Geospatial Analysis and Prediction of Human – Panther (*Puma concolor coryi*) Depredations in Collier County, Florida (2005-2018)

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ABSTRACT

The Florida Panther (*Puma concolor coryi*) is an endangered species with a recovery goal of 3 independent populations of 240 individuals each, planned to be achieved by habitat expansion and reintroduction into public and private lands. Landowner support for this effort is contingent on their tolerance of panther presence, which is directly related to their perception of panther associated risk. In order to address this potentially disproportionate perception of risk, this study aimed to (i) identify hotspots of depredation risk within the Collier County, (ii) quantify the influence of various landscape variables on depredation, and (iii) assess the utility of a depredation-based model, as opposed to established resource intensive telemetry models. I constructed a Maxent model of reported depredation incidents and relevant environmental variables, finding that it was significant with moderate performance. My model indicated that the highest probabilities of panther depredations occur in the low intensity urban – natural areas interface, contrasting with the literature on panther habitat models, which generally predict the highest probability of panther presences away from urban areas. This result suggests that depredations and observed panther habitat preferences may exhibit different spatial patterns and requires further research.

KEYWORDS

Depredation, depredation probability, depredation risk, Human Wildlife Conflict, Maxent, panther conservation

INTRODUCTION

The human wildlife interface has been plagued by conflict as human populations increase and expand their activities onto landscapes that have historically been wildlife habitat, resulting in an overall loss of biodiversity. Since the 1900s, the human population has grown beyond billions and become the primary ecological determinant on Earth, changing and appropriating the environment on local and global scales (Nyhus 2016). Accordingly, resources available to wildlife have diminished, in some cases driving species extinction (Parks and Harcourt 2002). Wildlife is constrained, with interactions devolving into conflicts (that is, interactions negative for one or both parties), exacerbated by high human density and resulting resource demand (Nyhus 2016). Factors such as agriculture commercialization (direct competition over land use), transportation expansion (as a source of collisions and habitat fragmentation), energy production, and human perception of risk (Nyhus 2016) are all contributing to human wildlife conflict (HWC). Humans have domesticated, exterminated, consumed, competed with, and recently implemented measures to mitigate conflict and conserve wildlife (García-Rangel and Pettorelli 2013). If not mitigated, HWC incurs consequences on humans: injuries/death, economic damages, and opportunity costs; and drive more species to extinction (Nyhus 2016), which negatively impacts humans through loss of intrinsic value and of ecosystem services. To mitigate these potential negative impacts, HWC must be alleviated.

The Florida Panther, *Puma concolor coryi*, is a subspecies of *Puma* that once ranged throughout the Southeast US but is currently limited to less than 5% of its previous range, with one documented breeding population in Southern Florida (U.S. Fish and Wildlife Service 2008). The panther, the state animal of Florida, has nearly faced the plight of the California Grizzly Bear, with the population estimated to have been less than 20 adult individuals in 1960s, prompting its listing on the Endangered Species List in 1967 (U.S. Fish and Wildlife Service 2008) and has since recovered to an estimated 230 adults (Florida Fish and Wildlife Conservation Commission 2019). The most recent Florida Panther Recovery Plan was revised in 2008 and stipulates delisting upon the establishment of 3 viable independent populations of 240 individuals each, via reintroduction and habitat expansion (U.S. Fish and Wildlife Service 2008).

Listing panthers has achieved significant results and largely eliminated one of the initial primary drivers of panther extinction: intentional human depredation of panthers (Roelke et al.

1993) by making take illegal, however, the consequences of population bottleneck and additional anthropogenic threats remain. Genetic variation plummeted within the population, with inbreeding exhibiting defects such as reduced reproductive rates and pathogen resistance, though the reintroduction of 8 female panthers from Texas has alleviated the negative effects (Johnson et al. 2010). Human population expansion and resulting increase in land use often directly compete with wildlife land use and thus is directly correlated to human wildlife conflict (Nyhus 2016). Panther populations are most threatened by the loss, fragmentation, and degradation of habitat (U.S. Fish and Wildlife Service 2008); with projections forecasting increases in Florida county populations and land use (Mulkey 2007), inevitably, more habitat will be altered for urban and agricultural uses. Additionally, human population increases will exacerbate panther road mortalities and constrain their range expansion (U.S. Fish and Wildlife Service 2008).

Perhaps the greatest barrier to panther recovery efforts such as reintroduction is human perception of the risk associated with panther coexistence, which directly determines their tolerance. As there are no longer sufficient public lands to provide adequate panther habitat to meet the delisting criteria, private lands must be included as panther habitat (U.S. Fish and Wildlife Service 2008), requiring cooperation of the landowners. There have long been trends of support toward wildlife conservation, with statewide surveys finding the overwhelming majority of respondents supporting conservation and reintroduction efforts (Bonnie et al. 2020), however, there have also been longstanding trends of divide between rural and urban/suburban support of conservation actions (Bonnie et al. 2020). News articles exemplified this, with local articles highlighting panther risk more than statewide (Jacobson et al. 2012). Indeed, rural Floridians are subjected to panther associated risks to a greater extent. Depredations are categorized as panther attacks on livestock or domestic animals, accordingly, those most impacted are the landowners living within panther ranges. As panther populations expand their range into private lands, depredations increase, landowners are increasingly concerned about their livestock and potential economic and emotional damages (Kreye et al. 2017).

Florida cattle ranchers have been observed to be mistrustful of government panther management, even perceiving agencies as “condescending” and “invasive,” perhaps adding to their disproportionately high perceptions of panther depredations and thus opposition to recovery efforts (Pienaar et al. 2015). While even cattle ranchers doubt high panther depredation rates and acknowledge that some livestock mortalities may be misattributed to panthers, panther depredation risk is often concatenated with other predator depredations and the resulting economic and psychological damages (Pienaar et al. 2015). Furthermore, some cattle ranchers have professed that they may employ a "shoot, shovel, and shut up" approach if they perceive panthers as an economic threat (Kreye et al. 2017). Nevertheless, many ranchers professed the desire for conservation, so long as the government involved them in decisions and properly compensated depredation losses, perceiving the ecosystem, and panthers, to be under their stewardship (Kreye et al. 2017).

Thus, it is essential to address the issue of depredation risk. Previous studies have primarily focused on correlating panther depredation risk with hunting habitat models derived from panther telemetry data, generally with high predictive accuracy (Thatcher et al. 2009, Jacobs et al. 2015). However, there has long been controversy on the conclusions of Florida panther telemetry studies, as the methodology of numerous studies is based on diurnal data, with other researchers finding diel telemetry data the most rigorous (Beier et al. 2003). Additionally, telemetry depends on a sample of the species, which, due to limited logistical resources, may not be entirely representative or costly to achieve (Beier et al. 2003, Aarts et al. 2008).

In this study, I generated depredation risk maps of the Florida Panther using the species distribution modelling program Maxent, with reported depredation incidents as the dependent variable and landscape conditions as the independent variables. In this the objectives are to (i) identify hotspots of depredation risk within the study area, (ii) quantify the influence of various landscape variables on depredation, and (iii) assess the utility of a depredation-based model, as opposed to established telemetry models. In determining areas and variables of risk, agencies can prioritize outreach to high risk communities and communities can be informed, determining the best course of action to mitigate risk. It is expected that depredation risk will be greatest in areas adjacent, or comprising, of suitable panther habitat (Jacobs et al. 2015). In predicting which locations are most susceptible to depredation and which contributing variables are impactful, mitigating measures such as translocation, guarding, and barriers (Nyhus 2016) are prioritized, minimizing expenditures and effort.

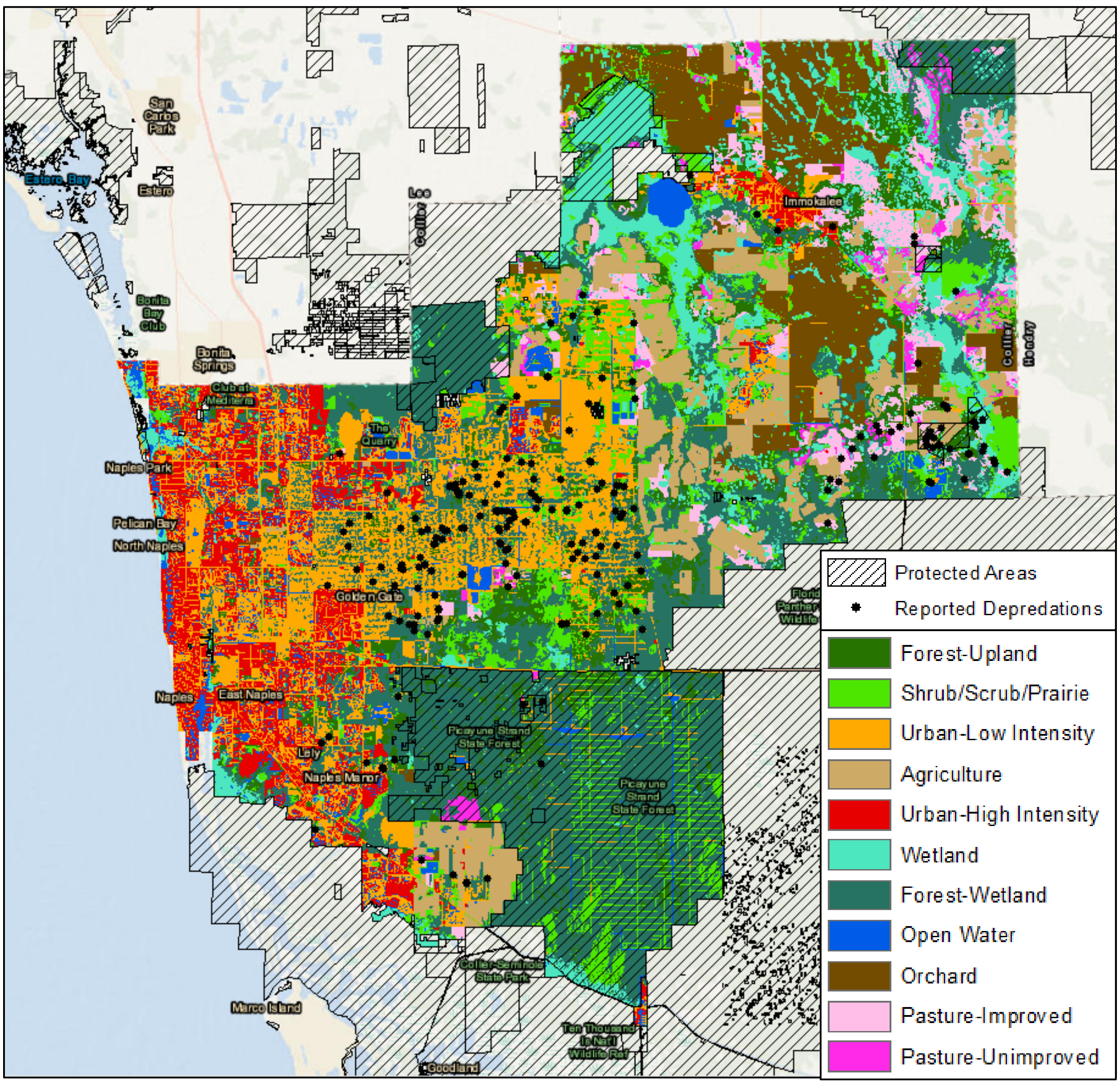
METHODS

Study Area

I conducted my study in Collier County, Florida, where the bulk of depredation reports the Florida Fish and Wildlife Commission (FWC) receives occur. Collier County contains a significant portion of panther habitat, with protected areas such as Big Cypress National Preserve, Fakahatchee Strand Preserve State Park, Florida Panther National Wildlife Refuge, and Picayune Strand State Forest composing the entirety of its southern half. Indeed, Collier is 68% conservation lands, ranking third among all other counties, and ranks first in total conservation land area with 882,120 acres (Florida Natural Areas Inventory 2020). The region consists of a variety of land covers, divided among public and private land uses. Public lands are predominantly freshwater wetlands and forests, of which 74% are federally owned (Florida Natural Areas Inventory 2020). Private lands add urban areas, agriculture, orchards, and pastures to the previous ecosystems. Private and protected lands are not mutually exclusive, with private individuals or organizations holding >1% of conservation land area (eighth in private conservation area per county) that provides panther habitat (Florida Natural Areas Inventory 2020). One focal land use, livestock pastures, has a long history. Cattle ranching in Florida began in the 16th Century under Spanish occupation, where the practice was to leave cattle largely unsupervised, therefore requiring the removal of predators, ie, the Florida Panther (Kreye et al. 2017). This trend remains, as current livestock owners continue to leave livestock unsupervised, even when aware that cattle losses are harder to monitor (Kreye et al. 2017).

Panther recovery is a demanding project as they are large solitary predators with expansive home ranges: 435–650 km^2 for males and 193–396 km^2 for females, with male home ranges having minimal overlap (Beier et al. 2003). There has been contention on the preferred habitat type being forest cover, as the majority of such studies used daytime telemetry (panthers are active mostly at night) (Beier et al. 2003), with other studies concluding that panthers are habitat generalists (excluding water bodies and severely disturbed land) that may use forest cover as hunting habitat but are not restricted to it (Comiskey et al. 2002). Recorded panther locations span all but the northwestern coastal area, avoiding the mostly densely urbanized areas. Several previous studies on panther habitat (Frakes et al. 2015, Jacobs et al. 2015) have limited their study area to the FWC defined priority panther conservation zones delineating primary panther habitat, secondary habitat, and dispersal areas (U.S. Fish and Wildlife Service 2008), however, this was discounted on the basis of depredations occurring outside of those zones. To narrow my study focus, I designated my study area to be outside of single use protected areas under the assumption that single use protected areas are designated solely for conservation and should not incur any major human uses, such as livestock farming, that provide depredation targets.

Figure 1: Study Area Land Cover. Reclassified land cover (Table 1) present in the study area. Wetland and upland forest are intentionally similar to help visualize uninterrupted forest cover.



Depredation

Depredation data was collected from the FWC database, which the agency compiles from reported and verified reports of depredations (Florida Fish and Wildlife Conservation Commission 2018). This data was subset to the study area, ranging from reported incidents in 2005 to 2018 and included livestock animals such as cattle and goats as well as domestic pet animals (eg, dogs and cats). Panther identity was classified by recording the telemetry collar identification number; however, the majority of attacking panthers were uncollared. There is a possibility that there might be a subset of uncollared panther range that the FWC telemetry data does not represent accurately. This, in addition to the fact that FWC telemetry data was primarily collected at diurnal periods, precluded the use of telemetry data in my model and inspired the third objective of this study, as panthers are primarily nocturnal and avoid other members of their species (Beier et al. 2003).

Environmental Variables

Eight environmental variables were collected from online databases (Table 2). Land cover was derived from the Cooperative Land Cover Map version 3.3 (CLC), a product of FWC and Florida Natural Areas Inventory (FNAI) most recently updated in 2018 (Florida Fish and Wildlife Conservation Commission and Florida Natural Areas Inventory 2018). I reclassified it into 11 major classes, loosely framed on the schemes of Jacobs et al. 2015 and Frakes et al. 2015 (Table 1). The 11 classes were further categorized according to whether they provided cover for panther movement or were forested, which panthers select for their home range (Beier et al. 2003, COX et al. 2006, Onorato et al. 2011). In addition to the land cover classes, computer generated building footprints (Microsoft 2018) and digital elevation models (DEM) (U.S. Geological Survey 2019) were collected for the study area. As while many previous studies, including Jacobs et al. 2015, included livestock density, I decided to exclude them on the basis that the data was on a global scale (Robinson et al. 2014) and appeared to have high error on the local scale of my study area, or were discrete at the county level. Additionally, less traditional livestock such as alpacas, or pet animals were not represented in the livestock density data sets.

Table 1: Land Cover Classification Scheme. Land cover was downloaded from the Cooperative Land Cover database, version 3.3, and reclassified according to their importance to panthers.

Land Cover Class	**#ID**	**Description**	**Cover**	**Forest**
Agriculture	4	Agricultural crops with low height	No	No
Forest-Upland	1	Forest on dry land habitat	Yes	Yes
Forest-Wetland	7	Forest on wetland habitat	Yes	Yes
Pasture-Improved	10	Pasture with managed vegetation	No	No
Pasture-Unimproved	11	Pasture with unmanaged vegetation	Yes	No
Open Water	8	Water bodies with depth (lakes, reservoirs)	No	No
Orchard	9	Agricultural tree crops that provide cover	Yes	No
Scrub/Brush/Prairie	2	Low vegetation with height that provides cover	Yes	No
Urban-High Intensity	5	Urban areas with little or no undisturbed land	No	No
Urban-Low Intensity	3	Urban/Rural areas with less disturbed lands	No	No
Wetland	6	Freshwater wetlands with little or no cover (swamps, marshes)	No	No

I processed the data into 10 m^2 raster grid cells, projected into the local Florida State Plane 901. Land cover data was again approximately based on Jacobs et al. 2015 and Frakes et al. 2015, with some subtractions and additions. Density and percentage data layers were calculated within a circular 4.5 km^2 area for each cell, as panthers were observed to utilize an area of 4.5 km^2 in a 24 hour day (Florida Fish and Wildlife Conservation Commission and Fish and Wildlife Research Institute 2014) (Table 2). From this, a circle of radius 90 m was subtracted from the center, as panthers move chiefly within 90 m from preferred habitat (Maehr and Cox 1999), eliminating potential confounding effects of cells located in nonpreferred habitat. Variables were tested for correlation and discarded if $R^2 > 0.50$ (Phillips 2008, Merow et al. 2013) and treated as continuous barring the categorical landcover classes.

Table 2: Environmental variables used in the study. Landscape variables processed and input into the species distribution modelling software Maxent.

Variable	Description	Hypothesized Relationship with Depredation
DEM (m)	Elevation	(+) Panthers prefer higher altitudes to hunt and minimum flooding (Daniel Kissling et al. 2009, Zarco-González et al. 2013, Frakes et al. 2015, Miller 2015)
Distance from Cover Edge (m)	Euclidean distance from cover class edge	(-) Panthers use edge as hunting habitat and generally stay within a certain distance (Maehr and Cox 1999, Laundré and Hernández 2003, Daniel Kissling et al. 2009, Miller 2015)
Forest Edge Density (m)	Density of forest class (upland and wetland) boundaries within 4.5 km^2 of a cell	(+) Panthers use edge as hunting habitat, especially when several prey species prefer edge habitat (Maehr et al. 1990, Waller and Alverson 1997, Maehr and Cox 1999, Laundré and Hernández 2003, Daniel Kissling et al. 2009, Miller 2015)
Forest Cover Percent	Percent forest (upland and wetland) within 4.5 km^2 of a cell	(+) Panthers prefer forest habitat in both day and nighttime (Beier et al. 2003, Onorato et al. 2011, Zarco-González et al. 2013, Miller 2015)
Improved Pasture Area (m)	Size of individual improved pasture patch	(-) Panthers favor cover habitat for stalking, preferring pasture patches (an non cover habitat) with a higher ratio of edge to area (Laundré and Hernández 2003, COX et al. 2006, Johnson et al. 2010)
Land Cover	Reclassified land cover from CLC v3.3	(Variable) (+) Panthers prefer forest habitat in both day and nighttime (Beier et al. 2003, Land et al. 2008, Onorato et al. 2011, Zarco-González et al. 2013, Miller 2015)
Prevalent Land Cover	Reclassified land cover (from CLC v3.3) with majority area within 4.5 km^2 of a cell	(Variable) (+) Panthers prefer forest habitat in both day and nighttime (Beier et al. 2003, Land et al. 2008, Onorato et al. 2011, Zarco-González et al. 2013, Miller 2015)
Building Density	Number of buildings within 4.5 km^2 of a cell	(-) Panthers avoid highly populated, disturbed areas (Comiskey et al. 2002, Beier et al. 2003, Frakes et al. 2015)

Modelling

The data was then input into Maxent version 3.3.3k, a free, open source machine learning software for modelling species distributions with presence only records (Phillips et al. 2006). The software maximizes entropy (or spread) in species distribution across the environmental conditions which the presence samples were observed, as compared to all other randomly generated points (background points), yielding a probability of presence map and variable relationship statistics (Elith et al. 2011). Maxent is popular for its ease of use, various nonlinear modelling functions, and for retaining high predictive power even among small sample sizes, commonly outperforming other methods (Elith et al. 2006, Hernandez et al. 2006, Wisz et al. 2008, Merow et al. 2013).

To determine the distribution and variables of panther depredation, I input the 263 reported depredation incidents within the study area into Maxent as the dependent sample presence data, with the environmental layers serving as the independent predictive variables. Maxent was run with 10 fold cross validation which maximizes data utilization and allows for the assessment of prediction uncertainty and function fitting error (Elith et al. 2011, Merow et al. 2013). Model performance was evaluated by the Area Under the Curve (AUC) of the Receiver Operator Characteristic (ROC) curve, which plots sensitivity on the y axis, measuring the accuracy of predicted presences, and one minus specificity on the x axis, which measures the accuracy of predicted absences (Phillips et al. 2006). An AUC value above 0.5 indicates that the model has a higher probability of correctly ranking random presence (ie, depredation points) and random background (pseudo absence) points than by random, with values approaching 1 identifying models with good fit (Phillips et al. 2006, Merow et al. 2013).

However, as AUC has a tendency of penalizing predictions outside of presence localities, thus ignoring potential model overfitting with increasing geographical extents, among other issues such as insensitivity to prevalence (Raes and Ter Steege 2007, Lobo et al. 2008, Merckx et al. 2011), I developed a null model for significance testing. The null model was constructed by randomly sampling 263 points (to match the observed depredation distribution) within the study area 100 times, input into Maxent under the same conditions as the depredation model, as per the methods of van Proosdij et al. 2016. The AUC value of each iteration was collected to create a null distribution, within which the depredation model's AUC value would need to rank 95th or above to be considered significant at a p-value of 0.05 (Raes and Ter Steege 2007, van Proosdij et al. 2016). Ranking above 95th in the null distribution would indicate that the model was more predictive than at random, correcting for the bias toward inflated AUC values in presence only models (van Proosdij et al. 2016).

RESULTS

Depredation

I found the panther depredation model to be of intermediate performance, with a mean AUC value of 0.872 across the 10 iterations run for 10 fold cross validation (minimum: 0.822, maximum: 0.907); while models above the 0.9 threshold are generally accepted to be high accuracy (Swets 1988, Manel et al. 2001). My model was significant, more accurately predicting panther depredations than the 100 generated null models (ie, the highest AUC value was from the depredation model), with a p-value of 0.01 finding strong evidence against my model being no more accurate than if by chance alone.

In examining the panther depredation risk map, it is seen that the highest predicted probabilities of depredations are predominantly where previous depredations have occurred (Figure 2). I further categorized depredation risk zones into a high risk class (0.6-1.0), identifying ~10% of my study area with predicted depredation risk above 60% (Figure 3).

Figure 2: Panther depredation risk map. The Maxent predicted probability of panther depredation across the study area.

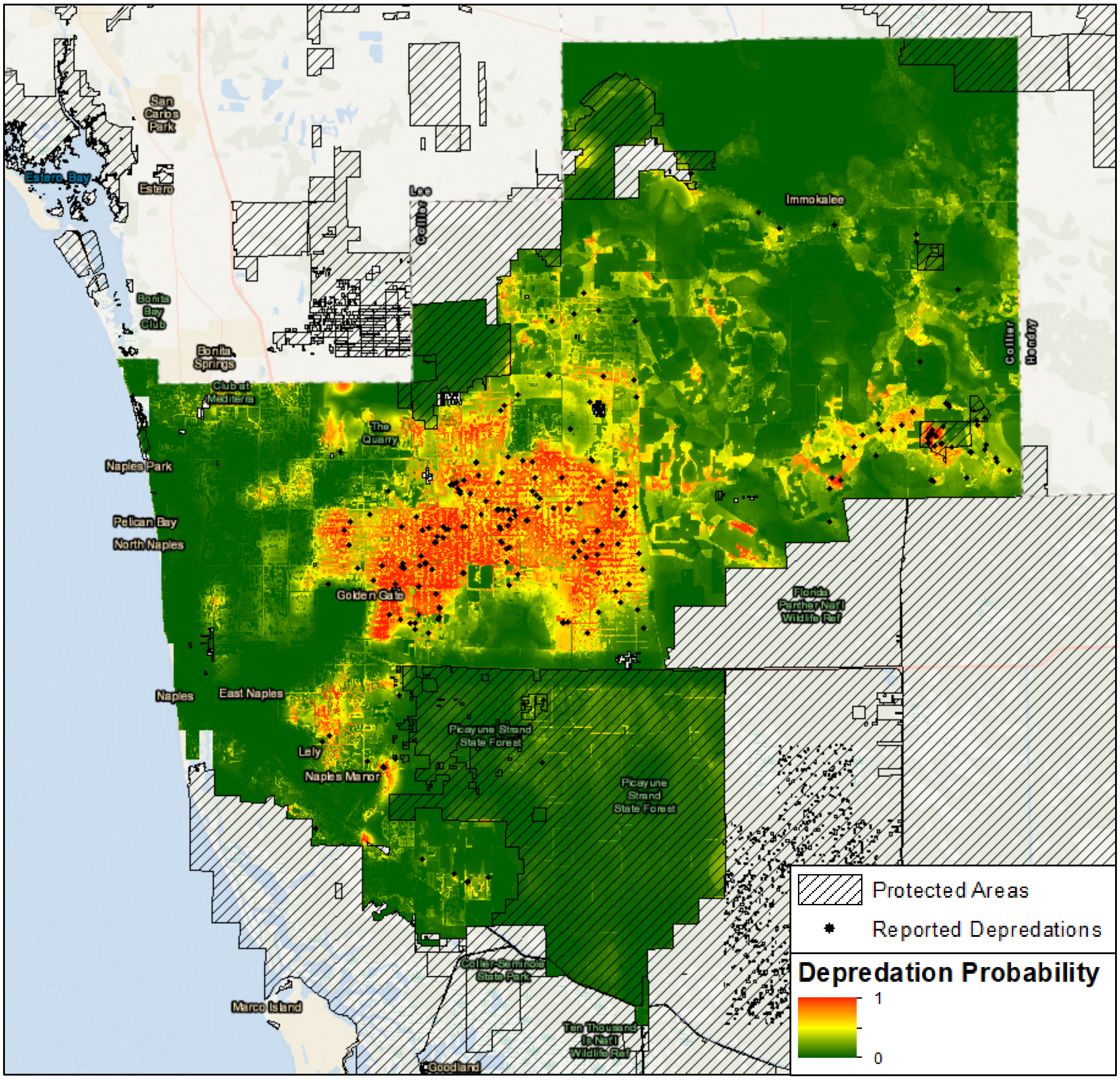
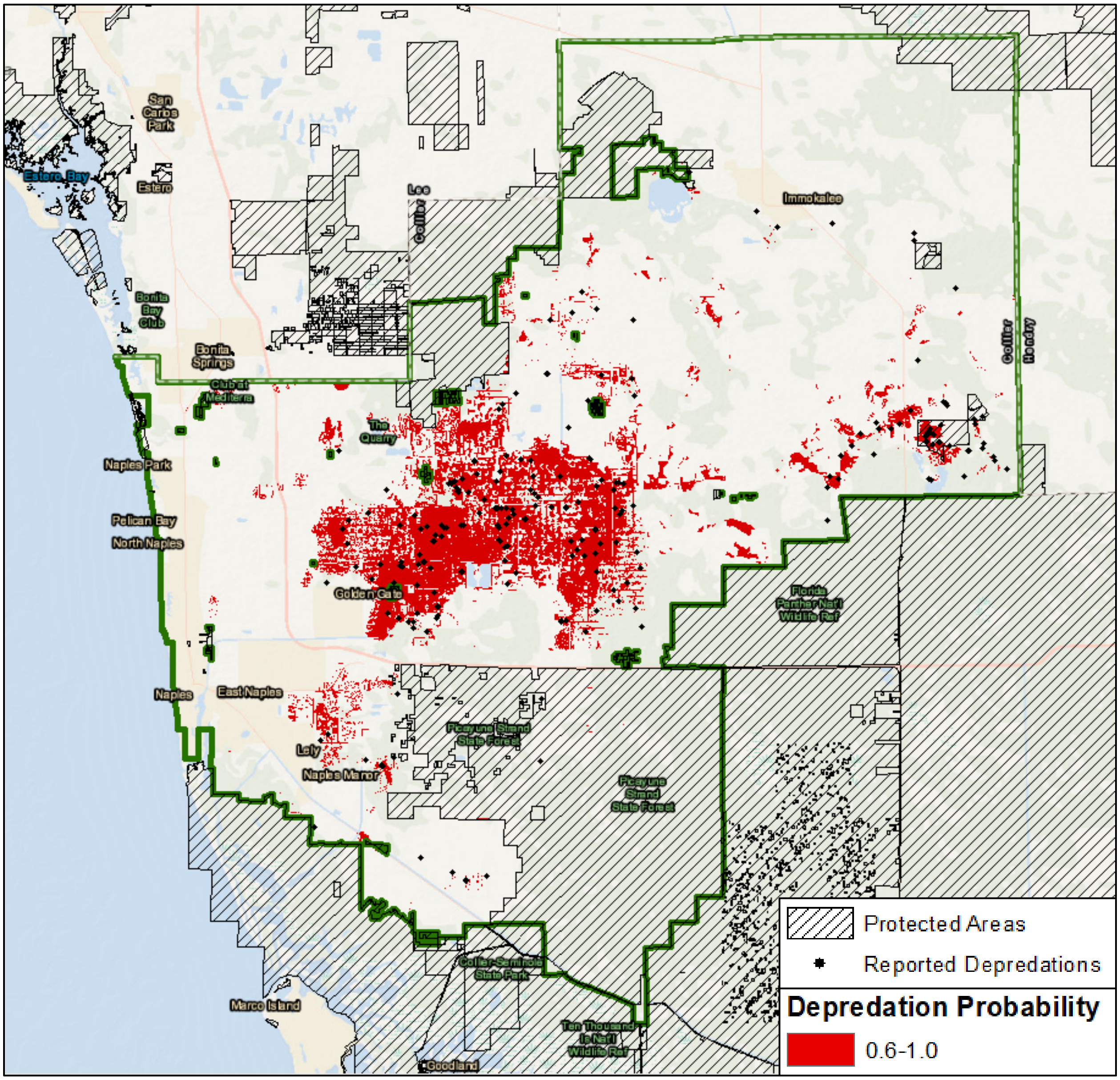


Figure 3: Classified panther depredation risk map. It is seen that low density urban areas are the most prone to panther depredations.



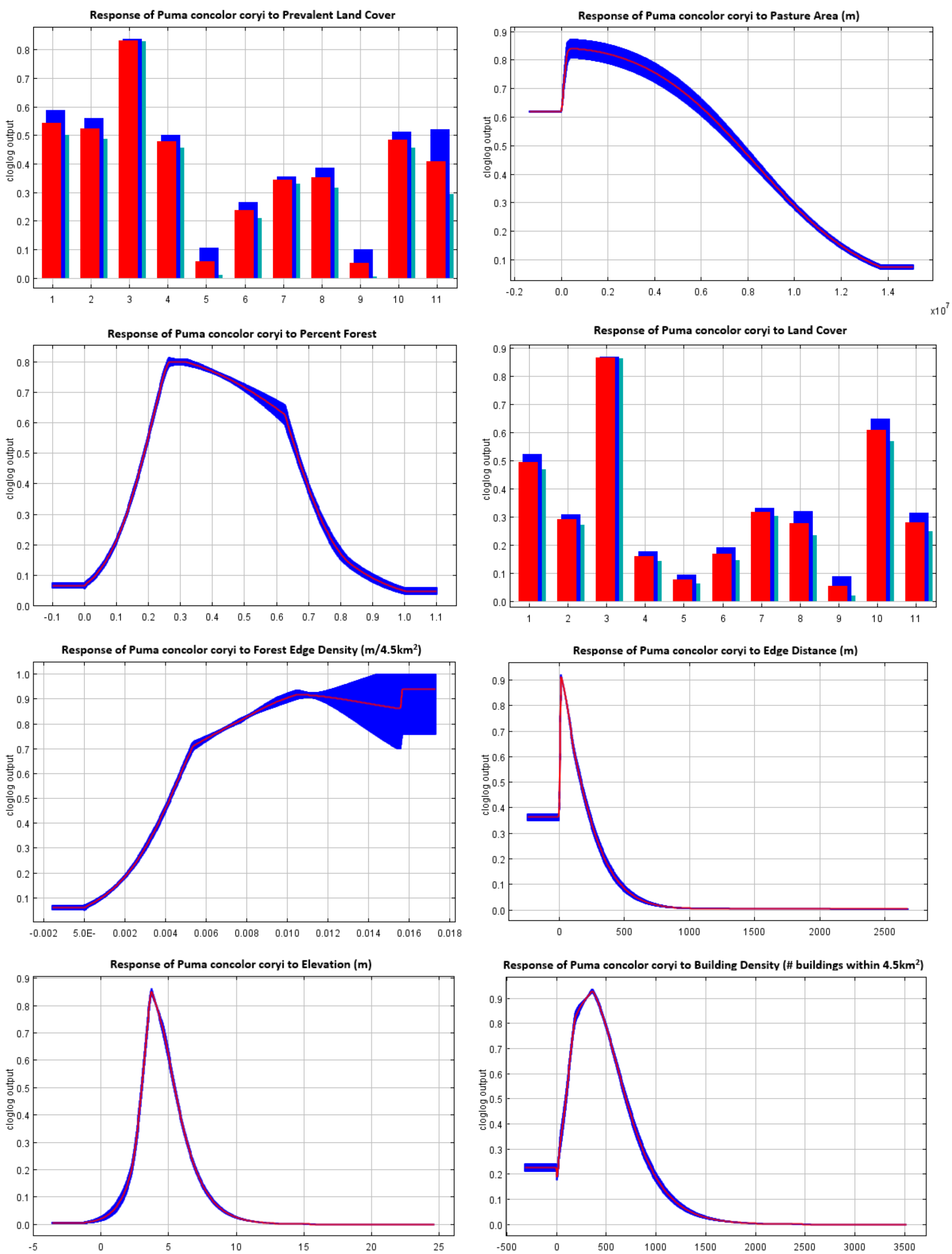
Environmental Variables

The environmental variables all had various levels of contribution to the probability of panther depredation (Table 3). Land cover type (29.7%) and forest edge (27.7%) overwhelmingly had the highest contribution to the model, with all other variables having contributions <15%. Improved pasture area had the lowest contribution at 1.6%. None of the variables had uniformly linear relationships with depredation probability, though there were observable trends. Distance from cover edge and pasture area had consistently negative relationships with depredation (Figure 4). Forest edge had a clear positive influence on depredations. Building density (peak: ~400 building/4.5km^2), elevation (peak: 4 m), and percent forest (peak: 2.5-6.5%) had peaks (Figure 4). The low intensity urban and improved pasture land cover classes had the highest probability of panther depredations (Figure 4).

Table 3: Environmental Variable Contributions. Percentage contribution of each variable to the Maxent Panther Depredation Model.

Variable	Contribution (%)
Land Cover	29.7
Forest Edge Density	27.7
Prevalent Land Cover	12.2
Building Density	11.3
DEM	9.2
Forest Cover Percent	6.5
Distance from Cover Edge	1.7
Improved Pasture Area	1.6

Figure 4: Environmental Variable Response Curves. Environmental variable relationship with panther depredation probability (See Appendix for full size images).



DISCUSSION

In conserving and coexisting with the endangered Florida panther, it is essential to address residents' perception of panther associated risk, which can directly determine their tolerance for panther presence (Pienaar et al. 2015, Rodgers and Pienaar 2018). My model was found to be significant and moderately accurate, identifying landscapes with (1) low intensity urban land use and improved pasture, (2) high forest edge, (3) intermediate forest percent, (4) low building density, (5) elevations above sea level, and (6) small improved pasture sizes to have high depredation risk. This is consistent with most panther habitat preference studies (Beier et al. 2003), yet presents a unique challenge in that the model is not optimizing for the most suitable panther habitats, instead on habitats that are on the urban edge, therefore contrasting with expected panther densities.

Depredation and environmental variables

My model found that the highest depredation probabilities occurred where low intensity urban and natural land uses interfaced. Low density residential housing areas with surrounding properties containing landcovers such as forests (upland or wetland) were predicted to have high depredation rates, following observed trends of panther edge habitat selection for hunting (Waller and Alverson 1997, Jacobs et al. 2015). Logically, the low intensity urban – natural area interface is one of the only feasible locations of depredation (besides pastures), providing panthers suitable hunting habitat from which to target domestic animals located in urban areas. This phenomenon also explains the relationship of forest percent to depredation probability, which is positive until about 30% forest cover and then declines (Figure 4**).** In a habitat suitability model, one would expect a uniformly positive relationship with forest percent and panther habitat selection (Frakes et al. 2015, Jacobs et al. 2015), however, when accounting for the location of domestic animals being on or near urban areas, it is impossible to have 100% forest cover. Similarly, panthers are observed to avoid populated areas (Beier et al. 2003), but building density shows a positive relationship until ~400 buildings per surrounding 4.5km^2 and low intensity urban land cover exhibits the highest probability of panther depredation (Figure 4). Low intensity urban areas contain panther attractants in the form of domestic animal prey, and are apparently below the threshold of repellant factors such as human population density and road density (Frakes et al. 2015).

Telemetry comparison

I found my panther depredation risk model to be of intermediate performance, comparable in accuracy to previous telemetry-based studies, answering the question of depredation-based model utility. In visually comparing my distribution of depredation probability with distributions of panther population (COX et al. 2006, Frakes et al. 2015, Florida Fish and Wildlife Conservation Commission et al. 2019) or panther habitat models (Thatcher et al. 2009, Jacobs et al. 2015) derived from telemetry data, there appear to be discrepancies on the map. Areas of high panther depredation probability are not always consistent with areas of high panther presence probability. This would suggest that zones of high depredation are not habitats which panthers are typically expected to select for. Indeed, several studies were restricted to the FWC designated priority panther conservation lands (Jacobs et al. 2015), excluding several areas with observed panther depredations.

Conventionally, urban or disturbed areas are found to be unattractive to panthers (Comiskey et al. 2002, Beier et al. 2003, Frakes et al. 2015), perhaps implying that panther depredations are outside of regular panther patterns. This is supported by findings of low frequency of pet and livestock prey in panther diets (Maehr et al. 1990, Caudill et al. 2019) and overall low calf depredation rates ranging from 0.5 to 5.3 % (1/219 calves Immokalee Ranch and 10/190 calves JB Ranch, respectively) annually (Jacobs et al. 2015). Within my study area, 263 depredations occurred on pets and livestock from 2005 to 2018, or an average of 20 depredations per year, over an area of > 2,000 km^2. The total number of depredations reported to the FWC is 304, over the span of 2004-2018, or ~22 depredations per year (Florida Fish and Wildlife Conservation Commission 2018). Under the assumption that panthers need to consume approximately 1 adult deer per week (or the equivalent) (Ackerman et al. 1986) and that there are 120-230 total individual panthers currently in Florida (Florida Fish and Wildlife Conservation Commission 2019), depredation events are exceedingly rare. In consideration of this rare status, it is potentially useful to consider depredation events separately from telemetry data in order to achieve more representative results, which my model tentatively illustrates.

Limitations

While the model was found to be significant, it is limited by the underlying assumptions of its data. In discussing telemetry and depredation-based models above, it was noted that telemetry data may not be as indicative of depredation events as would be liked, therefore casting issues on the criterion of my environmental variable selection. If the telemetry data is truly not representative of depredation data, the selection and processing of my environmental data that heavily relied on telemetry-based studies may not be optimally configured to predict depredation. Instead, variables derived solely from depredation occurrences should be implemented to remove the potentially confounding effects of telemetry-based study habitat preferences. For example, forest percentage within a certain area of a low intensity urban land cover or distance from buildings would be variables that apply more consideration toward the urban factor of depredations.

Additionally, the depredation data itself has restricted my model. As the depredations reported to the FWC are self-reported, there is a strong potential for non-response bias. Livestock farmers that encountered panthers threatening their livestock may believe it in their best interests to covertly and illegally dispose of the panther, or "shoot, shovel, and shut up" (Kreye et al. 2017), instead of reporting the depredation. Furthermore, it is difficult to identify the exact number of livestock lost to a specific predator, especially if the livestock is unsupervised (Pienaar et al. 2015). If this creates a systematic bias in the reported depredation data, the model accuracy will be stunted (Kramer-Schadt et al. 2013, Syfert et al. 2013, Yackulic et al. 2013). Ideally, community members would be trained to identify depredation incidents over a period of several years, such as in Sitati et al. 2003, with increased livestock supervision to reduce misidentified panther depredation incidents. The reported depredation data is also a total of only 263 incidents, paling in size when compared to telemetry based studies which had sample sizes in the thousands (Comiskey et al. 2002, Onorato et al. 2011, Frakes et al. 2015); for while Maxent handles small sample sizes well, larger sample sizes generally return higher AUC values and therefore higher performance (Hernandez et al. 2006).

Implications

The results of my study point at the need to examine depredation incidents independently and at a greater depth. My model highlighted the depredation risk of the low intensity urban – natural areas interface, providing agencies knowledge of at-risk communities to prioritize conflict mitigation discussions in and posing the question of whether telemetry-based studies are representative of depredation events, as they usually do not take into account urban attractive factors. Conversely, my depredation risk map can inform at-risk communities in planning their livestock management, changing to behaviors such as livestock supervision which deter panthers (Kreye et al. 2017). Perhaps the most important result is the significance and predictive accuracy of my depredation model, which specifies the importance of accurate and comprehensive depredation data collection, incentivizing community input, especially when livestock owners feel uninvolved or marginalized in panther conservation (Pienaar et al. 2015). In recognizing the communities most negatively affected by panther conservation, outreach can be targeted to ensure they do not bear the burden of conservation but instead perceive themselves to be relevant stakeholders, active and willing participants in future panther conservation efforts.

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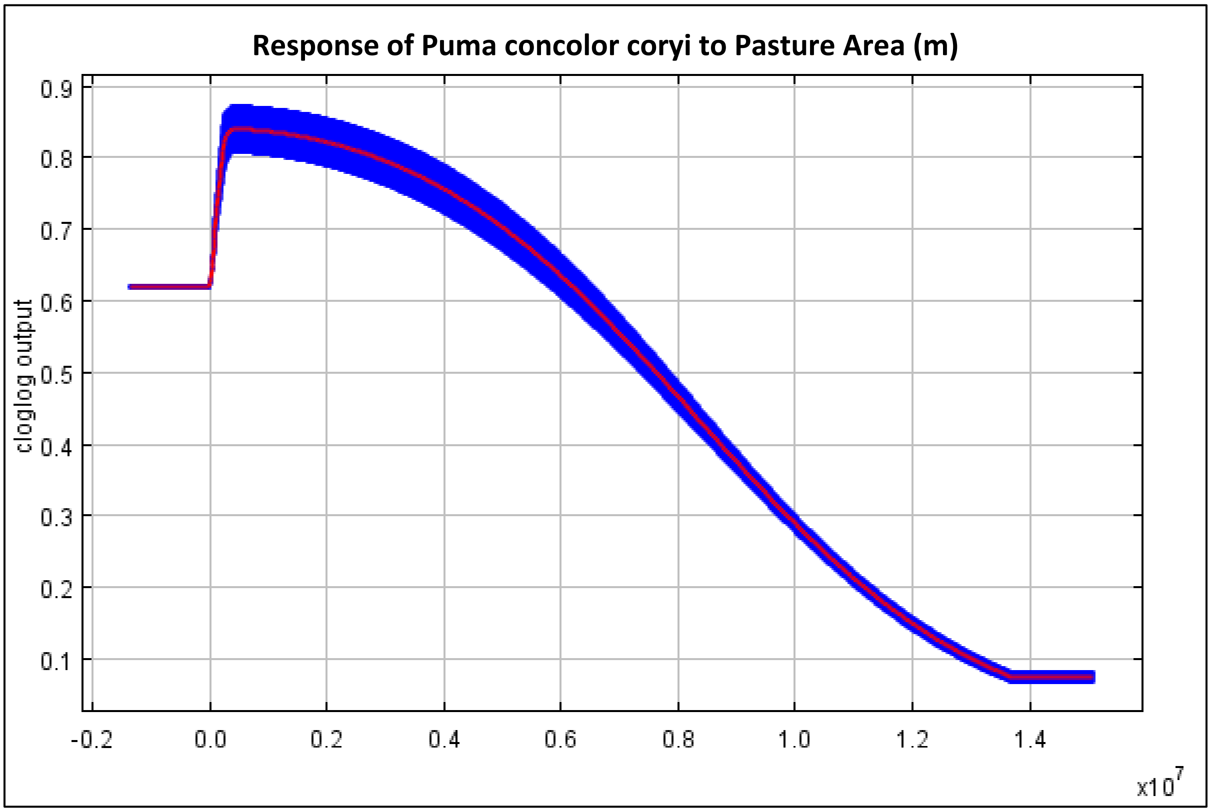
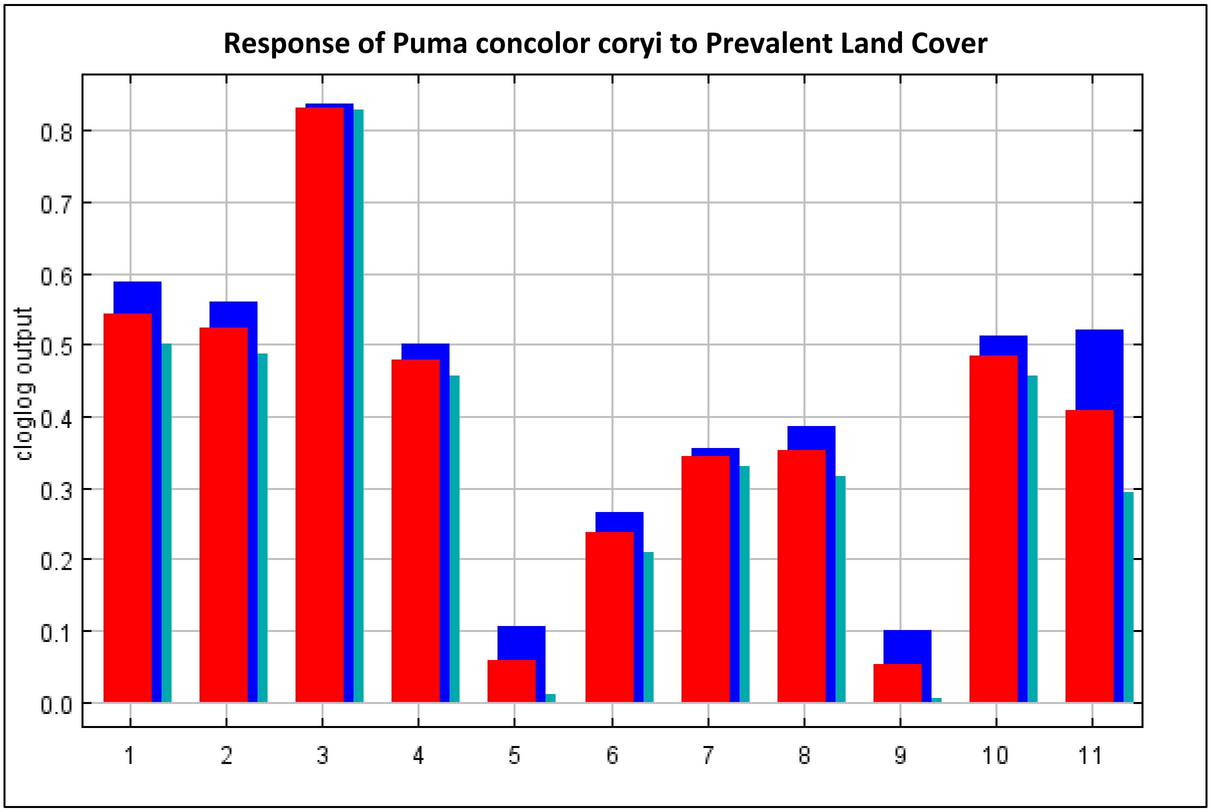
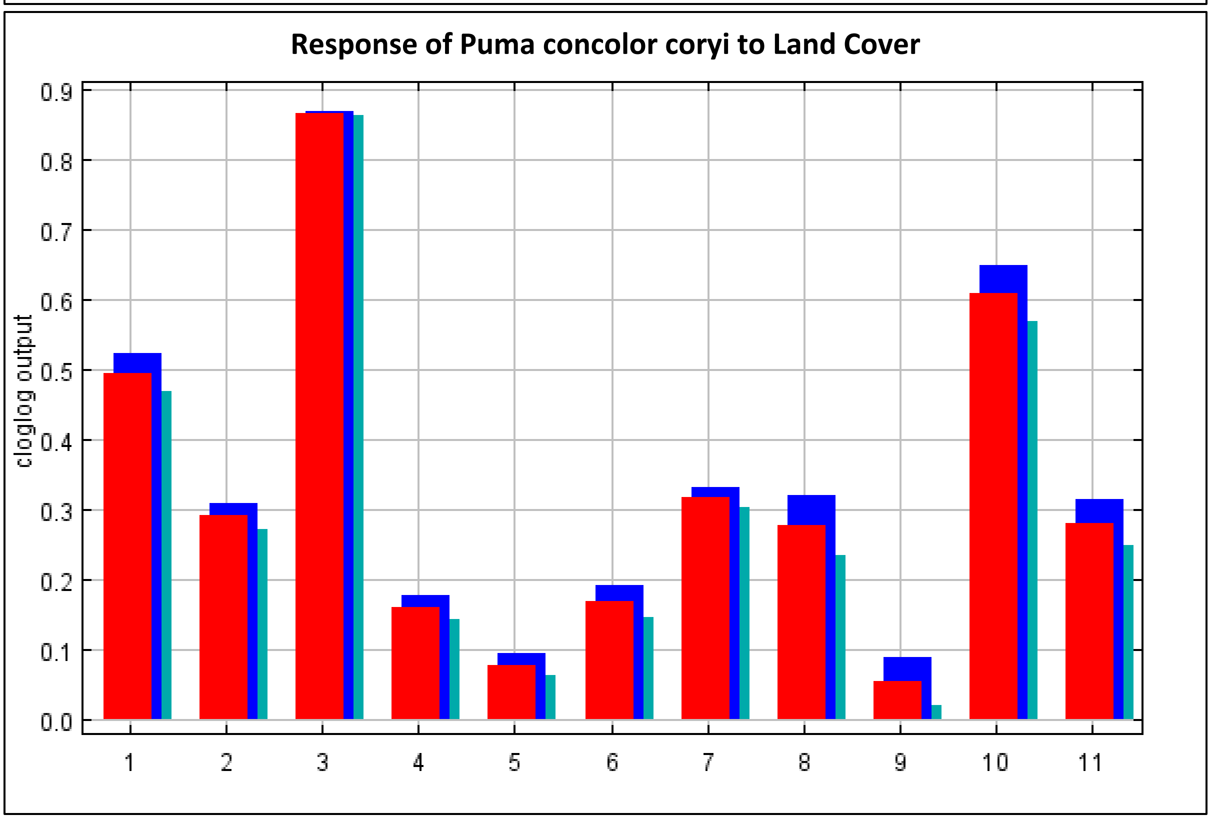
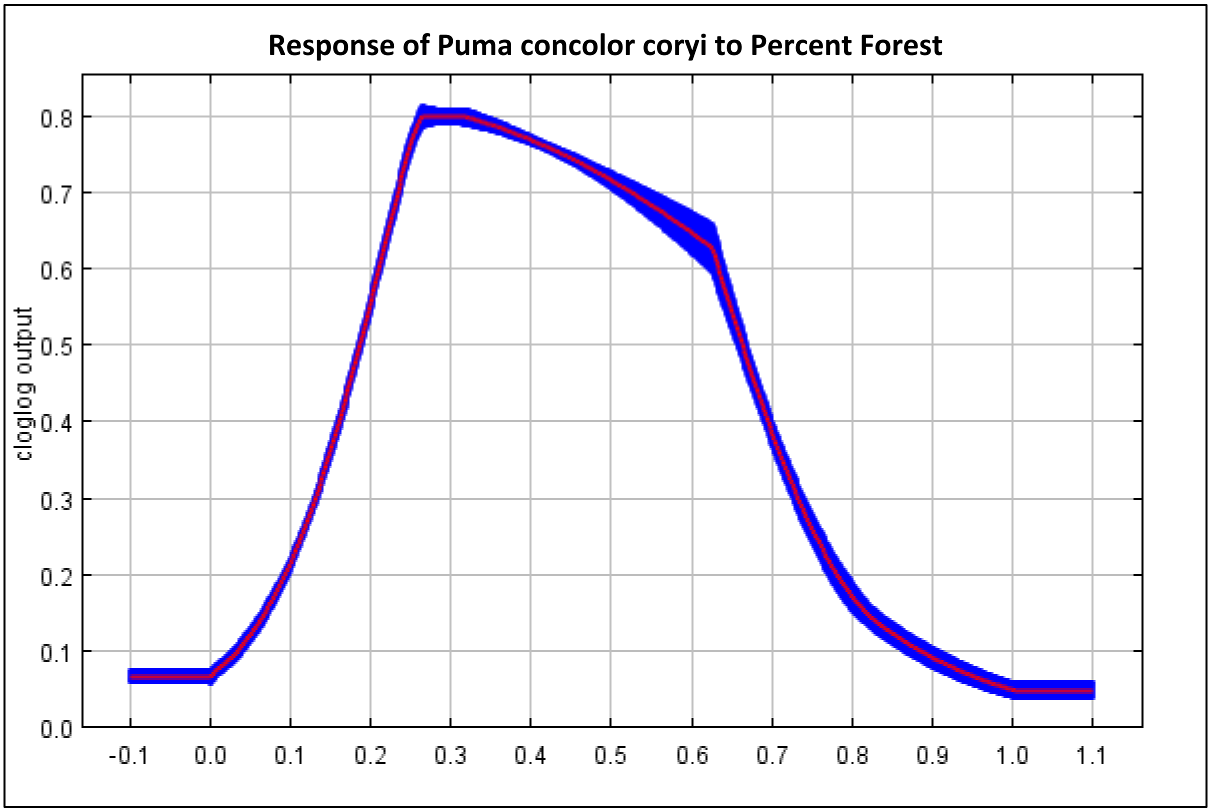
APPENDIX A: Environmental Response Curves

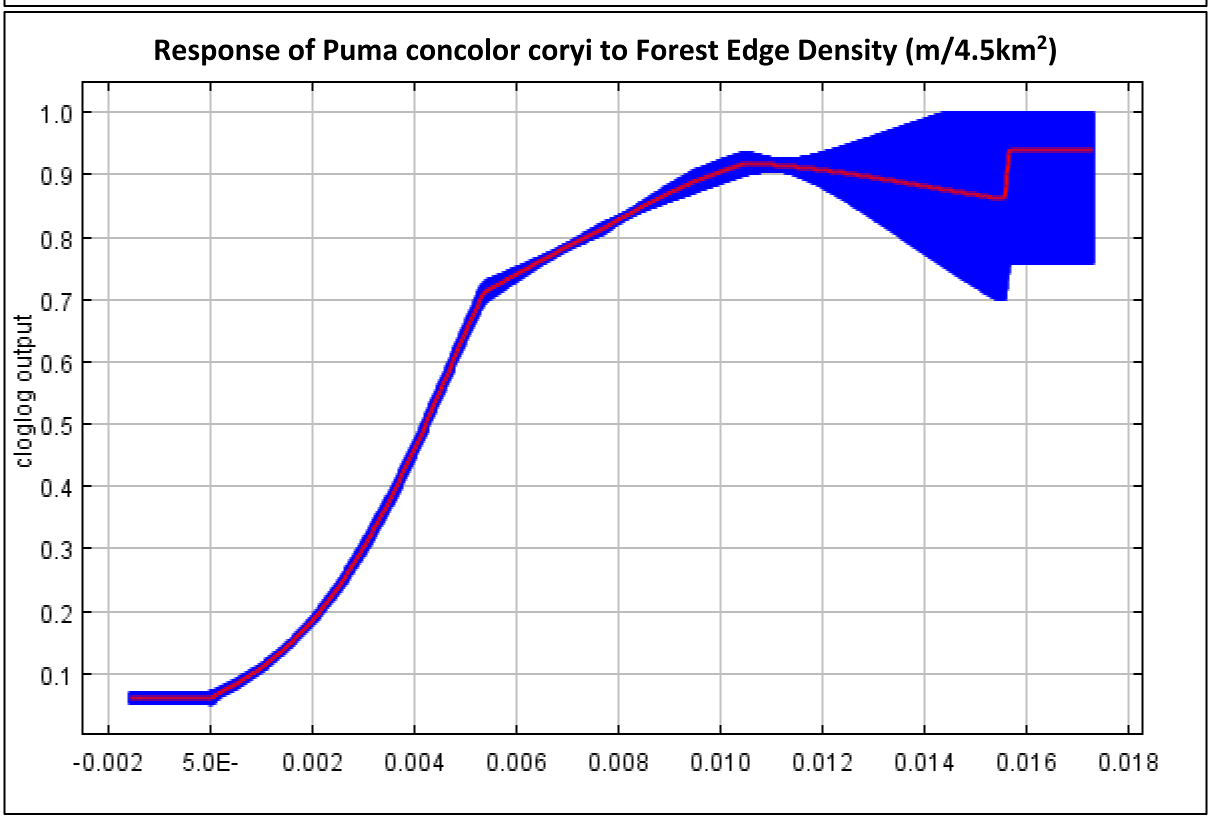
Figure 4: Environmental Variable Response Curves. Environmental variable relationship with panther depredation probability.

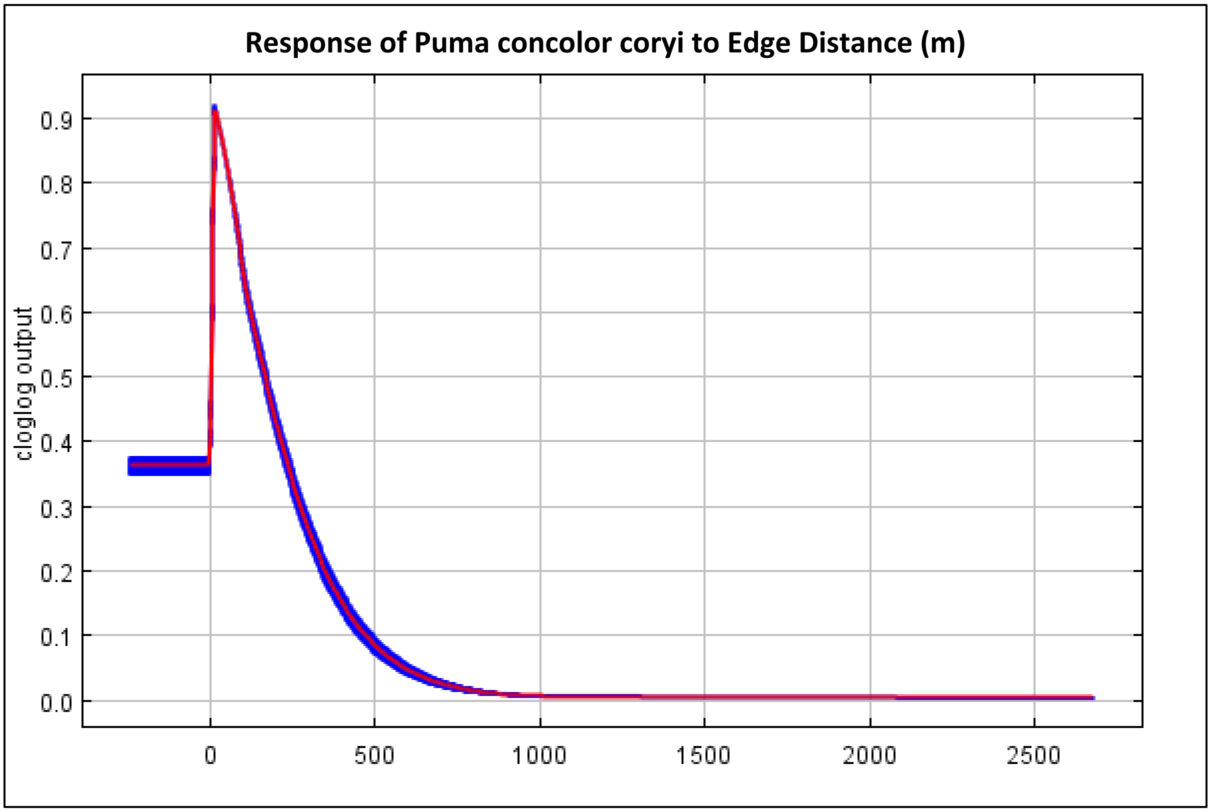


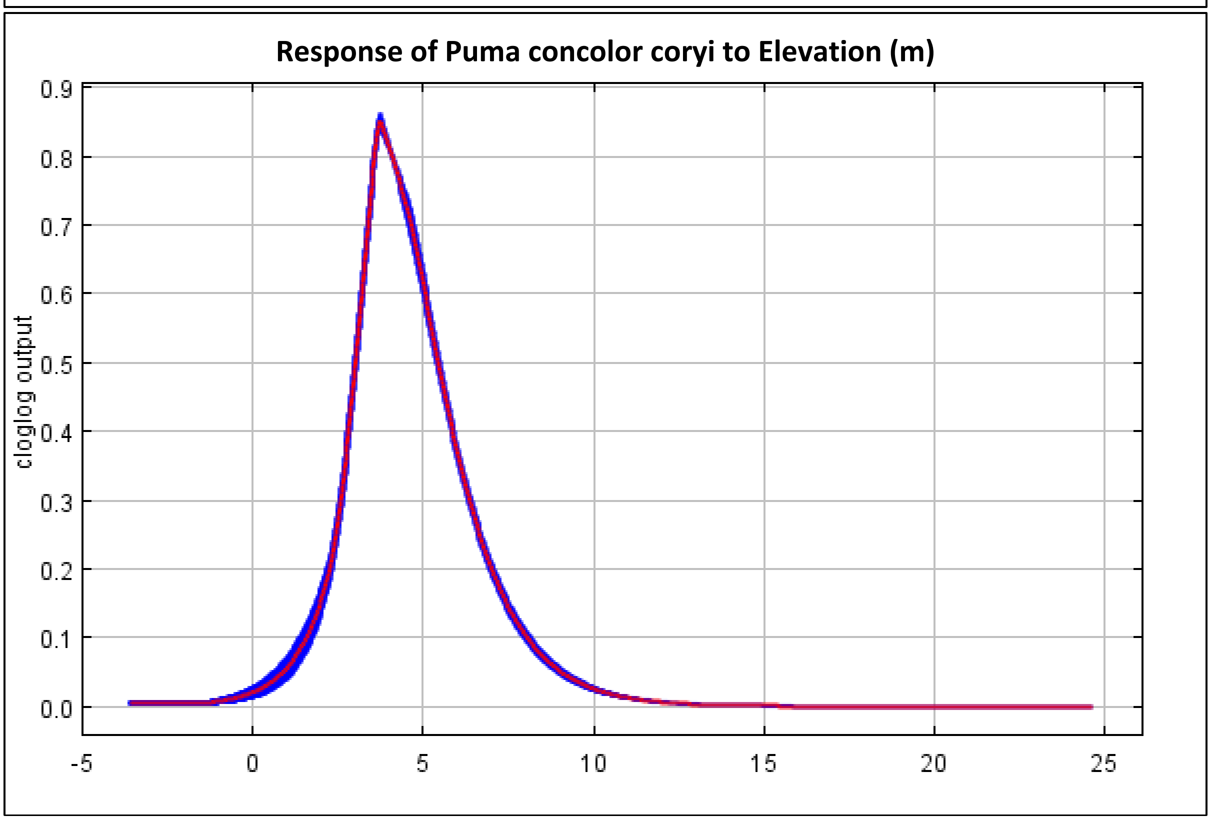

Response of Puma concolor coryi to Prevalent Land Cover
cloglog output
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1
2
3
4
5
6
7
8
9
10
11

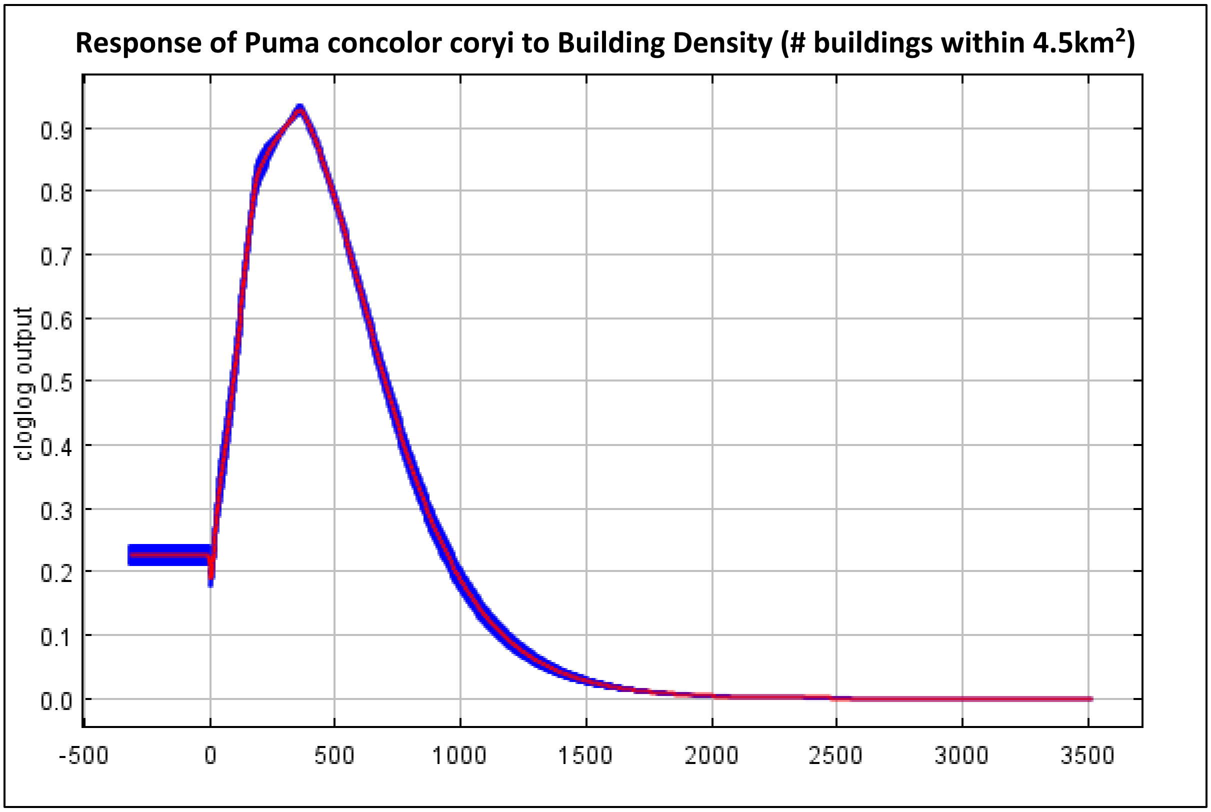

Response of Puma concolor coryi to Land Cover
cloglog output
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
2
3
4
5
6
7
8
9
10
11


Response of Puma concolor coryi to Percent Forest
cloglog output
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
-0.1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
1.1


Response of Puma concolor coryi to Forest Edge Density (m/4.5km²)
cloglog output
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
-0.002
5.0E-
0.002
0.004
0.006
0.008
0.010
0.012
0.014
0.016
0.018


Response of Puma concolor coryi to Edge Distance (m)
cloglog output
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
500
1000
1500
2000
2500


Response of Puma concolor coryi to Elevation (m)
cloglog output
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-5
0
5
10
15
20
25


Response of Puma concolor coryi to Building Density (# buildings within 4.5km²)
cloglog output
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
-500
0
500
1000
1500
2000
2500
3000
3500