SPATIAL ECOLOGY OF BOBCATS (LYNX RUFUS) ON EVERGLADES TREE ISLANDS

by

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A Thesis Submitted to the Faculty of

The Charles E. Schmidt College of Science

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

Florida Atlantic University

Boca Raton, FL

December 2020

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ACKNOWLEDGEMENTS

I wish to acknowledge my graduate advisor, Dr. Nathan Dorn, for his guidance and encouragement during the thesis writing process. I am also grateful to my thesis committee members Dr. Laura D'Acunto, Dr. Stephanie Romañach, and Dr. John Baldwin for their support throughout this project. I also wish to acknowledge the U.S. Geological Survey for funding my thesis project, as well as the Florida Fish and Wildlife Conservation Commission for supplying the data used in this project. Lastly, I would like to thank my current and former lab mates, Jeff Sommer, Nathan Barrus, and Christopher Hansen, for their support during my graduate experience.

ABSTRACT

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Title: Spatial Ecology of Bobcats (*Lynx rufus*) on Everglades Tree

Islands

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Thesis Advisor: Dr. Nathan Dorn

Degree: Master of Science

Year: 2021

Bobcats (*Lynx rufus*) that inhabit tree islands of the Everglades, an expansive wetland in southern Florida. Bobcats are understudied in Florida and wetland ecosystems, and my objective was to identify factors driving their use of tree islands. I hypothesized that tree island size, distance between islands, and clusters of islands might influence occupancy. Additionally, I tested for effects of water levels and the Burmese Python invasion on bobcat occupancy. I built detection histories using 1,855 bobcat images from camera traps set on 87 tree islands in a ~2,350 km² managed conservation area from 2005-2019 and tested hypotheses about bobcat use relative to habitat and hydrologic covariates. Bobcat occupancy was significantly diminished when Burmese python densities exceeded 2.5 pythons/km². Occupancy probability also increased with increasing densities of tree islands around the focal island. Effects of high water levels were less clear, but suggested a slight reduction in island occupancy with deeper water in the surrounding wetlands. My results suggest that managing for high tree island density

and low densities of Burmese pythons will have stronger effects on bobcat habitat use than specific water levels.

DEDICATION

I would like to dedicate this manuscript to my father, Frederick Buckman II, who shared his love of nature with his daughter so she may grow up to protect it. And to my mother, whose unrelenting support and understanding is has undoubtedly facilitated my success. Lastly, I dedicate this manuscript to my late grandfather, Fredrick Buckman I, whose passion for science and education was passed along to his granddaughter.

SPATIAL ECOLOGY OF BOBCATS (LYNX RUFUS) ON EVERGLADES TREE

ISLANDS

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INTRODUCTION

One of the growing focal areas of wildlife ecology research is identifying and describing the dynamic factors limiting species distributions (Krebs 2020, DeWitt et al. 2017). Wildlife distribution models often use a set of static habitat variables, although there is broad recognition that wildlife respond to dynamic landscapes (Wisz et al. 2013, Franklin 2010, Cardillo et al. 1999), Some wildlife distributions may change in response to habitat alteration (e.g. habitat loss, changing water levels) (Loftus and Eklund 1994, Gaines et al 2002, Schmiegelow and Mönkkönen 2002) or the introduction of a predator (Bellingham et al. 2010, Johnson et al. 2007), however additional research concerning time-varying habitat and landscape variables is necessary to help monitor terrestrial mammal species' distributions at the landscape scale.

Habitat use is defined as the physical and biological resources utilized by an animal, and may be applied to a range of scales, from individuals to populations. This set of resources is essential for survival and reproduction, which contribute to occupancy (Leopold 1933). For terrestrial mammals, habitat use is generally associated with vegetation structure and food availability (McDonald et al. 2005). Some terrestrial mammals inhabit wetlands (Fritzell 1988), though few are considered to be adapted to such environments. Several terrestrial mammal species are known to inhabit the expansive shallow and hydrodynamic wetlands of southern Florida (Meshaka et al. 2002, Blair 1935).

The most spatially extensive and continuously inundated wetland in Florida is the Everglades. The Greater Everglades watershed extends over 28,000 km² from the Kissimmee River south to Florida Bay (Davis & Ogden 1994). The Greater Everglades includes Big Cypress National Preserve to the west and is bordered by urban areas to the east (Figure 1; Gaiser et al. 2012). The central Everglades landscape consists of three Water Conservation Areas and Everglades National Park and was historically characterized by a slow yet constant shallow flow of water, forming a mosaic of ridges and sloughs with interspersed tree islands. The wetlands of the central Everglades typically remain flooded for 9-12 months and experience an annual wet and dry season; water depths typically peak in October and the shallowest conditions occur in May. Much of the central Everglades has been compartmentalized by roads and levees, which has drastically altered historic water flow patterns (Light and Dineen 2002). Today, the Everglades is undergoing a multi-decade restoration effort known as the Comprehensive Everglades Restoration Plan (CERP), which aims to decompartmentalize much of the Everglades and restore the historical hydroperiods and slow-moving sheet flow of water. Current water management affects the typical seasonal hydrologic conditions, creating areas with unnaturally high or low water levels, which can drastically affect the development and formation of tree islands (Wetzel 2002).

Tree islands are a unique and ecologically important habitat in the Everglades, providing vital nesting habitat for wading birds, herpetofauna, and are believed to serve as a high-elevation refuge for terrestrial mammals inhabiting wetlands during the wet season (Robertson and Frederick 2002). Tree islands are 18 to 160 cm higher than the surrounding ridge and slough wetland habitats (Gaiser et al 2012) and are generally tear-

shaped along a north-south axis consistent with the direction of historical water flow. Tree islands vary broadly in size from < 0.1 to > 70 hectares (Wetzel 2002). The elevated northern end of the island often remains dry under annual high-water conditions, and the lower south end is more prone to flooding. Drainage and compartmentalization in the 19th and 20th centuries dramatically altered the hydrology of the Everglades and dramatically damaged tree island vegetation and soil (Loveless 1959, Dineen 1972). Tree island coverage was reduced by > 60% between 1940 and 1995 in some areas (Sklar and van der Valk 2002). Although much of the Everglades hydropattern is intensively managed, it is unclear how water depth variations (flooding and drought) and landscape factors affect mammal occupancy of tree islands in the Everglades. Though mammals are not typical indicator species for wetland ecosystem restoration, some small mammals (i.e. rodents) are actively responding to Everglades restoration efforts (Romañach et al. 2021). It is also well-known that mammal biodiversity is significant and some mammals can have a functionally important role in trophic dynamics (Sinclair 2003), therefore a thorough understanding of mammal habitat use is essential for maintenance and conservation of ecosystems as well as individual species.

Much of the wildlife diversity in the Everglades is comprised of wading birds (~360 species) and herpetofauna (~63 species) (Crozier and Gawlik 2003; Meshaka et al. 2002). The Everglades also supports ~40 species of mammals (Meshaka et al. 2002). Most studies of mammals in the Everglades have focused on rodents and lagomorphs (Smith & Vrieze 1979, Mazzotti et al. 1981, McCleery et al. 2015, Romañach et al. 2021) or game species (MacDonald-Beyers & Labisky 2005). Several rodent species are often found in wetland systems given their adaptable nature (Conner et al. 2000), and play a

critical role in landscape composition and trophic dynamics (Ryszkowski 1975). Larger mammals (i.e. bobcats) will use wetlands if a significant food source is available (Fritzell et al. 1988). Mammals in the Everglades will utilize ridges and sloughs under drier conditions ("sawgrass prairie"), but seek refuge on tree islands for food, cover, and reproduction when water is higher in the surrounding wetlands. Some small mammals, such as the Marsh rice rat (Oryzomys palustris) are highly adapted to wetland conditions (Esher et al. 1978), are not deterred by the presence of deep water, and will occupy relatively small to medium-sized tree islands year-round (Gaines et al 2002). Some mammal species exhibit restricted movement during prolonged high water events. The lack of available resources during these events may have detrimental impacts on individuals and populations. The hispid cotton rat (Sigmodon hispidus) is less-adapted to water and will concentrate use on larger tree islands during the wet season (Gaines et al. 2002), potentially increasing predation risk. High water conditions can restrict whitetailed deer (Odocoileus virginianus) to foraging only on tree islands, where the vegetation quality is much lower than that of the ridge (MacDonald-Beyers and Labisky 2005). It is not well known how medium and larger mammalian predators use tree islands in the Everglades and this knowledge gap is particularly concerning to managers for predicting population responses of wildlife to changing water levels associated with water management and Everglades restoration. My study was conducted to better understand how an Everglades mesocarnivore, the bobcat (Lynx rufus), is distributed among tree islands in the Everglades, particularly with respect to hydrological and habitat variation.

Bobcats (Lynx rufus) are generalist mesocarnivores found throughout North America. Bobcat habitat selection is partly determined by seasonal prey abundances (Litvaitis et al. 1986; Boyle and Fendley 1987; Knick 1990) and presence of forested uplands such as hardwood hammock habitat (Clare et al. 2015, Lovallo and Anderson 1996, Maehr 1996). Bobcats also prefer fragmented landscapes and some edge habitats (Tigas et al. 2002; Dunagan et al. 2019; McNitt et al. 2020) and a study from Wisconsin reported a positive association between bobcat abundance and wetland edge (Clare et al. 2015). In general, bobcat populations are sensitive to anthropogenic habitat modification (Poessel et al. 2014) and competition with other carnivores like coyotes (Canis latrans) (Thornton et al. 2004). Although bobcat populations seem to be increasing in much of the United States, Florida is the only state that has reported population declines (Roberts & Crimmins 2010). Bobcat populations and habitat use have been generally described in great detail throughout most of their range (Chamberlain et al. 2003, Kamler and Gipson 2000, Lovallo and Anderson 1996, Rolley and Warde 1985), however additional information on bobcat use of large wetlands is lacking.

Bobcats in the Everglades inhabit a spatially and temporally variable mosaic of upland tree islands and wetland habitats. Previous bobcat research in southern Florida focused on food habits as well as home range overlap and potential competition between other large carnivores (Maehr 1996). This research focused on drier upland areas of the Everglades, such as Big Cypress National Preserve, which experiences a relatively shorter hydroperiod than most of the central Everglades. Annual home ranges for female bobcats in south Florida were estimated to be 7.0-19.0 km², whereas male home ranges were 16.0-70.0 km² (Maehr 1996).

The few studies of bobcat diet in Florida indicate they predominately prey upon small mammals such as rodents and rabbits (Smith and Vrieze 1979), with partial seasonal prey switch to more migratory and wading birds during the winter months (Maehr and Brady 1986). The switch is probably opportunistic as wading birds nest seasonally on tree islands (Crozier and Gawlik 2003). Additionally, there are occasional accounts of bobcats consuming other mesomammals such as raccoons (*Procyon lotor*) and opossums (*Didelphis virginiana*) and even larger mammals such as white-tailed deer (*Odocoileus virginianus*) (Maehr and Brady 1986; Labisky & Boulay 1998).

I was interested in identifying habitat variables such as tree island size, the distance between islands, and the number of surrounding tree islands (clustering), which may influence bobcat selection of tree islands. Bobcats may be more inclined to select tree islands with a shorter hydroperiod (i.e. wetlands that remain relatively dry with shallow water for most of the year) to avoid predators such as American Alligators (Alligator mississippiensis) which are often found in longer hydroperiod sloughs (Palmer and Mazzotti 2004, Barr 1997). I was also interested to determine whether the water depth dynamics of the Everglades affect bobcat selection of tree islands. As water depths increase, bobcats may become effectively "stranded" on tree islands, or may leave the ridge-slough wetlands entirely, seeking refuge in drier areas such as Big Cypress National Preserve to the west. Finally, I assessed the potential impact of Burmese pythons on tree island use by creating a python abundance variable from a spread model (Bonneau et al. 2016). Invasive Burmese pythons are linked to small mammal declines in the Everglades (Dorcas et al. 2012) and predicted to have negative effects on bobcats in south Florida (Soto-Shoender et al. 2020).

I investigated to impact of these landscape and hydrologic variables in addition to the potential density of an invasive species on the probability of bobcats utilizing tree islands. Using camera trap bobcat detection on tree islands from 2005-2019, I used occupancy models (Mackenzie et al. 2002) to measure these relationships at different temporal and spatial scales to understand bobcat habitat use in the Central Everglades.

STUDY AREA

My study was conducted in the managed area known as Water Conservation Area 3 (WCA-3). Water Conservation Area 3 is approximately 2,300 km² of topographically flat wetlands located just north of Everglades National Park in both Broward and Dade counties in southern Florida (Figure 1). The area is encompassed and dissected by canals and an interstate highway, I-75 (Figure 1). The landscape consists mainly of three habitats which vary in elevation and vegetative composition: ridges, sloughs, and tree islands. Ridge and slough wetlands make up >98% of habitat in WCA-3 (Sklar and van der Valk 2002). Sloughs stay continuously inundated most years with up to a meter of water or more in the wet season, and are typically dominated by water lilies (Nymphea odorata) or spikerushes (*Eleocharis* spp.). Ridges are topographically elevated by 10-25 cm compared to sloughs, inundated for 6-10 consecutive months in most years, and are dominated by sawgrass (Cladium jamaicense) and other grasses (Ogden 2005; Gaiser et al. 2012). Tree islands make up < 1.5 % of WCA-3, they vary in shape, size, and vegetative composition and are the only habitat that is typically dry year-round. Water depths vary seasonally by 50-90 cm with the subtropical climate and distinct wet/rainy (May-October) and dry seasons (November-April). Although most variations in water depth in the Water Conservation Areas are attributed to seasonal rainfall, water management also influences water depth because they are functionally impounded wetlands that receive and release water to adjacent canals (Figure 1; Light and Dineen 2002).

METHODS

Tree Island Selection

To assess bobcat use of tree islands, I obtained 1,855 bobcat photos collected from game cameras set by the Florida Fish & Wildlife Conservation Commission (FWC) across 87 tree islands in WCA-3 from 2005-2019. The full set of sampled tree islands and their locations are available in Appendix 1. Tree islands were selected based on a variety of objectives, but were mostly driven by a general objective of observing wildlife use during the wet season; the primary species of management concern was white-tailed deer (*Odocoileus virginianus*). FWC biologists also set cameras on islands for monitoring vegetative restoration activity. The particular group of islands sampled each year and the length of the sampling periods (Table 1) varied over the 15-year sample period based on management objectives, and duration of deep water conditions (i.e. exceeding 60 cm in WCA-3A North). After 2017, the islands were also sampled in the dry season.

Sampled islands came from all subregions of WCA-3 and included 39 tree islands in WCA-3A Northwest, 15 in WCA-3A Northeast, 13 in WCA-3A South, and seven in WCA-3B (Figure 2). An additional 13 spoil mounds, artificial islands built upon excavation of the canals and designed to maintain canal integrity, were sampled along the Miami Canal in WCA-3A North (Figure 2). Spoil mounds sampled by FWC were roughly rectangular-shaped and typically vary from about 0.5-1.0 hectares in size. The sampled tree islands ranged in size from 0.03 to 232.87 hectares, with a median size of 0.5 hectares.

Game cameras (TrailMAC Olympus, Trailsense Engineering LLC, Middleton, DE; Bushnell, Inc, Cody Overland Park, KS; Reconyx, Inc, Holman, WI) were placed on the head (northern end) of the natural tree islands, which tended to remain dry even during the months of deepest water. Cameras were placed on tree trunks approximately 1 m above ground at a ~10° downward angle to ensure small and large wildlife would trigger the camera. Cameras were programmed to take bursts of two or three consecutive images at one second intervals when triggered. From 2005-2017, a single camera was placed on each island, however from 2018-2019 two cameras were set at approximately 10-15 m apart, capturing different areas of the same game trail. Sampling periods (i.e., time intervals of active camera sets) ranged from 1-36 weeks with an average time of 8 weeks.

Occupancy Modeling

I used single-season site occupancy models (Mackenzie et al. 2002) to estimate both the probability of detection (*p*) and occupancy (ψ) of bobcats on tree islands. There is no prior information on bobcat movement rates or homes ranges in a ridge/slough mosaic habitat, therefore sampling periods were divided into 1-week and 2-week sampling intervals to assess occupancy at two different time scales. To fit these intervals, some dates at the end of the camera sampling period were considered labeled as "NA". Many tree islands were not sampled in consecutive years, and because I were interested in regional patterns of bobcat occupancy through time rather than colonization dynamics, each site (tree island) was considered independent with year added as a random effect. Models were constructed in the program R (R Core Team 2020) using the package unmarked (Fiske and Chandler 2011).

I determined the best detection probability model before determining an overall best model by fitting candidate detection models while holding occupancy constant and including sampling year as a random intercept. I modeled detection probability as a function of either reproductive season (season), the number of days since the camera was placed (time), the number of cameras on the island during the sampling period (cams), or combinations of the covariates. I ran each detection covariate alone to identify covariates that may influence bobcat detection, followed by a series of additive models based on these initial results for a total of seven models. I considered three covariates to predict bobcat detection probability on tree islands in WCA-3 (Table 2). Bobcats may avoid humans while placing cameras on tree islands, potentially limiting their initial detection probability. Therefore, I added a variable indicating the days since the camera was placed, labeled "time." The number of cameras placed on the island ("cams") may also influence detection probability. Lastly, I included a seasonal variable ("season") to indicate the reproductive time of year. The seasons were "spring" $(31^{st} \text{ Dec.} - 31^{st} \text{ May})$; mating and gestation), "summer" (31st May – 31st Aug.; birth and weaning), and "fall" $(31^{st} \text{ Aug.} - 31^{st} \text{ Dec.})$; no reproductive activity, but mothers are often accompanied by kittens). Due to the presumed increased use during the fall (mothers moving around with kittens), I anticipated bobcat detection probability to be higher in the fall than in the spring and summer. I used quasi-Akaike's Information Criterion (QAIC) to determine the best candidate detection model (Burnham and Anderson 1998).

I then used the most supported detection model parameters in all occupancy models. Nine covariates were used to assess bobcat occupancy on tree islands in WCA-3 (Table 3). The variables included spatial habitat variables (upland proximity/abundance),

hydrologic variables (wetland conditions over different temporal scales), and the modeled abundance of a putative invasive competitor/predator, the Burmese python (*Python bivittatus*). Additional information regarding these parameters (i.e., range, mean, and standard deviation) are available in Appendix 2.

To test for the effects of tree island size on bobcat use, the area (ha) was calculated by FWC in 2006 using aerial photos (ArcGIS, NAD83). The areas of all sampled tree islands are included in Appendix 1. Some species of bobcat prey inhabit large tree islands in high densities, whereas other species inhabit small tree island in high densities (Gaines et al. 2002), therefore I was unsure how area will impact bobcat selection of tree islands. I anticipated occupancy to increase on islands with shorter distances to other tree islands. To test for the effects of distance between islands I measured the shortest Euclidean distance (km) to the nearest tree island using ArcGIS. Nearest island distances did not cross canals or highways.

The amount of upland habitat and configuration/clustering of tree islands in WCA-3 may influence bobcat habitat use at some spatial scale around the focal island. I therefore assessed surrounding upland habitat in two ways at two scales. Total upland habitat within a particular area was quantified by calculating the proportion of the surrounding landscape that was upland habitat (e.g., tree islands), including the focal island. To address the configuration/clustering of tree islands, I summed the number of tree islands that fell within the buffer zone. Tree islands with <10% of their area inside the buffer zone were excluded. I calculated island density within a 2 km radius and a 3.5 km radius of the focal island centroid. A 2 km radius produced an area~12.57 km²) is similar to a female bobcat home range (7.0-19.0 km²) in southern Florida, and a 3.5 km

buffer (~38.48 km²) is similar to a male bobcat home range (16.0-70.0 km², Maehr 1996).

The proportion of total surrounding upland habitat was calculated by adding all upland area that fell within either the 2.0 or 3.5 km radius.

Water depths in the Everglades fluctuate from both seasonal changes (i.e. wet season or heavy rain fall) and water management decisions. The Everglades Depth Estimation Network (EDEN; Telis et al. 2014) provides daily interpolated water depths across the Everglades at a 400 m resolution from an array of water gages across the landscape. I used the application xyLocator to extract interpolated site-specific daily water depths (Data 2009). I then calculated the average daily water depth over the 1-week and 2-week sampling intervals.

The length of time the surrounding wetlands remains wet during a given interval (hydroperiod) may describe the long-term suitability of bobcat habitat. I used the xyLocator application to provide the variable "Days Since Dry," referring to the site-specific number of consecutive days (e.g. day 1, 2, 3, etc.) since the wetland became dry (0 cm; day 0). To calculate the relative hydroperiod, I summed the number of days the surrounding wetland was not dry (values > 0 cm) in the previous five years and divided by the total number of days in those five years. An area's hydroperiod tends to remain relatively stable over time with minor fluctuations. Most vegetation in the Everglades also responds to 4-5 year hydrodynamics (Sah et al. 2018), therefore a five year timespan is expected to capture all of these aspects.

To assess the impact of Burmese pythons on bobcat occupancy, I calculated a python density (pythons/km²) for each sampling site each year using the Reaction-Diffusion spread model of Bonneau et al. (2016). This model incorporates a several

parameters including an approximate growth rate, population size, and carrying capacity of Burmese pythons to recreate radiating density increases from the proposed epicenter of the invasion in 1995. Though these parameters were largely theoretical, the modeled python density was conceptualized to reflect both a spatial and temporal gradient with abundances increasing over time as python populations expanded and colonized new habitat in northern parts of the conservation areas. The rate of spread also appeared to align with anecdotal observations provided by resources such as the Early Detection and Distribution Mapping System (EDDMapS 2021) and other published work (McCleery et al. 2015). Additional information regarding these methods is available in Appendix 3.

I tested occupancy covariates for multicollinearity to prevent adding correlated covariates to the same model. The only variables that displayed collinearity were the proportion of upland area at the 2.0 km and 3.5 km buffer scales, as well as the number of tree islands at the 2.0 and 3.5 km buffer scales, therefore these variables were not included in the same occupancy models.

I tested each occupancy covariate (with year included as a random effect in each model) alone to determine variables with relatively high significance based on P-value. I then constructed a series of additive models to combine habitat and hydrologic variables. In addition, I assessed the potential for an interactive effect of the average daily water depth variable (w_avg) with either tree island size (area) or the distance to the nearest tree island (dist_island), resulting in a total of 23 candidate occupancy models, including the null model. This process was conducted at both the 1-week and 2-week interval scales, using quasi-Akaike's Information Criterion (QAIC) to determine the most parsimonious model.

Models were validated using two methods. I first assessed model goodness of fit for the top model of the 1-week and 2-week sampling interval using a parametric bootstrapping approach developed by Mackenzie and Bailey (2004). I implemented this using the mb.gof.test function in the R package AICmodavg with 10,000 bootstrap simulations. The observed and bootstrapped data were compared using a χ^2 statistic where a p-value > 0.05 indicated adequate model fit. These comparisons resulted in insignificant p-values for the best models at both the 1-week and 2-week sampling intervals. I then assessed model accuracy by calculating the area under the receiving operator characteristic curve (AUC) in R using the package PresenceAbsence (Freeman and Moisen 2008). In addition, I calculated the root mean squared error (RMSE) between the predicted model and true state as a secondary measure of model accuracy.

RESULTS

Bobcats were detected on 33 out of 87 tree islands in WCA-3 from 2005-2019. The majority of bobcat detections occurred on tree islands in WCA-3A North; 16 in Northwest, seven in Northeast, and six spoil mounds along the Miami Canal. Bobcats were detected on an additional four tree islands just south of I-75. Bobcat were not detected on tree islands sampled in WCA-3B. Additional information regarding the locations and distributions of tree islands with bobcat detections can be found in Appendix 4.

Significant covariates in both the detection and occupancy models were relatively consistent at both the 1-week and 2-week interval scales with minor differences. In most cases the dominant variables and interpretations were equivalent. The full set of detection models and respective QAIC scores at both the 1-week and 2-week sampling intervals are available in Appendix 5. All three detection covariates influenced the probability of bobcat detection on tree islands (Table 4). While reproductive season (season) and the number of cameras (cams) had a relatively weak effect, the number of days since the camera was placed (time) had a strong predicted negative effect in all models.

Three models estimating occupancy at the 1-week interval scale had similar QAIC scores (within Δ QAIC = 0.49; Table 5), but the parameter estimates for two covariates common in all three models were consistent and qualitatively similar; python density and the number of islands in either a 2 km or 3.5 km radius were both highly significant and similar in all models at both the 1-week and 2-week sampling intervals

(Table 6). The estimates (β) and predicted effects of each covariate were relatively consistent across every model, therefore I chose the model with the lowest QAIC as the top model. The python density covariate had a strong negative effect on bobcat occupancy (Figure 3A); the probability of bobcat occupancy approached zero at a projected density of ~3 pythons/km². The number of islands within 2.0 km had a strong positive effect on bobcat occupancy at the 1-week interval scale (Figure 3B). Although the best model for the 2-week interval sampling period included the number of islands in a 3.5 km radius, the predicted effect at both scales indicated that the bobcat occupancy probability was ~75% at five tree islands in the surrounding wetlands, and approached 100% at ten tree islands or more in the surrounding wetlands. The most supported model for the 1-week sampling interval also included the average daily water depth, Although the estimate for average daily water depth was negative (Table 6), the predicted negative effect of depth on occupancy was clearest at depths from 0-10 cm and less certain with deeper water depths (Figure 3C). The full set of occupancy models and respective QAIC scores at both the 1-week and 2-week sampling interval are available in Appendix 6.

DISCUSSION

This is one of the first quantitative studies of mammal use of tree islands in the central Everglades, a large wetland area for which water depth is considered an important determinant of mammal habitat use. I were successfully identified factors influencing bobcat use of tree islands in the Greater Everglades. The most significant variables for predicting bobcat occupancy indicated that an important invader, the Burmese python, has diminished habitat use and that the higher densities of islands were perceived as relatively better habitat. Water depth in the surrounding wetlands had a weaker impact, although the variable was still present among the top occupancy models.

There is increasing evidence linking Burmese pythons to the decline of small mammals such as rodents and lagomorphs (Dorcas et al. 2012, McCleery et al. 2015, Sovie et al. 2016) which make up the bulk of bobcat prey in south Florida. Bobcat habitat use is often driven partly by prey availability (Litvaitis et al. 1986; Boyle and Fendley 1987; Knick 1990), therefore the effects of prey depletion by an invasive competitor is highly plausible. Previous research has suggested that bobcats in south Florida may be affected by Burmese pythons through either direct predation or indirect competitor effects (Soto-Shoender et al. 2020), and bobcats have been previously discovered in the stomach of Burmese pythons from the Everglades (Snow et al. 2007). There is increasing evidence linking Burmese pythons to the decline of small mammals such as lagomorphs (Dorcas et al. 2012, McCleery et al. 2015, Sovie et al. 2016) which make up the bulk of

bobcat prey in south Florida. Bobcat habitat use is often driven partly by prey availability (Litvaitis et al. 1986; Boyle and Fendley 1987; Knick 1990), therefore the effects of prey depletion by python competiton is highly plausible.

Whether by predation risk of competition bobcats may directly avoid habitats with Burmese pythons in the surrounding area. The reaction-diffusion model used to extract the Burmese python densities was based on a theoretical spread model with several variables generalized assumptions (Bonneau et al. 2016); the exact densities in the wetlands around the islands were not known. Nevertheless, pythons have been removed from islands in the Everglades near the sampled tree islands and levees around WCA-3. The spread model results align with removal data (Bonneau et al. 2016) as pythons moved across the landscape, and previously published accounts of Burmese python detections and additional evidence suggests that pythons (and python predatory effects) increased across WCA-3 over the duration of the study (McCleery et al. 2015). In a mark-recapture study in spring 2013, there were no marsh rabbit (Sylvilagus palustris) predation events by Burmese pythons detected on levees around a stormwater treatment wetlands immediately north of WCA-3 (McCleery et al. 2015), suggesting the effects of pythons on mammals in WCA-3 North should have been relatively weak prior to 2013. Despite the presumed expansion of the python invasion from the southwest to the northeast across the study area, bobcats were still detected on the northern islands in WCA-3 but it appears that bobcats are no longer present in WCA-3 south of Alligator Alley (I-75). Prior to 2011, I obtained photos of bobcats from FWC on at least four tree islands just south of Alligator Alley (see Appendix 4), but since 2011, these tree islands

have been surveyed extensively without any detections, suggesting a potential extirpation aligning with parts of the invaded range where pythons have achieved higher densities.

The habitat variable of greatest importance for bobcat occupancy was tree island density in a 2.0 km or 3.5 km radius. The inclusion of this variable and lack of support for other habitat variables suggests something other than a simple amount of upland habitat or nearness to other islands was perceived as important by the bobcats. Some wetlands areas were characterized by large, relatively isolated tree islands, whereas others were characterized by clusters of smaller tree islands. Some species of bobcat prey like small rodents are known to forage on ridges but seek refuge on tree islands, contributing to a preference for wetland edge habitat (Gaines et al. 2002), which is greater in a landscape with many smaller tree islands, therefore bobcat occupancy could be responding to small mammal habitat quality. A study in Wisconsin also suggested that wetland edge may be important habitat for small rodents, which may be increasing bobcat occupancy probability in those habitats (Clare et al. 2015).

The significance of tree island density for bobcat habitat use in the central Everglades coincides with general landscape restoration concerns and implies that long-term hydrologic shifts associated with drainage and compartmentalization may have reduced the suitability of the central Everglades. Tree island densities have diminished significantly since the 1940s, and drastic changes to hydropatterns can cause rapid changes in density (Wetzel 2002). In neighboring Water Conservation Area 2 (WCA-2; Figure 1), ~85% of tree islands disappeared between 1965 and 1970 due to overflooding (Wetzel 2002). In the study area (WCA-3), there was a 60% loss of tree islands between 1940 and 1995 caused by drainage and compartmentalization. The tree island area,

proportion of total upland area, and number of tree islands in a 2.0 or 3.5 km radius were calculated using aerial measurements by FWC in 2006. The rate of potential tree island loss in WCA-3 is unknown for the duration of the study at this time, but aerial images do not suggest any large change over the past 15 years (unpublished observations, FWC personal communications). Though there is potential to have overlooked some minor changes in tree island size or density in WCA-3 from 2005-2019, the significance of the tree island density covariate (P-value < 0.001) at either the 2.0 or 3.5 km scale and the strong predicted effects of this variable (Figures 3 and 4) should not be dismissed.

The tree island area, distance to the nearest tree island, and the proportion of uplands in a 2.0 km or 3.5 km radius were not among the best candidate models, suggesting they are not as influential as tree island density. The tree island area variable was calculated in 2006 and it is possible that some changes happened during the study, but inspection of images from early and late in the study for a subset of islands suggested there were no large changes (>10%) in island size. Additionally, the hydroperiod variable was not included in any of the best candidate models, suggesting that long-term inundation patterns of the wetlands surrounding a tree island does not influence bobcat use. Although tree island elevation may contribute to bobcat occupancy, elevations for the majority of sampled tree islands were not measured at any point from 2005-2019.

Although the average daily water depth appeared in the best candidate models at both the 1-week and 2-week interval scales, this effect was not easily discernable above the first 0-10 cm. The predictions at those depths indicate that a nearly dry Everglades landscape has consistently higher bobcat occupancy than an Everglades with > 10 cm of water around the islands. This is not indicating a negative effect of high water on bobcat

occupancy. The effect of water depth was somewhat stronger at the 2-week interval scale, however there was still uncertainty at depths of ~15-70 cm (Figure 3C, Figure 4C). Only a relatively small number of tree islands (< 20%) were sampled when water depths exceeded 70 cm, although much of the Everglades wetlands experience water depths that regularly exceed 70 cm (Busch et al. 1998; Givnish et al. 2008; Todd et al. 2010). Although there appears to be more certainty at depths of 75-100 at the 2-week interval scale, additional sampling of tree islands in areas exceeding depths of 70 cm would be required to confirm the use of islands at such deeper water depths. Wetland use by some wildlife species are heavily influenced by fluctuations in water depths, such as American alligators (Alligator mississippiensis; Kushlan and Jacobsen 1990) or wading birds (Lantz et al. 2011), which can drastically affect foraging ability and reproductive success. However, my results indicate that tree island use by bobcats may not be sensitive to water depths between 10 and 50 cm. The upper-end of an adult bobcat's shoulder height is ~50 cm (Landry 2017), therefore depths exceeding 50 cm might be considered unfavorable (bobcats will be swimming). Nevertheless, if prey concentrate on islands at deeper water depths, then islands surrounded by deep water could become more profitable for predators like bobcats until prey are depleted.

MANAGEMENT IMPLICATIONS

Our results suggest that landscape changes related to Everglades degradation (e.g. loss of tree islands, Sklar and van der Valk 2002) and the effect of an invasive competitor/predator may have detrimental impacts on bobcat use of tree islands. Tree island coverage in the Everglades has been reduced extensively in the Everglades, and this loss is largely attributed to changes in drainage and compartmentalization. However, additional drastic hydrologic changes and high water velocity related to water management can prevent new tree islands from developing (Wetzel 2002), therefore these factors should be considered with regard to Everglades restoration efforts, especially those related to decompartmentalization (Wetzel et al. 2017). Bobcat occupancy may have previously been limited by habitat or prey availability, however the presence of an invasive competitor appears to be a more current and significant limitation. My results provide evidence that the conservation of tree islands and maintaining a high tree island density plus and management of invasive Burmese pythons are more important criteria for bobcat habitat in the Everglades than managing for specific water levels.

Table 1: Number of tree islands sampled, average number of weeks, and sub-regions of WCA-3 sampled by FWC by year from 2005-2019.

TABLES

Year	Number of tree islands sampled	Avg. Sampling Period (weeks)	WCA-3 Sub-regions
2005	3	1	3B
2006	31	2	3ANW
2007	13	7	3ANW; MC
2008	15	8	3ANW; 3ANE; 3AS; MC
2009	10	10	3ANW; 3ANE; 3AS
2010	12	18	3ANW; 3ANE; 3AS
2011	2	11	3AS
2012	13	7	3ANW; 3ANE; 3AS; 3B
2013	8	7	3ANW; 3ANE; 3AS
2014	0	NA	NA
2015	14	10	3ANW; 3ANE; 3AS
2016	14	12	3ANW; 3ANE; 3AS, 3B
2017	15	16	3ANW; 3ANE; 3AS; 3B;
			MC
2018	29	5	3ANW; 3ANE; 3AS; 3B;
			MC
2019	16	10	3ANW; 3ANE; 3AS; MC

Table 2: Candidate covariates for detection models

Covariates	Sub-category	Description
Time		Number of days since camera was placed
Cameras		Number of cameras placed on tree island
Season		Reproductive season
	Spring	31 st Dec. – 31 st May
	Summer	31 st May – 31 st Aug.
	Summer	31 st Aug – 31 st Dec.

Table 3: Candidate covariates for occupancy models

Covariates	Description
Area	Tree island area in hectares
Dist_island	Distance to the nearest tree island or levee (km)
Prop_up2.0	Proportion of surrounding upland habitat (km²) in 2.0 km radius buffer zone from island centroid
Isl_up2.0	Number of islands in 2.0 km radius buffer zone from island centroid
Prop_up3.5	Proportion of surrounding upland habitat (km²) in 3.5 km radius buffer zone from island centroid
Isl_up3.5	Number of tree islands in 3.5 km radius buffer zone from island centroid
Python	Relative modeled Burmese python density per km ² closest to island centroid by year
W_avg	Average daily water depth (cm) across sampling interval
Hydro	Hydroperiod or proportion of days the surrounding uplands is wet from previous five years.

Table 4: Model selection results for covariates highly influencing detection probability p of bobcats on tree islands in WCA-3 from 2005-2019 at the 1-week interval scale. K = number of parameters.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
p(season + time + cams)	6	2825.54	0.00	0.68	0.68
p(season + time)	5	2828.40	2.86	0.16	0.84
p(season + cams)	5	2829.50	3.96	0.09	0.94
p(cams)	3	2832.05	6.51	0.03	0.96
All other models			>7		

Table 5: Model selection results for covariates highly influencing occupancy probability Ψ of bobcats on tree islands in WCA-3 from 2005-2019 at the 1-week interval scale. * = best set of detection parameters. K = number of parameters.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
$p(*)\Psi(python + isl_up2.0 + w_avg$	9	2709.42	0.00	0.38	0.38
$p(*)\Psi(python + isl_up2.0)$	8	2709.84	0.42	0.31	0.69
$p(*)\Psi(python + isl_up2.0 + hydro)$	9	2709.91	0.49	0.30	0.98
All other models			> 7		

Table 6: Coefficient estimates (β), standard error (SE), and P-value for occupancy (Ψ) and detection (p) for parameters in the best candidate model for predicting bobcat occupancy on WCA-3 at the 1-week interval scale.

Parameter	Covariate	β	SE	P-value
Ψ	Intercept	-4.03	0.48	> 0.001
	python	-1.99	0.38	> 0.001
	isl_up2.0	0.04	0.006	> 0.001
	w_avg	-0 .17	0.11	0.122
p	Intercept	-1.50	0.25	> 0.001
	season:spring	-0.01	0.19	0.951
	season:summer	-0.37	0.20	0.064
	time	-0.005	0.002	0.019
	cams	0.365	0.16	0.019

Table 7: Model selection results for covariates highly influencing detection probability p of bobcats on tree islands in WCA-3 from 2005-2019 at the 2-week interval scale. K = number of parameters.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
p(season + time + cams)	6	2683.37	0.00	0.55	0.55
p(season + time)	5	2684.70	1.33	0.28	0.83
p (season + cams)	3	2686.00	2.63	0.15	0.97
All other models			>7		

Table 8: Model selection results for covariates highly influencing occupancy probability Ψ of bobcats on tree islands in WCA-3 from 2005-2019 at the 2-week interval scale. * = best set of detection parameters. K = number of parameters.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
$p(*)\Psi(python + isl_up3.5 + w_avg)$	9	2614.90	0.00	0.54	0.54
$p(*)\Psi(python + isl_up2.0 + w_avg)$	9	2616.64	1.74	0.23	0.77
$p(*)\Psi(python + isl_up3.5)$	8	2618.08	3.18	0.11	0.88
$p(*)\Psi(python + isl_up2.0)$	8	2619.63	4.73	0.05	0.93
$p(*)\Psi(python + isl_up3.5 + hydro)$	9	2719.69	4.78	0.04	0.98
$p(*)\Psi(python + isl_up2.0 + hydro)$	9	2621.45	6.55	0.02	1.00
All other models			>7		

Table 9: Coefficient estimates (β), standard error (SE), and P-value for occupancy (Ψ) and detection (p) for parameters in the best candidate model for predicting bobcat occupancy on WCA-3 at the 2-week interval scale.

Parameter	Covariate	β	SE	P-value
Ψ	Intercept	-3.24	0.47	> 0.001
	python	-1.70	0.40	> 0.001
	isl_up3.5	0.01	0.003	> 0.001
	w_avg	-0.29	0.13	0.02
p	Intercept	-1.92	0.22	> 0.001
	season:spring	-0.14	0.17	0.416
	season:summer	-0.25	0.18	0.169
	time	-0.003	0.002	0.092
	cams	0.43	0.13	0.001

FIGURES



Figure 1. The Greater Everglades wetlands and surrounding regions of southern Florida including the Water Conservation Area 3 (WCA-3; dark gray) where the study was conducted.

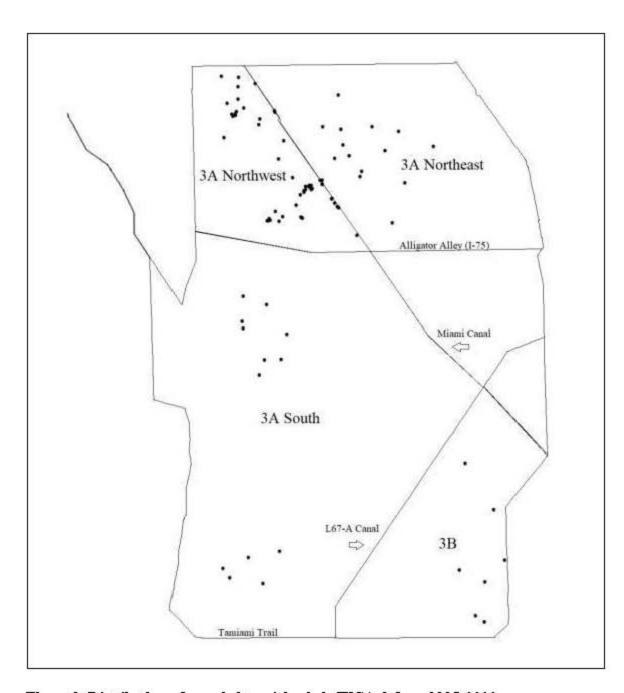


Figure 2: Distribution of sampled tree islands in WCA-3 from 2005-2019

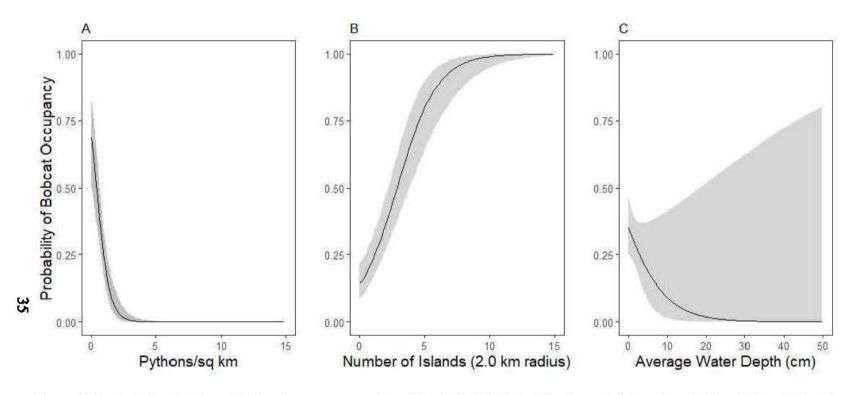


Figure 3: Projected estimates of bobcat occupancy on tree islands in WCA-3 at the 1-week interval scale for relative (A) python density, (B) number of tree islands in a 2.0 km radius of island centroid, and (C) site-specific average daily water depth over the 1-week sampling interval.

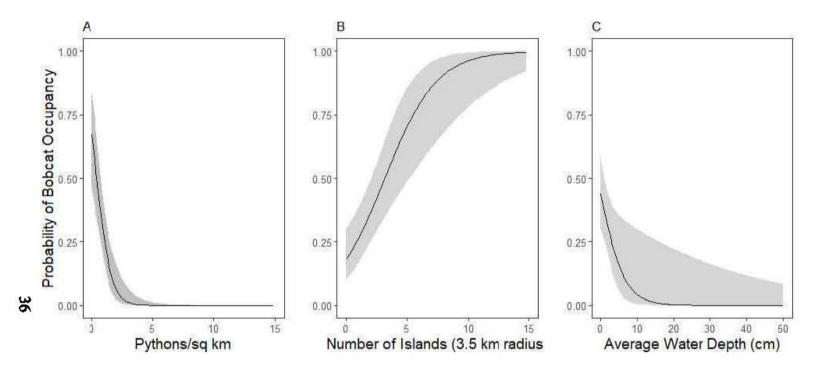


Figure 4: Projected estimates of bobcat occupancy on tree islands in WCA-3 at the 2-week interval scale for relative (A) python density, (B) number of tree islands in a 3.5 km radius of island centroid, and (C) site-specific average daily water depth over the 2-week sampling interval.

APPENDICES

APPENDIX A: TREE ISLANDS SAMPLED IN WATER CONSERVATION AREA 3

Table A1: All tree islands sampled by the Florida Fish and Wildlife Conservation Commission from 2005-2019, including tree island ID, location (longitude and latitude) and subregion in Water Conservation Area 3, and area in hectares. 3ANW = WCA-3 Northwest, 3ANE = WCA-3A Northeast, 3AS = WCA-3 South, 3B = WCA-3B.

	ID	CONSERVATION AREA SUBREGION	LONGITUDE	LATITUDE	AREA (HECTARES)
	22	3ANW	-80.7351	26.17647	0.035915
	131	3AS	-80.7749	26.10174	1.368779
	137	3AS	-80.7493	26.09359	1.270523
ည္အ	157	3AS	-80.7763	26.07673	2.754391
∞ [172	3AS	-80.7268	26.06439	13.057128
	211	3AS	-80.7515	26.03895	22.805080
	216	3AS	-80.733	26.03929	11.143459
	248	3AS	-80.7572	26.02402	20.598121
	396	3B	-80.5303	25.93539	9.160183
	444	3B	-80.4994	25.88927	26.430960
	472	3AS	-80.7354	25.84812	232.872665
	490	3AS	-80.7699	25.84201	6.551393
	499	3B	-80.4871	25.83894	2.594897
	509	3B	-80.5371	25.82922	38.272205
	532	3AS	-80.7536	25.81624	4.770757
	564	3B	-80.509	25.81676	28.846660
	597	3B	-80.5199	25.78312	5.847946

ID	CONSERVATION AREA			
	SUBREGION	LONGITUDE	LATITUDE	AREA (HECTARES)
609	3B	-80.5099	25.77702	12.232077
631	3ANW	-80.799	26.32114	0.995838
632	3ANW	-80.7926	26.2941	5.429244
633	3ANW	-80.7822	26.28575	0.488017
634	3ANW	-80.7875	26.28307	0.479017
635	3ANW	-80.7864	26.28102	0.610539
636	3ANW	-80.7834	26.28377	0.325344
637	3ANW	-80.7834	26.28215	0.480402
638	3ANW	-80.7577	26.27293	0.690147
640	3ANW	-80.7562	26.27859	2.622143
642	3ANW	-80.7959	26.26008	0.549585
645	3ANW	-80.7739	26.28935	0.118826
649	3ANW	-80.7804	26.29805	0.181024
650	3ANW	-80.7804	26.31061	0.360848
651	3ANW	-80.7796	26.32028	0.156325
655	3ANW	-80.7298	26.25653	2.755482
659	3ANW	-80.7116	26.20256	0.103064
661	3ANW	-80.7163	26.19218	7.402202
665	3ANW	-80.7017	26.21199	0.194106
666	3ANW	-80.6997	26.21193	0.684518
667	3ANW	-80.6983	26.20918	0.306329
668	3ANW	-80.7023	26.21119	0.154866
669	3ANW	-80.7018	26.2106	0.247753
670	3ANW	-80.7057	26.21102	0.150035
671	3ANW	-80.7061	26.20806	0.144009

ID	CONSERVATION AREA SUBREGION	LONGITUDE	LATITUDE	AREA (HECTARES)
672	3ANW	-80.7077	26.20691	0.840447
673	3ANW	-80.7073	26.20541	0.272280
674	3ANW	-80.6998	26.20801	0.141068
675	3ANW	-80.7111	26.18034	0.275466
676	3ANW	-80.7097	26.17996	0.288994
677	3ANW	-80.7093	26.17948	0.245535
681	3ANW	-80.7314	26.18092	0.173601
684	3ANW	-80.7464	26.17914	0.291884
685	3ANW	-80.7453	26.17735	0.990475
686	3ANW	-80.7471	26.17695	2.259717
687	3ANW	-80.7487	26.17719	0.301693
688	3ANW	-80.7391	26.18614	1.892548
697	3ANE	-80.6695	26.30219	4.015904
703	3ANE	-80.6669	26.26818	2.141598
706	3ANE	-80.6645	26.25233	1.170613
711	3ANE	-80.6734	26.2392	4.596508
713	3ANE	-80.6577	26.24133	0.282491
714	3ANE	-80.6438	26.22616	2.852573
719	3ANE	-80.6103	26.17459	1.289730
726	3ANE	-80.5644	26.25062	1.520720
841	3ANE	-80.5963	26.21429	0.246881
867	3AS	-80.7754	26.07032	1.020083
870	3ANW	-80.7205	26.22002	0.529407
907	3ANE	-80.6324	26.27044	0.464580
919	3ANE	-80.6873	26.21709	0.100272

ID	CONSERVATION AREA SUBREGION	LONGITUDE	LATITUDE	AREA (HECTARES)
999	3AS	-80.7903	25.82191	0.937804
1007	3ANE	-80.6454	26.22056	0.372734
1017	3ANW	-80.7356	26.23877	0.071900
1028	3ANE	-80.618	26.24645	0.261355
1030	3ANE	-80.603	26.26587	0.280139
1052	3ANE	-80.6866	26.27074	0.118767
1062	3AS	-80.7977	25.83126	0.320540
4023	MC	-80.7617	26.31403	0.507047
4074	MC	-80.7402	26.28681	0.532341
4075	MC	-80.7398	26.28545	0.384651
4176	MC	-80.69	26.21703	1.080320
4179	MC	-80.6876	26.2129	0.442650
4180	MC	-80.6873	26.21339	0.462597
4197	MC	-80.6769	26.19872	0.590838
4198	MC	-80.6767	26.19934	0.628721
4203	MC	-80.6738	26.19459	0.538291
4209	MC	-80.6706	26.1906	0.446910
4210	MC	-80.6703	26.19092	0.519857
4212	MC	-80.6692	26.18952	0.496349
4251	MC	-80.649	26.16211	0.725527

APPENDIX B: COVARIATE PARAMETERS

Table B1: Covariate parameters, including covariate name, description, minimum, maximum, mean, and standard deviation.

Parameter values for "w_avg" and "hydro" are based on the 1-week sampling interval scale.

	Covariate	Min	Max	Mean	Standard Deviation	Description
	year	2005	2019	NA	NA	Sampling year
	area	0.04	232.87	4.39	8.66	Tree island area in hectares
4	dist_island	0.007	2.30	0.35	0.46	Distance to nearest tree island or levee in kilometers
42	prop_up20	0.001	0.28	0.02	0.02	Proportion of upland area in 2.0 km radius of island centroid
	isl_up20	0	56	24	16.33	Number of tree islands in 2.0 km radius of island centroid
	prop_up35	0.0005	0.08	0.02	0.01	Proportion of upland area in 3.5 km radius of island centroid
	isl_up35	1	112	56	34.36	Number of tree islands in 3.5 km radius of island centroid
	python	0.0003	77.48	12.54	14.98	Relative modeled python density closest to island centroid
	w_avg	0.00	102.29	32.70	20.49	Average daily water depth across interval
	hydro	0.25	1.00	0.88	0.13	Proportion of days surrounding uplands is wet from previous 5 years

APPENDIX C: BURMESE PYTHON DATA

Modeled Burmese python densities were provided by the Reaction-Diffusion model of Bonneau et al. (2016). This model simulated a projected expansion of Burmese pythons in southern Florida over time from the presumed invasion year in 1995 at 508790 Easting, 2821227 Northing (UTM coordinates, zone 17, northern hemisphere). Expansion projections were based the parameters of intrinsic growth rate, carrying capacity, and a known population density in a given area, which were used to calculate a diffusion coefficient (i.e. individual dispersion rate). This model made a critical assumption that individual Burmese pythons can disperse in any direction (characterized as a "random walk"), resulting in a growing circular radiation across years. This radiation data for each year was exported as an excel file containing relative Burmese python densities across southern Florida a 1 km² grid scale. This grid data was then projected in ArcMap (NAD83), and tree islands sampled for that particular year were assigned the modeled Burmese python density data point closest to the island centroid.

APPENDIX D: TREE ISLAND WITH BOBCAT DETECTIONS

Table D1: Tree islands in WCA-3 with bobcat detections at some point from 2005-2019, including tree island ID, location (longitude and latitude) and subregion in Water Conservation Area 3, and the years bobcats were detected on each island. 3ANW = WCA-3

Northwest, 3ANE = WCA-3A Northeast, 3AS = WCA-3 South, 3B = WCA-3B.

	ID	CONSERVATION AREA SUBREGION	LONGITUDE	LATITUDE	YEARS BOBCATS DETECTED		
	131	3AS	-80.7749	26.10174	2009, 2010		
44	137	3AS	-80.7493	26.09359	2010		
_	211	3AS	-80.7515	26.03895	2011		
	631	3ANW	-80.799	26.32114	2013		
	632	3ANW	-80.7926	26.2941	2018		
	633	3ANW	-80.7822	26.28575	2018		
	640	3ANW	-80.7562	26.27859	2006, 2009, 2012, 2015		
	650	3ANW	-80.7804	26.31061	2006		
	655	3ANW	-80.7298	26.25653	2006, 2009, 2015, 2016, 2018		

	ID	CONSERVATION AREA SUBREGION	LONGITUDE	LATITUDE	YEARS BOBCATS DETECTED
	659	3ANW	-80.7116	26.20256	2018
	661	3ANW	-80.7163	26.19218	2012, 2013, 2015, 2016
	666	3ANW	-80.6997	26.21193	2018, 2019
ľ	667	3ANW	-80.6983	26.20918	2006
	672	3ANW	-80.7077	26.20691	2006, 2008, 2019
	673	3ANW	-80.7073	26.20541	2018
45	675	3ANW	-80.7111	26.18034	2008
-	676	3ANW	-80.7097	26.17996	2006
	686	3ANW	-80.7471	26.17695	2008, 2012
	697	3ANE	-80.6695	26.30219	2008, 2012, 2017, 2018, 2019
	703	3ANE	-80.6669	26.26818	2019
	706	3ANE	-80.6645	26.25233	2012, 2015, 2018, 2019
	711	3ANE	-80.6734	26.2392	2008, 2015, 2016, 2017, 2018, 2019
	713	3ANE	-80.6577	26.24133	2018

	ID	CONSERVATION AREA SUBREGION	LONGITUDE	LATITUDE	YEARS BOBCATS DETECTED
	714	3ANE	-80.6438	26,22616	2009, 2018, 2019
	719	3ANE	-80.6103	26.17459	2019
	867	3AS	-80.7754	26.07032	2009, 2010
	1017	3ANW	-80.7356	26.23877	2018, 2019
ŀ	4074	MC	-80.7402	26.28681	2007
•	4176	MC	-80.69	26.21703	2017, 2018
46	4179	MC	-80.6876	26.2129	2018, 2019
	4180	MC	-80.6873	26.21339	2007, 2018, 2019
	4198	MC	-80.6767	26.19934	2007, 2008
	4203	MC	-80.6738	26.19459	2007, 2019

APPENDIX E: DETECTION MODELS

Table E1: Model selection results for all models estimating detection probability p of bobcats on tree islands in WCA-3 from 2005-2019 at the 1-week interval scale. K = number of parameters. p(.) = null model.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
p(season + time + cams)	6	2825.54	0.00	0.68	0.68
p(season + time)	5	2828.40	2.86	0.16	0.84
p(season + cams)	5	2829.50	3.96	0.09	0.94
p(cams)	3	2832.05	6.51	0.03	0.96
p(season)	4	2832.69	7.15	0.02	0.98
p(time)	3	2833.38	7.84	0.01	1.00
p(.)	2	2836.54	11.00	0.003	1.00

Table E2: Model selection results for all models estimating detection probability p of bobcats on tree islands in WCA-3 from 2005-2019 at the 2-week interval scale. K = number of parameters. p(.) = null model

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
p(season + time + cams)	6	2683.37	0.00	0.55	0.55
p(season + cams)	5	2684.70	1.33	0.28	0.83
p(cams)	3	2686.00	2.63	0.15	0.97
p(time)	3	2691.40	8.03	0.01	0.98
p(season + time)	5	2691.47	8.10	0.01	0.99
p(season)	4	2693.34	9.97	0.004	1.00
p(.)	2	2694.45	11.08	0.002	1.00

APPENDIX F: OCCUPANCY MODELS

Table F1: Model selection results for all models estimating occupancy probability Ψ of bobcats on tree islands in WCA-3 from 2005-20019 at the 1-week interval scale. * = best set of detection parameters. K = number of parameters. $p(*)\Psi(.) = \text{null model}$.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
$p(*)\Psi(python + isl_up2.0 + w_avg$		2709.42	0.00	0.38	0.38
$p(*)\Psi(python + isl_up2.0)$	8	2709.84	0.42	0.31	0.69
$p(*)\Psi(python + isl_up2.0 + hydro)$	9	2709.91	0.49	0.30	0.98
$p(*)\Psi(python + isl_up3.5 + w_avg)$	9	2717.56	8.14	0.007	0.99
$p(*)\Psi(python + isl_up3.5 + hydro)$	9	2717.91	8.49	0.005	1.00
$p(*)\Psi(python + isl_up3.5)$	8	2718.80	9.38	0.005	1.00
$p(*)\Psi(python + dist_island + w_avg)$	9	2740.98	31.57	5.3e-3	1.00
$p(*)\Psi(python + dist_island)$	8	2745.78	36.36	4.8e-9	1.00
$p(*)\Psi(python + dist_island + hydro)$	9	2747.75	38.33	1.8e-9	1.00
$p(*)\Psi(python + area)$	8	2751.21	41.79	3.2e-10	1.00
$p(*)\Psi(python)$	7	2759.05	49.64	6.3e-12	1.00
$p(*)\Psi(python + prop_up3.5)$	8	2759.05	50.40	4.3e-12	1.00
p(*)Ψ(isl_up2.0)	7	2769.78	60.36	3.0e-14	1.00
<i>p</i> (*)Ψ(isl_up3.5)	7	2776.61	67.19	9.7e-16	1.00
$p(*)\Psi(w_avg \times dist_island)$	9	2792.79	83.37	3.0e-19	1.00
$p(*)\Psi(w_avg x area)$	9	2800.97	91.55	5.0e-21	1.00
<i>p</i> (*)Ψ(prop_up3.5)	7	2801.75	92.33	3.4e-21	1.00
p(*)Ψ(dist_island)	7	2805.55	96.13	5.1e-22	1.00
<i>p</i> (*)Ψ(area)	7	2807.18	97.76	2.2e-22	1.00
$p(*)\Psi(w_avg)$	7	2814.65	105.23	5.4e-25	1.00
<i>p</i> (*)Ψ(prop_up2.0)	7	2819.31	109.89	5.2e-25	1.00
$p(*)\Psi(\text{hydro})$	7	2825.01	115.59	3.0e-26	1.00
<i>p</i> (*)Ψ(*)	6	2825.54	116.12	2.3e-26	1.00

Table F2: Model selection results for all models estimating occupancy probability Ψ of bobcats on tree islands in WCA-3 from 2005-2019 at the 2-week interval scale. * = best set of detection parameters. K = number of parameters. $p(*)\Psi(.) = \text{null model}$.

Model	K	QAIC	ΔQAIC	QAIC weight	Cumulative weight
$p(*)\Psi(python + isl_up3.5 + w_avg$	9	2614.90	0.00	0.54	0.54
$p(*)\Psi(python + isl_up2.0 + w_avg)$	9	2616.64	1.74	0.23	0.77
$p(*)\Psi(python + isl_up3.5)$	8	2618.08	3.18	0.11	0.88
$p(*)\Psi(python + isl_up2.0)$	8	2619.63	4.73	0.05	0.93
$p(*)\Psi(python + isl_up3.5 + hydro)$	9	2619.69	4.78	0.05	0.98
$p(*)\Psi(python + isl_up2.0 + hydro)$	9	2621.45	6.55	0.02	1.00
$p(*)\Psi(python + dist_island + w_avg)$	9	2625.08	10.18	0.003	1.00
$p(*)\Psi(python + dist_island)$	8	2631.28	16.38	1.5e-4	1.00
$p(*)\Psi(python + area)$	8	2631.69	16.79	1.2e-4	1.00
$p(*)\Psi(python + dist_island + hydro)$	9	2633.15	18.25	5.9e-5	1.00
$p(*)\Psi(python + prop_up3.5)$	8	2635.49	20.59	1.8e-5	1.00
$p(*)\Psi(python)$	7	2636.50	21.60	1.1e-5	1.00
$p(*)\Psi(isl_up3.5)$	7	2656.09	41.19	6.1e-10	1.00
p(*)Ψ(w_avg x dist_island)	9	2659.39	44.49	1.2e-10	1.00
$p(*)\Psi(isl_up2.0)$	7	2659.68	44.78	1.0e-10	1.00
$p(*)\Psi(\text{prop_up3.5})$	7	2663.59	48.69	1.4e-11	1.00
$p(*)\Psi(w_avg x area)$	9	2665.98	51.08	4.4e-12	1.00
$p(*)\Psi(area)$	7	2671.32	56.42	3.0e-13	1.00
$p(*)\Psi(w_avg)$	7	2672.58	57.76	1.6e-13	1.00
$p(*)\Psi(\text{dist_island})$	7	2672.66	57.76	1.6e-13	1.00
<i>p</i> (*)Ψ(prop_up2.0)	7	2677.24	62.34	1.6e-14	1.00
$p(*)\Psi(\text{hydro})$	7	2681.61	66.71	1.8e-15	1.00
<i>p</i> (*)Ψ(*)	6	2683.37	68.47	7.3e-16	1.00

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