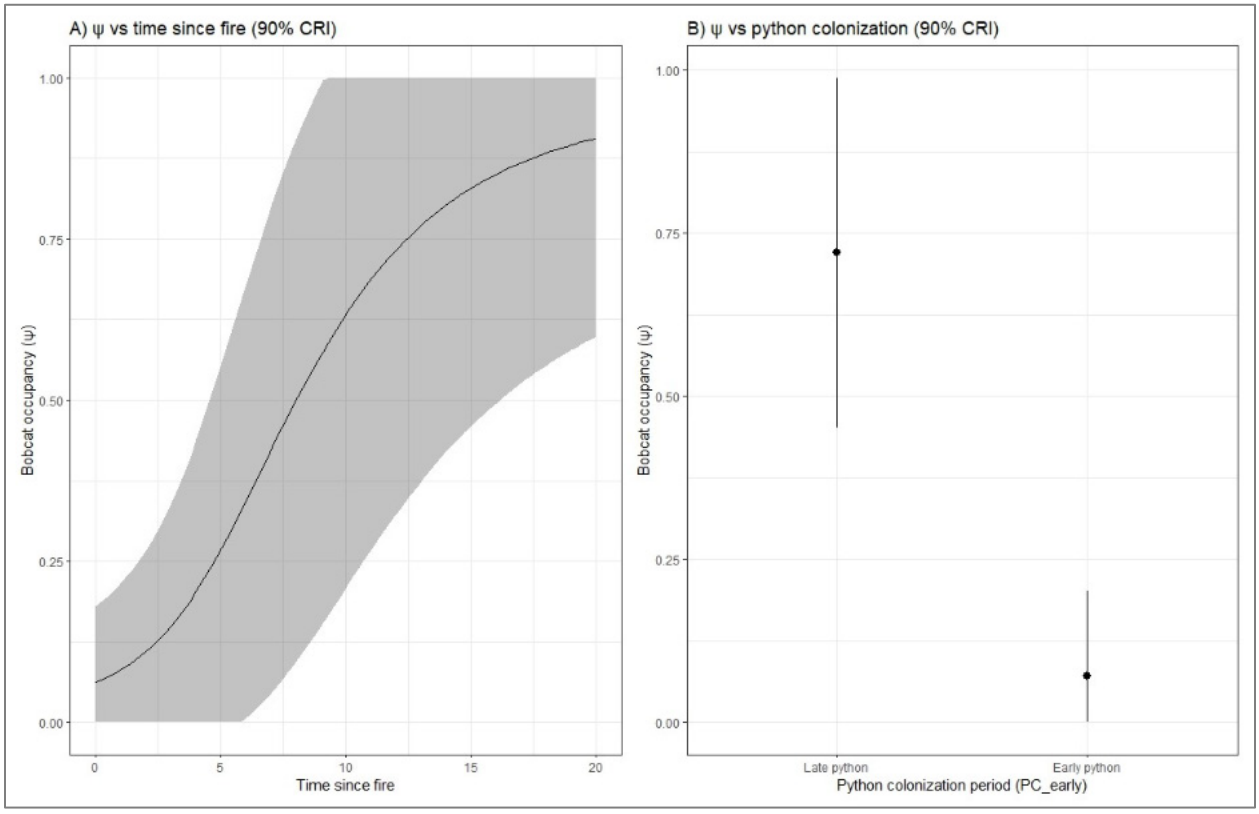

Figure 11. Predicted bobcat occupancy (ψ) and 90% CRI as a function of python colonization period (late and early) and time since the last fire.
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For opossums, occupancy was best explained by a combination of hydrologic conditions and python colonization (Table 8). The top-supported model included the variable total days inundated and python colonization (inund_PCearly; ΔLOOIC = 0). A closely related model that included time since fire also received comparable support (ΔLOOIC = 1.58) but the addition of this variable did not improve model fit. All remaining models, including those emphasizing python colonization timing or single covariates, were substantially less supported (ΔLOOIC ≥ 4). Within the best-supported model, opossum occupancy declined with increasing inundation (β = −1.08, 90% CRI: −1.81 to −0.35) and with python colonization (β = −2.41, 90% CRI: −3.64 to −1.19), suggesting opossums are likely sensitive to wetter conditions and the python invasion (Figure 12).

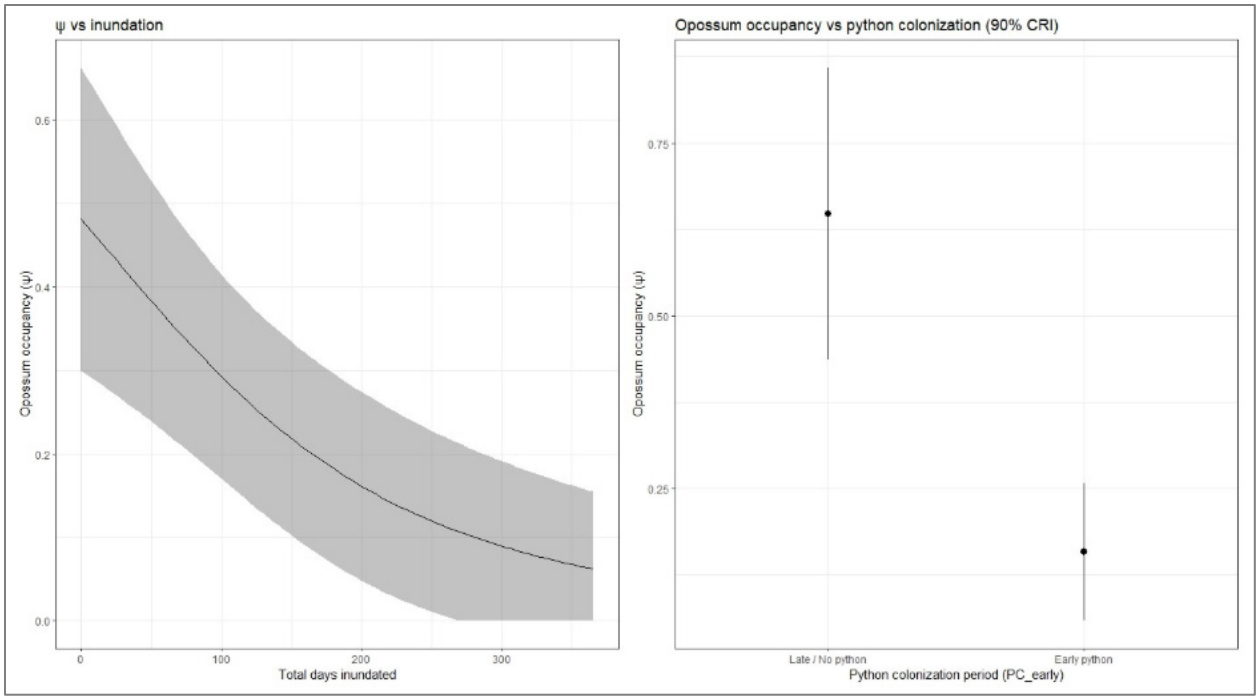

Figure 12. Predicted opossum occupancy (ψ) and 90% CRI as a function of days of inundation and python colonization.
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Model selection indicated several competing models (ΔLOOIC < 2) to best explain gray squirrel occupancy (Table 8). These competing models included variables accounting for variation in fire, hydrology and vegetation communities. However, only the best model (inund_only) had a variable with a 90% CRI that did not include 0. As the number of inundation days increased the occurrence of squirrels decreased ($\beta = -0.76$, 90% CRI: -1.51 to -0.01). Models incorporating water depth, fire history, vegetation or python colonization timing did little to explain squirrel occupancy. Overall, these results suggest that gray squirrel occupancy only decreases in continually wet areas (Figure 13) but is affected by little else.

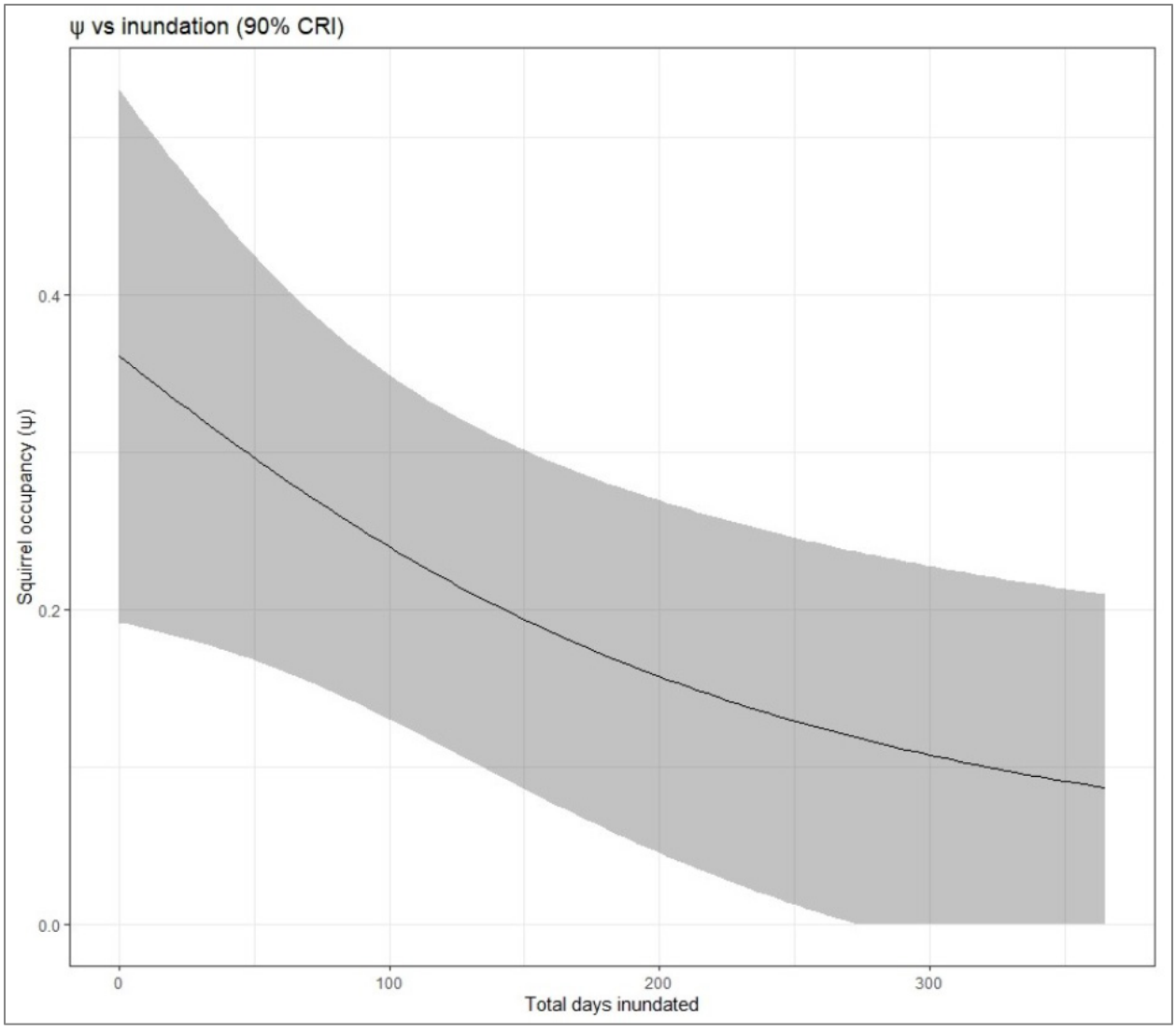

Figure 13. Predicted gray squirrel occupancy (ψ) and 90% CRI as a function of days of inundation. *NPS / UNIVERSITY OF FLORIDA*

Objective 4

Future Monitoring

To establish a robust framework for future wildlife monitoring within Big Cypress National Preserve (BICY), several strategic adjustments to survey protocols and management actions are recommended. Given that mammal detection rates within BICY were exceedingly low, viable occupancy modeling for most species was only achievable by incorporating data from external reference sites. Consequently, it is recommended that monitoring efforts continue to include these external sites to ensure sufficient data for effective population measurement and monitoring. While expanding the number of sampling sites within BICY might increase total detections, the associated labor costs are substantial. Instead, a more cost-effective approach to improve detection probability involves extending the survey duration to four weeks. To maintain longitudinal consistency with

legacy datasets, researchers must adjust detection histories to a 28-day standard, employing “NA” values for days 15–28 for all previous survey records.

The efficacy of attractants was also evaluated, revealing that sardine-based baiting significantly increased the number of occupied sites for bobcats, raccoons, and opossums without deterring other taxa. Future surveys should therefore adopt this baiting protocol as a standard. However, despite these efforts, several carnivore species—including formerly common species such as the striped skunk and red fox, as well as cryptic species like the Everglades mink and long-tailed weasel—remained undetected. We recommend that BICY initiate targeted efforts using specialized lures and alternative baits, such as rodents, to confirm the presence or absence of these species. Furthermore, specific attention should be directed toward the round-tailed muskrat, a species of conservation concern that was not captured by the current survey design; specialized transect surveys are recommended to assess this population.

To improve the precision of environmental covariates, the installation of remotely monitored water wells is advised to provide more granular data on water depth and inundation levels. Furthermore, while the current volume of imagery allowed for manual sorting, future large-scale efforts should utilize automated platforms such as MegaDetector to increase processing efficiency.

Finally, our findings align with recent research indicating a precipitous decline in mid-sized mammals, with data suggesting that invasive Burmese pythons are a primary driver of this trend (Reichert et al. 2017; Taillie et al. 2021). We recommend an expansion of python detection and removal programs. Efforts should remain focused on the continued trial, refinement, and development of novel detection and removal methodologies to mitigate the ecological impact of this invasive predator.

Discussion and Management Recommendations

Looking over an 11-year period in BICY and adjacent protected areas of southwest Florida, we found that four out of six mammals we examined showed clear reductions in occurrence. Specifically, we found that marsh rabbit, opossums, raccoons and deer exhibited high (>83%) probabilities of decline. These changes align with the northern and westward expansion of pythons (Guzy at al. 2023) and patterns seen in other areas of the Greater Everglades (Taillie et al. 2021), where declines in deer, marsh rabbit, and raccoon have all been linked to recent python invasions. Moreover, the current association between the timing of the python invasion and reduced occupancy of most of these same mammals further strengthened the linkages between pythons and mammal decline. Specifically, we found clear and strong patterns linking reduced occurrence of deer, marsh rabbits, bobcats, and raccoons in areas where pythons have occurred for longer periods of time. Combined, this evidence suggests that pythons are probably the main drivers of the decline in mammal species in BICY and southwest Florida.

Bobcats showed elevated occurrence in areas with longer periods of time since their last fire and lower occurrence in areas where pythons had been longer. Their association with long delays in fires could indicate the areas are transitioning towards hardwood forests (McLeod et al. 2025), as bobcats typically select for woodier vegetation (Buckman et al. 2024). Reductions in bobcat occurrence associated with the python invasion are supported by previous research showing similar patterns (Buckman et al. 2024) and are likely a function of direct mortality or competition for food (Dorcas et al. 2012; McCleery et al. 2015; Soto-Shoender et al. 2020).

While pythons appeared to be associated with the decline of some species, other species also appeared to respond to different features of the environment. For example, opossums, which also declined over the 11-year period, showed a negative response to increasing water inundation. Across BICY, the areas associated with the longest inundation periods were freshwater marshes and prairies that often lack the tree structure that semi-arboreal opossums often need (Wait and Ahlers 2020).

We only found one species, the eastern gray squirrel, that increased throughout our study area over the 11-year period. While squirrel populations can fluctuate with resource pulses and diseases (Ostfeld and Keesing 2000; Tompkins et al. 2003), we do not have a clear explanation for the pattern of increased occurrence over the study. Nonetheless, it appears to be decoupled from python activity as their current distribution was, like opossums, negatively associated with longer water inundation. More than opossums, eastern gray squirrels utilize tree canopy for foraging, moving and resting (Dunham et al. 2019) and are accordingly unlikely to be found in inundated prairie vegetation. Their use of tree canopy may also limit their exposure to pythons that spend most of their time on the ground (Whitney et al. 2021).

Our findings suggest that changes in the mammal community are likely to affect a host of ecological processes. Reductions in mammalian herbivores (e.g., deer and marsh rabbits) may influence vegetation structure, nutrient cycling, and plant recruitment (Dirzo et al. 2014; Estes et al. 2011). Similarly, declines in seed dispersers and consumers (e.g., raccoons, opossums, and white-tailed

deer) may alter plant community composition and regeneration dynamics (Dirzo et al. 2014). At higher trophic levels, predator–prey interactions may also be affected by reduced prey availability (Estes et al. 2011; Ripple and Beschta 2012). Finally, declines in mammalian species that provide scavenging services (e.g., raccoons and opossums) may disrupt the flow of energy and nutrients through the ecosystem (DeVault et al. 2003).

To mitigate further mammal declines in BICY and adjacent areas, as well as throughout the Greater Everglades, there is an urgent need to develop affordable and scalable approaches for addressing the python invasion in south Florida. Despite ongoing research and some success from contract snake-hunters, snitch snakes (Guzy et al. 2023), and the use of live mammals as bait (McCampbell et al. 2024), no management tool has yet proven capable of addressing the problem at the scale required. Because the spatial extent of the invasion can easily overwhelm the resources available to protected areas such as BICY, an important first step may be to identify areas of high ecological value or locations that support concentrations of sensitive species. Once identified, managers can strategically deploy existing and experimental python-removal tools to create refugia for the reserve's most vulnerable species.

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