Title: Optimizing Survey Conditions for Burmese Python Detection and Removal Using Community Science Data

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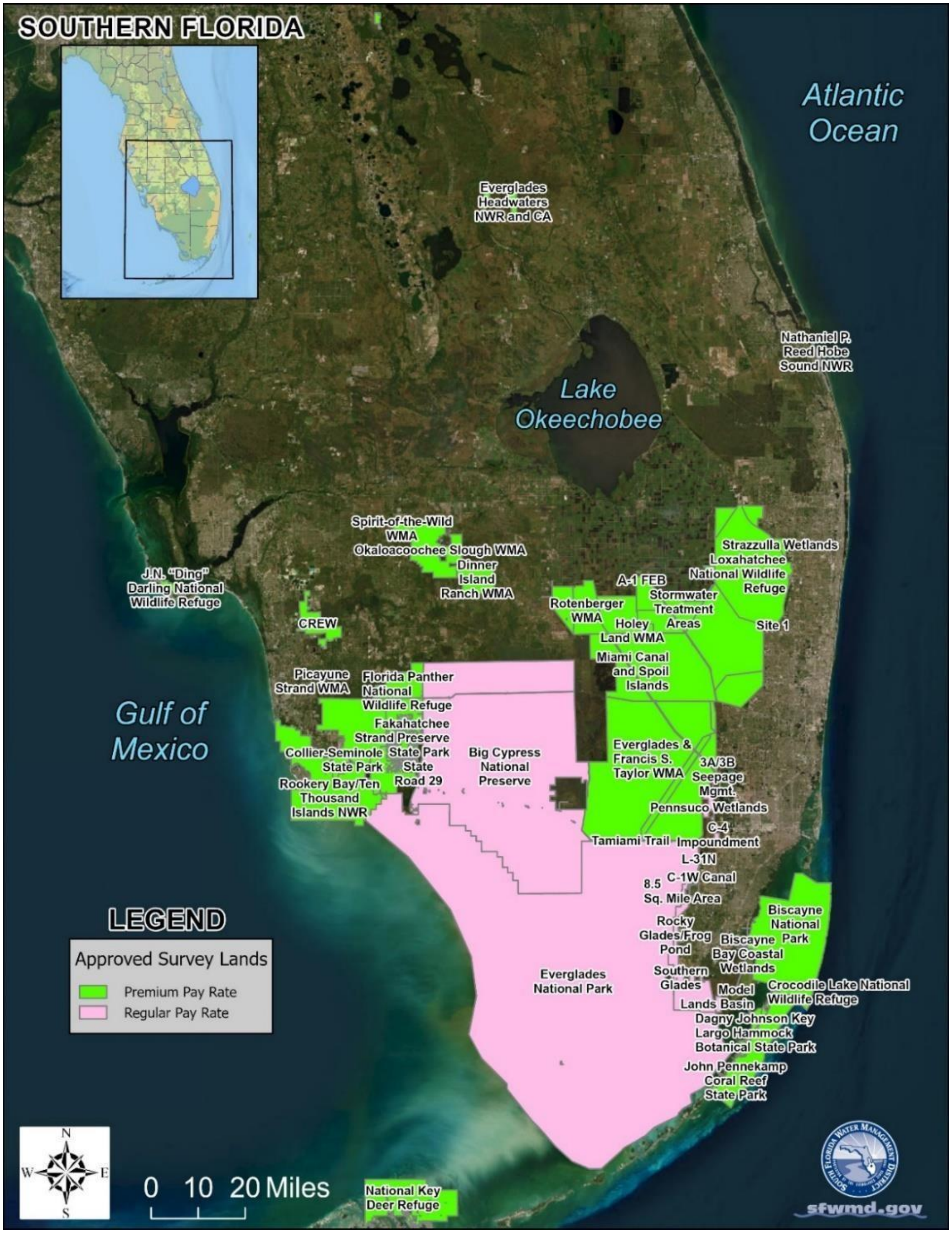
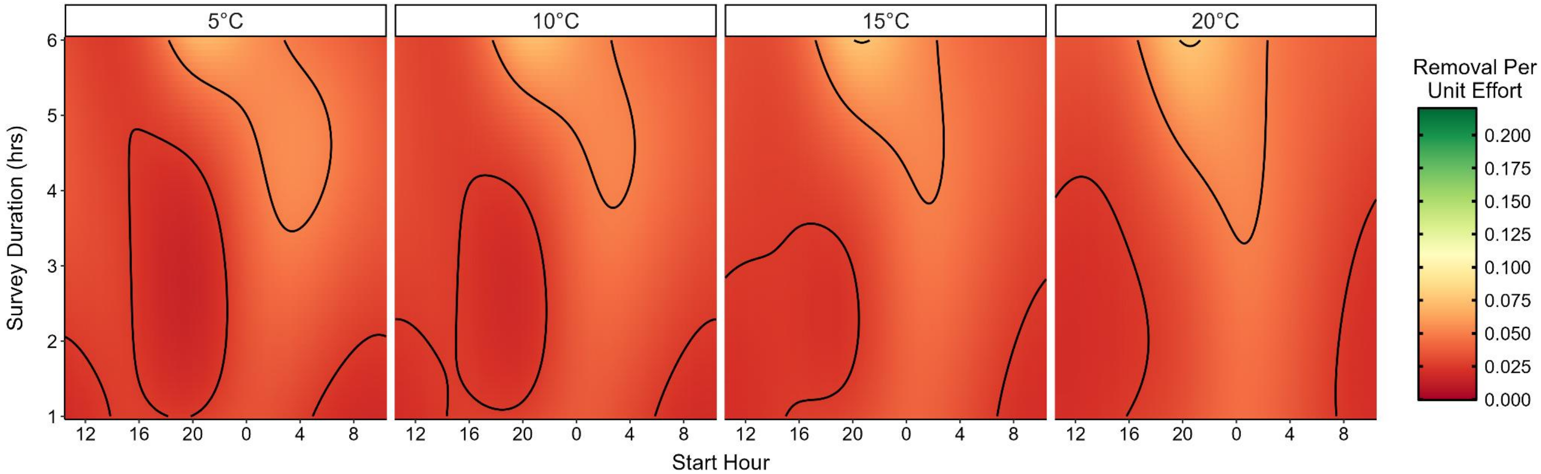

SOUTHERN FLORIDA
Atlantic Ocean
Everglades Headwaters NWR and CA
Nathaniel P. Reed Hobe Sound NWR
Lake Okeechobee
Spirit-of-the-Wild WMA
Okaloacoochee Slough WMA
Dinner Island Ranch WMA
Strazzulla Wetlands
Loxahatchee National Wildlife Refuge
A-1 FEB
Stormwater Treatment Areas
Rotenberger WMA
Holey Land WMA
Site 1
J.N. "Ding" Darling National Wildlife Refuge
CREW
Miami Canal and Spoil Islands
Picayune Strand WMA
Florida Panther National Wildlife Refuge
Gulf of Mexico
Fakahatchee Strand Preserve State Park
Collier-Seminole State Park
State Road 29
Big Cypress National Preserve
Everglades & Francis S. Taylor WMA
3A/3B Seepage Mgmt.
Rookery Bay/Ten Thousand Islands NWR
Pennsuco Wetlands
C-4 Impoundment
Tamiami Trail
L-31N
C-1W Canal
8.5 Sq. Mile Area
LEGEND
Approved Survey Lands
Premium Pay Rate
Regular Pay Rate
Biscayne National Park
Rocky Glades/Frog Pond
Biscayne Bay Coastal Wetlands
Everglades National Park
Southern Glades
Model Lands Basin
Crocodile Lake National Wildlife Refuge
Dagny Johnson Key Largo Hammock Botanical State Park
John Pennekamp Coral Reef State Park
N
W
E
S
0 10 20 Miles
National Key Deer Refuge
sfwmd.gov

Supplementary Figure S1. Approved SWMFD PEP survey properties. Hourly pay rate associated with each property is denoted by fill color: standard (green) or premium (pink). Premium pay rate is used to incentivize contractors to survey for pythons in regions with low python abundance. Satellite imagery was generated using ArcGIS Pro version 3.1.2 (ESRI, Redlands, CA, USA; https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview)



Supplementary Figure S2. Morning surveys become moderately productive at climatically extreme cold temperatures. Predicted survey efficiency (removal per unit effort) according to variation in survey interval and air temperature. Contour lines correspond to breaks in figure legend. Facet labels correspond to temperature utilized for simulated survey. A minimum daily temperature of 10°C is in the 7th percentile for minimum daily temperature values for the Homestead General Aviation Weather Station recorded between 6/1/1990 and 2/1/2024. All simulated surveys conducted in this figure were conducted during the mid-dry season in February corresponding to the associated panel in Figures 2C and 4A

Parametric Coefficients				
Covariate	Estimate	Standard Error	Z-Statistic	P-Value
(Intercept)	**-1.05**	**0.43**	**-2.48**	**0.013**
season2wet	0.21	0.20	1.02	0.306
Smooth Terms				
Covariate	Effective Degrees of Freedom	Reference Degrees of Freedom	χ2-Statistic	P-Value
s(airt.c)	**2.52**	**9.0**	**16.13**	**0.015**
s(julian)	**2.66**	**8.0**	**19.16**	**0.002**
ti(julian,airt.c)	0.00	12.0	0.00	0.413
te(start_minutes,survey_hr)	**7.52**	**19.0**	**472.01**	**< 2e-16**
ti(start_minutes,survey_hr,airt.c)	**3.46**	**48.0**	**8.76**	**0.014**
s(baro.diff):season2dry	0.40	9.0	0.69	0.191
s(baro.diff):season2wet	0.26	9.0	0.37	0.242
s(wnds.mph)	0.32	9.0	0.54	0.221
s(radt.kwm2)	0.00	9.0	0.00	0.819
s(etp.mm)	0.00	9.0	0.00	0.826
s(humi.perc)	0.00	9.0	0.00	0.316
s(baro.mm)	0.19	9.0	0.27	0.249
s(rain.mm)	0.00	9.0	0.00	0.848
te(illum_start,illum_end)	0.00	23.0	0.00	0.924
s(moon_start4)	0.55	3.0	0.69	0.294
s(year)	0.86	2.0	3.15	0.095
s(station3,station2,station1)	5.61	20.0	63.69	0.046
s(contractor)	**40.69**	**60.0**	**408.88**	**< 2e-16**
s(alone_or_assist)	**0.94**	**1.0**	**93.93**	**3.98e-5**
s(PATRIC_property_equiv)	**9.31**	**116.0**	**33.15**	**0.031**
s(survey_type)	**2.29**	**6.0**	**16.14**	**0.003**

Supplementary Table S1. Summary of POR GAMM model results. Significant terms indicated in bold.

Parametric Coefficients				
Covariate	Estimate	Standard Error	T-Value	P-Value
(Intercept)	**-1.20**	**0.36**	**-3.35**	**8.28e-4**
season2wet	0.14	0.23	0.60	0.552
Smooth Terms				
Covariate	Effective Degrees of Freedom	Reference Degrees of Freedom	F-Statistic	P-Value
s(airt.c)	**0.86**	**9.0**	**1.27**	**0.008**
s(julian)	**7.46**	**18.0**	**2.40**	**5.47e-5**
ti(julian,airt.c)	**2.02**	**12.0**	**0.82**	**0.007**
te(start_minutes,survey_hr)	**7.90**	**19.0**	**32.07**	**< 2e-16**
ti(start_minutes,survey_hr,airt.c)	**4.23**	**48.0**	**0.46**	**3.22e-4**
s(baro.diff):season2dry	0.00	9.0	0.00	0.527
s(baro.diff):season2wet	**3.04**	**9.0**	**1.65**	**0.005**
s(wnds.mph)	3.24	9.0	1.10	0.094
s(radt.kwm2)	0.00	9.0	0.00	0.534
s(etp.mm)	0.00	9.0	0.00	0.578
s(humi.perc)	0.00	9.0	0.00	0.418
s(baro.mm)	0.42	9.0	0.11	0.179
s(rain.mm)	0.00	9.0	0.00	0.730
te(illum_start,illum_end)	0.00	23.0	0.00	0.895
s(moon_start4)	1.57	3.0	1.29	0.087
s(year)	0.80	2.0	2.07	0.079
s(station3,station2,station1)	4.41	20.0	2.39	0.132
s(contractor)	**44.02**	**60.0**	**13.82**	**< 2e-16**
s(alone_or_assist)	**0.93**	**1.0**	**95.69**	**1.18e-4**
s(PATRIC_property_equiv)	**16.04**	**116.0**	**0.79**	**0.007**
s(survey_type)	**2.65**	**6.0**	**5.07**	**1.26e-4**

Supplementary Table S2. Summary of RPUE GAMM model results. Significant terms indicated in bold.

Supplementary Equation S1. Formula specification provided to `mgcv` for POR model.

$$
\begin{aligned}
&capture \sim season2 + s(airt.c, bs = 'ts') + s(julian, bs = 'cc') + \\
&\quad ti(julian, airt.c, bs = 'ts') + te(start\_minutes, survey\_hr, bs = c('cc', 'ts')) + \\
&\quad ti(start\_minutes, survey\_hr, airt.c, bs = c('cc', 'ts', 'ts')) + \\
&\quad s(baro.diff, by = season2, bs = 'ts') + s(wnds.mph, bs = 'ts') + \\
&\quad s(radt.kwm2, bs = 'ts') + s(etp.mm, bs = 'ts') + s(humi.perc, bs = \\
&\quad 'ts') + s(baro.mm, bs = 'ts') + s(rain.mm, bs = 'ts') + \\
&\quad te(illum\_start, illum\_end, bs = c('ts', 'ts')) + s(moon\_start4, bs = 're') + \\
&\quad s(year, bs = 're') + s(station1, station2, station3, bs = 're') + \\
&\quad s(contractor, bs = 're') + s(alone\_or\_assist, bs = 're') + \\
&\quad s(PATRIC\_property\_equiv, bs = 're') + s(survey\_type, bs = 're')
\end{aligned}
$$

Supplementary Equation S2. Formula specification provided to `mgcv` for RPUE model.

$$
\begin{aligned}
&snakes \sim season2 + s(airt.c, bs = "ts") + s(julian, bs = "cc", k = 20) + \\
&\quad ti(julian, airt.c, bs = c("ts", "ts")) + te(start\_minutes, survey\_hr, bs = \\
&\quad c("cc", "ts")) + ti(start\_minutes, survey\_hr, airt.c, bs = c("cc", "ts", "ts")) + \\
&\quad s(baro.diff, by = season2, bs = "ts") + s(wnds.mph, bs = "ts") + \\
&\quad s(radt.kwm2, bs = "ts") + s(etp.mm, bs = "ts") + s(humi.perc, bs = \\
&\quad "ts") + s(baro.mm, bs = "ts") + s(rain.mm, bs = "ts") + \\
&\quad te(illum\_start, illum\_end, bs = c("ts", "ts")) + s(moon\_start4, bs = "re") + \\
&\quad s(year, bs = "re") + s(station1, station2, station3, bs = "re") + \\
&\quad s(contractor, bs = "re") + s(alone\_or\_assist, bs = "re") + \\
&\quad s(PATRIC\_property\_equiv, bs = "re") + s(survey\_type, bs = "re")
\end{aligned}
$$

Supplementary Methods

Visualization of Univariate Smooths

We employed a consistent method for visualizing and interpreting the effect of significant univariate smooth terms from our RPUE and POR models. Central to this analysis was a custom function, *scaled_smooth_estimates,* which facilitated the extraction and scaling of smooth estimates from both models to the response scale.

For each model, smooth estimates corresponding to significant predictors were retrieved, as identified by their p-values. These smooth estimates, initially derived as splines within the GAMM framework, represent the relationship between the predictors and the response variable. To transform these estimates into a format with increased interpretability, the function added the respective model's intercept to each smooth estimate. This step anchored the estimates to the baseline level of the response variable, which is the removal probability in the POR model and the number of snakes removed in the RPUE model. The function then computed confidence intervals for these scaled estimates, offering a quantified measure of uncertainty around the predicted effects. Additionally, both models employed an inverse link function transformation on the smooth estimates and their confidence intervals. In the POR model, this transformation involved converting estimates from the logit scale back to the probability scale. Conversely, in the RPUE model, which is structured around a negative binomial family, the transformation converts log-scale predictions back to the count scale. Notably, all RPUE model estimates were fit with input data featuring a survey duration of one hour, effectively scaling values to RPUE.

Visualization of Multivariate Smooths

In both our RPUE and POR models, we found significant tensor product interaction terms. These multivariate smooths necessitated the use of distinct analytical approaches to visualize their effects.

To visualize the interaction between survey start time, survey duration, and air temperature, we generated predictions of survey outcome (POR or RPUE) across a range of these values using the *fitted_values* from the package "gratia" (Simpson 2023). The smooths not relevant to this prediction (e.g., contractor ID) were passed to the `exclude` argument in this function to prevent altering predictions with extraneous terms. Simulated surveys were initiated at 5-minute intervals throughout the day. At each interval, the survey duration was varied from one to six hours, covering the 19.5^{th} to 89.8^{th} percentiles, in 5-minute increments. This was repeated four times for each model, representing the mean normal monthly temperature of February, May, August, and November. These months were chosen to represent the middle of the dry season, the end of the dry season, the middle of the wet season, and the end of the wet season, respectively. For the RPUE model, raw predictions were divided by simulated survey duration **plus two**. If this calculation is not performed RPUE increases asymptotically as survey duration approaches zero which is likely not realistic or useful within a management context. Thus, this intercept term can be conceptualized as representing the fixed time costs associated with conducting a survey (travel to/from site, gear preparation and disinfection) and therefore scales RPUE to actual survey effort. Adding this term modified predicted optimal survey intervals which more closely reflected survey intervals practiced by contractors. Additionally, minor changes to this value (± 1) did not significantly alter result topology.

For the significant interaction between Julian day and air temperature in the RPUE model, we gathered 30-year (1991-2020) daily average temperature data from the Miami Homestead General Aviation Airport weather station (https://www.weather.gov/wrh/Climate?wfo=mfl; accessed 19 December 2023). We used these values to contextualize our model predictions within Florida's climate. This was achieved by generating a series of temperature values corresponding to daily average air temperature ± 5°C in increments of 0.25°C for each Julian day. For each of these temperature value and day of year combinations we performed a simulated 3-hour survey, predicted survey RPUE via the function fitted_values, and scaled predicted values to RPUE via the methodology described above.