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A DYNAMIC LANDSCAPE OF FEAR: HUMAN IMPACTS ON CARNIVORE COMMUNITIES

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A DYNAMIC LANDSCAPE OF FEAR: HUMAN IMPACTS ON CARNIVORE COMMUNITIES

By

Tru McAlister Hubbard

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A DYNAMIC LANDSCAPE OF FEAR: HUMAN IMPACTS ON CARNIVORE COMMUNITIES

This thesis by Tru McAlister Hubbard is recommended for approval by the student's Thesis Committee and Department Head in the Department of Biology and by the Dean of Graduate Education and Research.

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ABSTRACT

A DYNAMIC LANDSCAPE OF FEAR: HUMAN IMPACTS ON CARNIVORE COMMUNITIES

By

Tru McAlister Hubbard

Mammalian carnivores play complex and sometimes keystone roles in structuring terrestrial ecosystems and facilitating biodiversity by driving trophic cascades that link predators to prey to plant communities. Carnivores have emerged as excellent ecological models that provide evidence that intraguild (IG) interactions (e.g., resource competition, intraguild predation) can reverberate across trophic levels, significantly affecting and even driving ecological processes. Yet, terrestrial carnivores have suffered the largest range contractions of all species on Earth in the last two centuries due to human activity. The profound impacts of various human activities on wildlife communities extend beyond physical changes in Earth's land surface (i.e., agriculture, infrastructure, urbanization) to actual human presence on the landscape, which can influence wildlife behavior by disrupting movement, forcing changes in diel activity patterns, and mediating predator-prey interactions. Collaborating with Snapshot USA researchers, I explored variation in carnivore spatiotemporal activity and assessed carnivore co-occurrence by constructing diel activity density curves, applying multi-species occupancy models, and calculating attraction-avoidance ratios (AARs). My results suggest that carnivore responses to anthropogenic and environmental factors vary dependent on their status in the community (e.g., reproductive condition, subordinate, dominant), and coexistence is likely only possible through behavioral mechanisms allowing for plasticity in temporal, spatial, and dietary niches.

DEDICATIONS

I dedicate my master's thesis work to my incredible thesis and research advisor Dr. Diana Lafferty who has guided and supported me over the last two years. You encouraged me take on new challenges and be creative throughout my research process, helping me to learn new skills and build connections within the science community to propel my future endeavors. I am grateful that I had the opportunity to work with such an amazing mentor, instructor, and researcher to look up to throughout my graduate program. You have been a pleasure to work with and I could not have accomplished my goal without you.

I also dedicate my thesis to my family, thank you for all the support you have given me since I first started playing with frogs and bugs in the backyard to helping me pursue my passion and career working with wildlife. You have all played a role in making me the person that I am today, and I am grateful to have you all be a part of my journey. Mom, you have been there every step of the way throughout my schooling and this accomplishment would not have been possible without your love and support.

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INTRODUCTION

1.1 Human impacts on carnivore communities

Mammalian carnivores play complex and sometimes keystone roles in structuring terrestrial ecosystems and facilitating biodiversity by driving trophic cascades that link predators to prey to plant communities (Suraci et al., 2019). Carnivores have emerged as excellent ecological models that provide evidence that intraguild (IG) interactions (e.g., resource competition, intraguild predation) can reverberate across trophic levels, significantly affecting and even driving ecological processes (Lombardi et al., 2020). However, worldwide most large carnivores are experiencing rapid population declines because of human-driven landscape change and disturbance of critical carnivore habitat (Ripple et al., 2014), yet human impact can extend beyond physical changes in Earth’s land surface (i.e., urbanization, farming). For example, actual human presence on the landscape, which experiences seasonal differences and is not spatially or temporally predictable, influences wildlife behavior by disrupting movement (Tucker et al., 2018), forcing changes in diel activity patterns (Gaynor et al., 2018), and mediating predator-prey interactions (Smith et al., 2015). In fact, growing evidence suggests human presence can result in a dynamic landscape of fear (Frid and Dill, 2002), referring to the relative level of predation risk as peaks and valleys reflecting the level of fear an individual prey experiences in different parts of its habitat that can induce stress responses and reduce fitness (Laundre et al., 2010). Researchers have been using methods such as vigilance observations and foraging surveys of plants to quantify wildlife predation risk or the ‘landscape of fear’, which can be highly influenced by human activity across the landscape (Laundre et al., 2010). In particular, carnivores are especially affected by human disturbance due to the human ‘super predator’ perception (Suraci et al., 2019; Smith et al., 2015; Clinchy et al., 2016), causing carnivores to respond by modifying their habitat use and behavior driving widespread changes of community and ecosystem-level processes (Smith et al., 2015; Wilmers et al., 2013). Thus, understanding the drivers of spatial and temporal dynamics as well as species co-occurrence among carnivore guild members across multi-use landscapes, can provide novel insights that can be used by natural resource managers to facilitate recolonization and population of diverse ecological communities by promoting multi-species carnivore conservation (Ripple et al., 2014).

Furthermore, prior research has focused primarily on large carnivores that play a key role in maintaining ecological communities but make up a small portion of carnivore species worldwide. Mesocarnivores are small to medium in size (i.e., <15kg) and make up the majority of the carnivore community. The group is made up of highly adaptable species that are diverse in their ecology and behavior, yet little research has focused on the role they play in community structure (Roemer et al., 2009). For example, many small North American carnivores (i.e., kit fox [*V. macrotis*], black-footed ferrets [*Mustela nigripes*], kit fox [*V. velox*]) suffered apparent consequences following the extirpation of wolves, which allowed coyote populations to grow and expand as they moved into increasingly urbanized landscapes (Linnell and Strand, 2000). The ability of mesocarnivores to adapt to new environments and actively avoid competition both within and between species is a vital strategy for carnivore coexistence (López-Bao et al., 2016), therefore it is critical to further investigate these species and the relationships they share within their communities.

1.2 Diversity of the U.S. carnivore guild

The multi-use lands and variable land cover across the U.S. provide excellent systems to investigate a diverse carnivore community's temporal and spatial patterns, but further delving into finer-scale variation across the local Marquette rural-wildland interface provides an opportunity to understand the more subtle effects of human presences and forms of recreation. The area has a flourishing outdoor recreation scene (e.g., snowmobiling, mountain biking, hunting, hiking) that fluctuates seasonally, and supports a diverse carnivore guild (e.g., American black bear [*Ursus americanus*], gray wolf [*Canis lupus*], red fox [*Vulpes vulpes*], bobcat [*Lynx rufus*], fisher [*Martes pennant*], marten [*Martes americanus*], striped skunk [*Mephitis mephitis*]) as well as a myriad of prey species (e.g., white-tailed deer [*Odocoileus virginianus*], eastern gray squirrel [*Sciurus carolinensis*], eastern chipmunk [*Tamias striatus*]) that are found throughout much of the US.

1.2 Research Overview

As human-dominated landscapes continue to expand worldwide, understanding how carnivores respond to anthropogenic effects is becoming increasingly important. I investigated the responses of multiple carnivore species to human disturbance at various scales across the U.S., as well as their interactions with each other. In my first chapter, I focused my study in a small area of the Upper Peninsula of Michigan to further understand the temporal and spatial patterns of American black bears in response to human activities. Over the past several decades black bears recolonized parts of their historic range in many areas, thus the Upper Peninsula of Michigan may serve as an excellent model system to inform bear management in areas where the black bear population is growing, as well as areas that black bears have not previously inhabited. In my second chapter, I investigate the carnivore community of the United States by using Snapshot USA 2019 data with the bobcat as a focal species. I examined spatial and temporal patterns of nine carnivore species to determine if the bobcat functions in a mesocarnivore or *de facto* apex predator capacity, and also determined the strength of various factors driving differences among dominant and subordinate carnivores within the U.S. carnivore guild.

1.CHAPTER ONE: HUMAN RECREATION IMPACTS SEASONAL VARIATION IN AMERICAN BLACK BEAR (*URSUS AMERICANUS*) ACTIVITY AND OCCUPANCY ACROSS THE URBAN-WILDLAND INTERFACE

1. Introduction

Large mammalian carnivores are often elusive, wide-ranging species that have a history of controversial conservation due to mixed human perceptions (Chapron et al., 2014; Lute et al., 2020) and contentious decision-making regarding management, resulting in most carnivore species experiencing continued rapid population declines and loss of habitat worldwide (Ripple et al., 2014; Gantchoff and Belant, 2017). As anthropogenic development continues to increase, carnivores' large home range size, low population densities, high metabolic demands associated with large body size (Ripple et al., 2014), and direct persecution due to hunting (Smith et al., 2014; Kays et al., 2016; Schipper et al., 2008; Støen et al., 2015; Stillfried et al., 2015) make them especially vulnerable to landscape changes. Yet, there are still many causes for conservation optimism due to the successful recolonization of some large carnivores across large swaths of their historic ranges despite substantial human-modified changes to the global landscape (Chapron et al., 2014; LaRue et al., 2012; Evans et al., 2017). Thus, the importance of effective land management and planning that balances the needs of humans and wildlife (Lute et al., 2020; Cove et al., 2019) is critical for promoting effective global carnivore conservation and recolonization (Evans et al., 2017).

As urban environments continue to extend their reach, growing evidence suggests that human activity results in a dynamic landscape of fear (Frid and Dill, 2002), in which wildlife, particularly carnivore species with a history of persecution by humans, perceive humans as 'super predators' (Smith et al., 2015; Clinchy et al., 2016; Suraci et al., 2019) and respond by modifying their habitat use and behavior (Smith et al., 2015). Changes in predator-prey interactions (Smith et al., 2015), shifts in diel activity patterns (Gaynor et al., 2018; Suraci et al., 2019; Smith et al., 2018) and wildlife movement (Tucker et al. 2018) associated with human activities have led to increased sightings, nuisance reports, and even increased harvest reports of some species, as well as an unprecedented rise in reported interactions between humans and carnivores (Carter et al., 2010). In particular, increased outdoor human recreation, which has become a popular incentive for nature-based tourism and conservation of natural ecosystems, has the potential to cause high levels of ecosystem disruption that may impact carnivore populations and lead to the deterioration of biodiversity (Naidoo and Burton, 2020; Kays et al., 2017). For example, as prey habituate to human activities associated with nature-based tourism I expect responses to predation risk to be reduced, thus bolder individuals will experience increased vulnerability to predators where humans are predominant across the landscape (Geffroy et al., 2015). Observing the impacts of human recreation is challenging, wildlife responses to recreation activities can be subtle and vary dependent on species, while tracking human presence across the landscape is unpredictable and difficult to monitor in wild areas (Naidoo and Burton, 2020). Urbanization, human population growth, and recreational opportunities are responsible for driving people farther into areas where carnivore populations persist, making carnivore behavioral plasticity an important trait for co-existing in increasingly common human landscapes (Støen et al., 2015).

The recolonization of many carnivores in North America is a result of species becoming more tolerant of developed areas and human activity (Evans et al., 2018; Evans et al., 2017; Gantchoff and Belant, 2017), allowing them to persist in human-dominated landscapes and even exploit human resources (Smith et al., 2018; Evans et al., 2017). For example, in urban environments the American black bear (*Ursus americanus*), an omnivorous carnivore, is capable of modifying their foraging behavior (Evans et al., 2018) to consume human subsidies such as garbage, fruit trees, and birdseed (Carlos et al., 2009; Johnson et al., 2018). Although black bears have been recolonizing their former range and even dispersing into new environments (i.e., urban landscapes) over the past couple decades (Evans et al., 2017; Ditmer et al., 2018; Carter et al., 2010), anthropogenic attractants can lead to increases in the number of bear-human conflicts. Indeed, American black bears are the most abundant large carnivore in the world (Ripple et al., 2014), utilizing an array of landcover types (i.e., forest, shrubland, wetland), as well as occupying exurban areas (Evans et al., 2018) that have lower housing density and slower development. In the state of Michigan, the American black bear population is increasing and expanding farther south in the Lower Peninsula (McFadden-Hiller et al., 2016), presenting challenges for wildlife managers, and a growing indifferent public opinion of the species (Ladle et al., 2018; Wilbur et al., 2018; McFadden-Hiller et al., 2016). Following successful reintroductions, black bears are once again reclaiming parts of their historic ranges in the southeastern U.S. in Arkansas and Louisiana (Gantchoff and Belant, 2017) and are recolonizing portions of Mississippi, eastern Texas, Oklahoma (Lustig et al., 2021), Missouri (Gantchoff and Belant, 2017), portions of urban Connecticut (Evans et al., 2018), and father north into New York (Sun et al. 2017) and Maine. Variation in land use among these regions (i.e., forest, agriculture, housing density) and differences in wildlife management policies (i.e., hunting season vs. no hunting season) can have a significant effect on the success of recolonizing populations (Cove et al., 2019;Evans et al., 2018). As such, understanding the influence human activity has on the spatial and temporal dynamics of black bears is critical to determine successful management practices of growing carnivore populations that persist across human-dominated landscapes.

For the American black bear, the period of hyperphagia when bears consume excessive food and water to gain weight as they enter the period of inactivity known as hibernation, plays a key role in their life history and is susceptible to influence caused by changing patterns of human activity, seasonal food availability, and climate (Johnson et al., 2018). For example, increasing temperatures and expanding urbanization have been postulated to reduce the time of hibernation, further increasing the number of bear-human conflicts along the urban-wildland interface (Johnson et al., 2018). Increased human activity in remote wild areas, particularly during annual bear hunting seasons, have been observed to cause circadian shifts in black bear temporal activity, increasing overall nocturnal activity (Støen et al., 2015). Human hunters acting as top predators are restricted in their predation to particular areas and times of the day and year in which hunting is allowed, thus black bears may be able to predict their spatial and temporal variation (Stillfried et al., 2015). In the Upper Peninsula of Michigan (U.P.), recreational bear hunting (2019 U.P. Bear Hunting Season: September 11-October 26; ~91,582km^2) began in 1925 and has become a long-standing tradition to manage bear populations, but in 2012 license quotas were dropped significantly due to expressed concerns from DNR biologists and bear hunting clubs (Michigan DNR, 2021). Further, the investigation of black bear spatial and temporal behavior during the period of “activity” in the U.P. offers tangible evidence for understanding how recolonizing black bear populations use multi-use lands and respond to anthropogenic activity, which is essential for conservation of black bears in areas where they have not previously persisted and as they recolonize portions of their historic range.

To better understand the influence of human activity on the seasonal spatial and temporal patterns of the American black bear, I used camera traps to examine anthropogenic and environmental factors that have the potential to influence black bear activity and occupancy across the urban-wildland interface of Marquette MI. The U.P. is home to most of Michigan's black bears and hosts a stable population that has increased by about 1% since the year 2000 (i.e., ~9,699 bears -- Michigan DNR, 2021). The pairing of a stable black bear population and popular outdoor recreation scene that hosts a range of activities throughout the year makes this study area an ideal ecological model for evaluating black bear behavior relative to human recreation patterns on a seasonal scale. Thus, my research objectives were to (1) determine whether black bears exhibit significant differences in spatial and temporal activity patterns before and after hibernation, while also considering the variation in human activity throughout the year, (2) determine which types of human activity and environmental factors influence black bear detection and occupancy across the landscape, and (3) determine if black bear display a shift in their activity patterns given the onset of hunting season. I predicted that black bear activity would be driven by the energy demands of hyperphagia before hibernation causing black bears to occupy a greater proportion of the landscape when resources are scarce, as well as the need for larger quantities of food and nutrients for cubs following hibernation that will increase black bear activity level when resources are plentiful. Finally, I predicted that black bears would exhibit greater nocturnality in the fall due to the increased risk associated with direct persecution by hunting, leading to an increased importance of protected areas before hibernation.

2. Materials and Methods

2.1 Study Area

I conducted my study in the U.P. of Michigan in the northeast region of Marquette County, along the urban-wildland interface just north of the peninsula's largest city, Marquette (46.5436° N, -87.3954° W). The 60km^2 study area (Fig. 1.1) is bordered to the east by Lake Superior and covers an area that includes several popular outdoor recreation areas (e.g., Harlow Lake, Sugarloaf Mountain, North Country Trail) as well as commercial forest lands that experience considerable seasonal changes throughout the year. Snow cover generally lasts from November to the following April with average temperatures reaching 74.5°F in July and dropping to 12.5°F in January (Weather Atlas). The area is under mixed management including Michigan Department of Natural Resources, The Nature Conservancy, and Hancock Timber Management Group. Land cover across the study area is diverse and includes coniferous, deciduous, and coniferous-deciduous-mixed forests, wetlands, occasional meadows, sand dunes, rocky outcrops, as well as a vast Lake Superior shoreline. In addition to myriad land cover, this thriving ecosystem supports a diverse carnivore guild (e.g., gray wolf [*Canis lupus*], red fox [*Vulpes vulpes*], bobcat [*Lynx rufus*], fisher [*Pekania pennanti*], marten [*Martes americanus*], striped skunk [*Mephitis mephitis*]), as well as various prey species (e.g., eastern gray squirrel [*Sciurus carolinensis*], eastern chipmunk [*Tamias striatus*], American red squirrel [*Tamiasciurus hudsonicus*], and white-tailed deer [*Odocoileus virginianus*]).

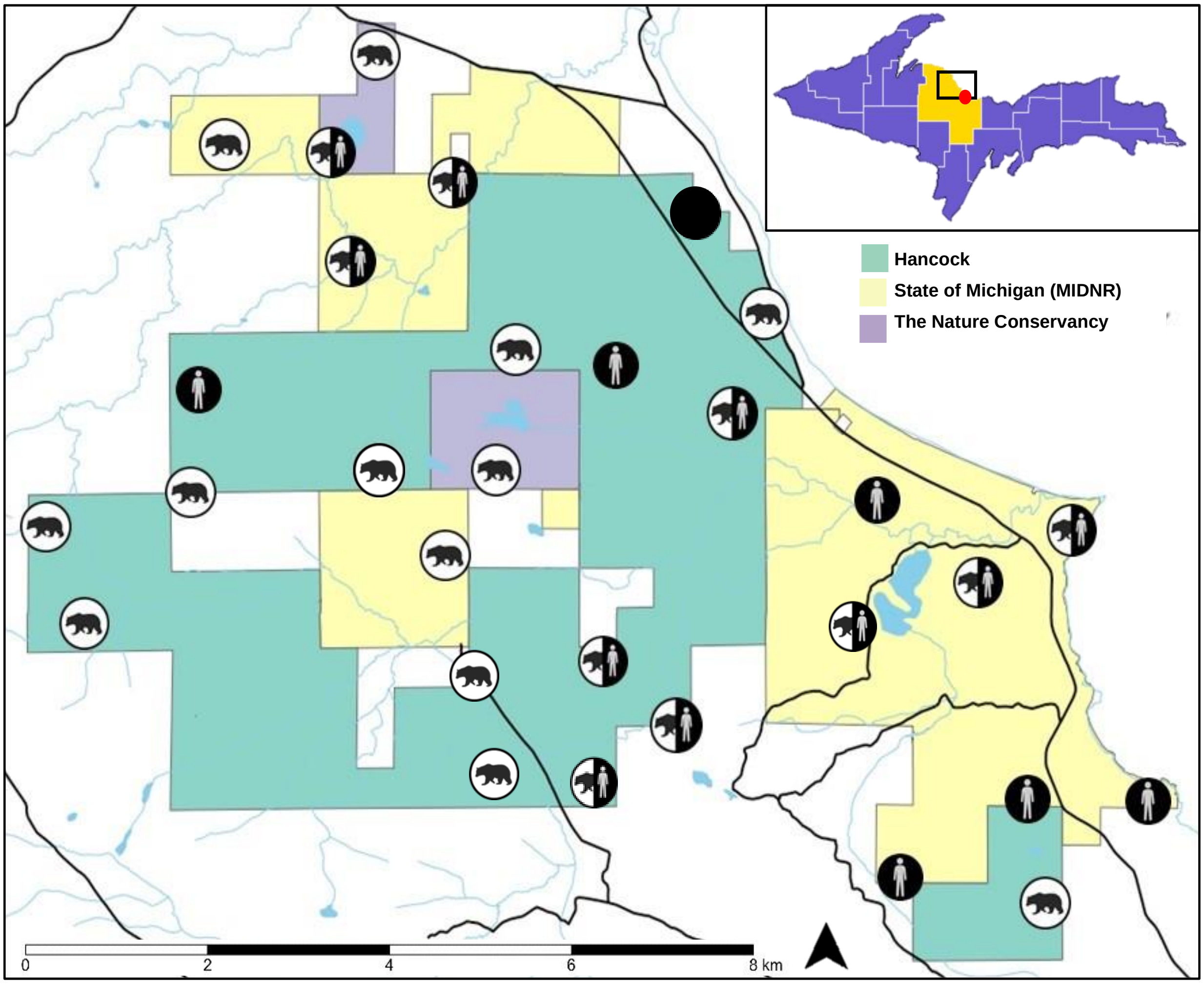

Figure 1.1 | Map of 60km^2 study area displaying current land management with circles indicating locations of camera traps and whether black bear, human, or both or none (i.e., solid black circle) were detected. Inset map of the Upper Peninsula of Michigan with Marquette County highlighted, study area indicated, and city of Marquette marked with red dot.

2.2 Camera Trap Surveys

I deployed 30 trail cameras (Primos Proof Generation 2) equipped with infrared flash across the rural-wildland interface of Marquette, Michigan between August 31 and September 8, 2019. To determine camera locations, I overlaid a 1 km^2 grid across the study area and subsequently used a randomization method in the R package spatialEco (Evans, 2021) to identify a single random point for each of the 40 grid cells across my study area. While I only deployed 30 cameras, generating an additional 10 points allowed deployment flexibility in the rare event a grid cell was not usable (e.g., land ownership changes not registered on county plat maps [private land]). Upon arriving at the approximate center of a grid cell, I searched for animal signs (e.g., animal trails, scat, etc.) within 100m of the center point to identify locations that may increase the probability of capturing wildlife images. Cameras were strapped tightly 0.5m (Diaz-Ruiz et al. 2015) above the base of trees within a 60° window of north to reduce direct sunlight (Moore et al. 2020), and when possible, along linear features (e.g., river, trail, etc.) with no addition of bait or lure. Camera settings were chosen to increase the probability of capturing and accurately identifying fast-moving carnivores, thus cameras recorded multiple photographs per trigger, at a rate of 1 frame per second, re-triggering immediately if the animal was still in view (Kays et al., 2017; Moore et al., 2020; Parsons et al., 2019).

I exchanged SD cards every 2-3 months, except during the winter when many cameras were not accessible. In early November 2019, cameras were shifted to a height of 1m above the ground in preparation of snowfall and any further height adjustments were made based on weather conditions and individual site conditions. As I was capturing images along an urban-wildland interface, images were sorted and all license plates and human faces were blurred to remove identifiable features. Following this procedure all images were organized in events and/or subjects based on a 5s window (i.e., images were grouped if they were taken within 5s of the previous image) and were uploaded to the Yooper Wildlife Watch project on Zooniverse (https://www.zooniverse.org/projects/bergq105/yooper-wildlife-watch), an online imagery platform where wildlife images can be uploaded, managed, identified, and archived. Using this online platform allows for the global engagement of citizen scientists, as well as an efficient way to quickly gather species information and image metadata for further data analysis. After completion of subject identification, independent wildlife observations or detections were determined using a 30-minute interval between the same species, assuming that if it were shorter, I was observing the same individual (Tian et al., 2020; Allen et al., 2020). To stay consistent, this method was used for both black bear and any human related detections, noting that on heavily traveled human trails there may have been different individual humans passing within 30 minutes of each other.

3. Data Analysis

3.1 Analysis – Temporal Activity

Daily activity patterns of American black bears and humans were analyzed using the package "overlap" (Meredith and Ridout, 2020) in RStudio version 1.3.1073 (RStudio Team, 2020). Time was converted to radians to create kernel density estimation curves for **(1)** black bears before hibernation (i.e., all detections following camera deployment in September and before the final bear siting in the fall) and **(2)** black bears after hibernation (i.e., all detections following the first bear detection in the spring and before the month of September). The same was done for humans, domestic dogs, and vehicles using the timeframe established by the temporal span of black bear detections. Overlap estimates were made for black bears before and after hibernation as well as for the different types of human activity using the overlap coefficient (Δ), which is scaled from 0 to 1, where ($\Delta=1$) signifies complete overlap (Ridout and Linkie, 2009; Tian et al., 2020; Allen et al., 2020). I also investigated the effect of cub presence on black bear daily activity patterns to determine if their presence contributed to significant changes in activity but given the smaller sample size of cub detections, I calculated this metric using combined data for both the before and after hibernation (Lashley et al., 2018). Further, activity level estimates were calculated using the package "activity" (Rowcliffe et al., 2021) by fitting a flexible circular distribution to calculate the proportion of time a single species or group of individuals is active within a 24-hour period (Ridout and Linkie, 2009). After calculating activity level estimates, I used a Wald test to determine whether there was a significant difference between the black bear activity level before and after hibernation, as well as between black bears and differing types of human impact. Finally, I extracted temperature data from the black bear images to plot monthly and hourly changes to determine if black bears display any threshold for activity based on temperature.

3.2 Analysis – Occupancy Modelling

I created single species, single-season occupancy models to determine: **(a)** the probability of black bear detection at a site and **(b)** the probability of a site being occupied by a black bear given a number of anthropogenic and environmental variables before and after hibernation (MacKenzie et al., 2006). Binary detection histories (1 = detected, 0 = not detected) were created for the black bear before hibernation and after hibernation at each camera site. I accounted for imperfect detection by using weekly sampling occasions (Before: n=13; After: n=18), which reduced the number of observations where the count of detections is zero (Naidoo and Burton, 2020, MacKenzie et al., 2003). Camera trappers were not included when running occupancy models due to my presence at every site, which could impact the results. Data for environmental covariates and some human impact covariates, which consisted of large-scale human factors across the landscape, were extracted from geo-spatial layers available on the government Landfire database (https://www.landfire.gov/), USDA database (https://www.nass.usda.gov/), and SEDAC (https://sedac.ciesin.columbia.edu/). All data for human recreation covariates, which included fine-scale human presence across the landscape, were calculated from my collected camera dataset.

I checked for correlations between all numeric covariate pairs using the package corrplot (Wei and Simko, 2017) with a threshold of 0.7 to indicate high correlation for eliminating covariates that encompass the same variation from my final models. Highly correlated covariates included human count, humans on-foot, domestic dogs, and humans on non-motorized recreation vehicles (i.e., bikes), which all had correlation values greater than 0.9. Covariates were grouped into three categories **(1)** human impact, **(2)** human recreation, and **(3)** environmental impact (Table 1.1). Single-species occupancy models were run to compare each covariate's effect on black bear occupancy, with the covariate ‘season’ accounting for the difference before and after hibernation as well as when hunting season occurred. After removing the highly correlated covariates, I retained human presence, human population density, and season in my final model. I also investigated the probability of detecting black bears at individual sites based on whether sites were located in protected areas as well as variable by season, which I predicted would have a significant effect on black bear detections.

Table 1.1 | Summary of environmental and human covariates included in occupancy models based on values for each camera site before and after hibernation. (*) Indicates significant effect.

Model/Covariate	**Description**	**Max**	**Min**	**AIC Value**
Human Impact				
**Human Presence*	yes/no	NA	NA	480.70
**Human Population Density*	pop. density per 1km sq.	10.35	0	481.12
Road	distance to nearest road (m)	1541.60	8.69	483.54
Land Ownership	Hancock, Nat. Conservancy, MIDNR	NA	NA	484.57
Protected Land	yes/no	NA	NA	484.37
Human Recreation				
** Human Count*	total # of humans	589	0	481.84
**Human On-Foot*	total # of humans on foot	14.97	460	482.20
**Human Non-Motorized*	total # of non-motorized rec.	129	0	482.33
**Domestic Dog Presence*	yes/no	NA	NA	482.77
Recreation Vehicle Presence	yes/no	NA	NA	485.14
**Passenger Vehicle Presence*	yes/no	NA	NA	483.09
Utility Vehicle Presence	yes/no	NA	NA	484.80
Gun Present	yes/no	NA	NA	484.69
**Sum of Human Activity*	# of dogs, humans, and vehicles	1034	0	482.84
Environmental Impact				
Landcover Type	primary forest species (i.e., hemlock, etc.)	NA	NA	484.85
Water Source	nearest water source (m)	781	10	485.14
Elevation	meters above sea level	435.02	183.06	484.85
Season	before hibernation/after hibernation	NA	NA	483.37

4. **Results**

Detections were recorded before hibernation (i.e., September 1st, 2019 to November 26th, 2019 and September 1st, 2020- September 8th, 2020 [95 days]) and after hibernation (i.e., April 12th, 2020 to August 30th, 2020 [141 days]) for a total of 110 detections, 15 of which had a mother and cub, 2 of which had multiple adults, and 2 of which had only multiple cubs. Of the total detections, 46 were recorded before hibernation while 66 were recorded after hibernation. Black bear detections were captured at 23 of the 30 camera sites with 42 independent black bear detections recorded at a single location. Upon further investigation, this location had a mother and cub frequently visiting the camera and likely denning nearby, yet other adults were still distinguishable when reviewing images collected at this site (Table 1.2). Approximately 48% of all black bear detections included direct physical interaction by the black bear with the camera.

Human detections totaled 1,191 with on-foot making up 898 of the detections and non-motorized accounting for 163 detections. There was an increase in human activity rate following hibernation in the spring by approximately 0.40 detections per day or about 9% (Before: 4.3/day; After: 4.7/day). Further, images were inspected for the presence of guns (i.e., hunters), which were recorded only before hibernation at three different sites and 13 independent detections (Table 1.2).

Domestic dog detections totaled 611 with 480 collared dogs being captured at six different sites, 124 non-collared dogs being captured at seven sites, and seven detections where collars were indeterminate. Non-collared dogs made up approximately 20% of the total dog detections. Before hibernation, we recorded 1.8 dog detections per day and after hibernation 3.1 per day, thus there was approximately a 41% increase in the rate of dog detections in the spring (Table 1.2).

We recorded 113 independent detections of vehicles that were grouped into three categories: **(1)** recreational vehicle (i.e., four-wheeler, ATV, snowmobile), **(2)** passenger vehicle (i.e., average car or truck), and **(3)** utility vehicle (i.e., logging truck, dump truck, etc.). Vehicles were recorded at five different camera sites with a total of 43 recreational vehicles, 47 passenger vehicles, and 24 utility vehicles. Vehicles were recorded at a rate of 0.4/day after hibernation and a rate of 0.5/day before hibernation for an approximate 20% increase (Table 1.2).

Table 1.2 | Summary of detections for American black bears, humans, domestic dogs, and vehicles before and after hibernation.

Species	# of Locations	Before Hibernation	After Hibernation	Total
Black bear				
Adult/Subadult	23	46	50	96
Cubs	10	13	16	29
Human				
On-foot	18	372	526	898
Non-motorized	1	34	129	163
With gun	3	13	0	13
Dog				
Collared	6	125	355	480
Not collard	7	49	75	124
Vehicle				
Recreational	5	20	23	43
Passenger	3	36	11	47
Utility	2	16	7	23

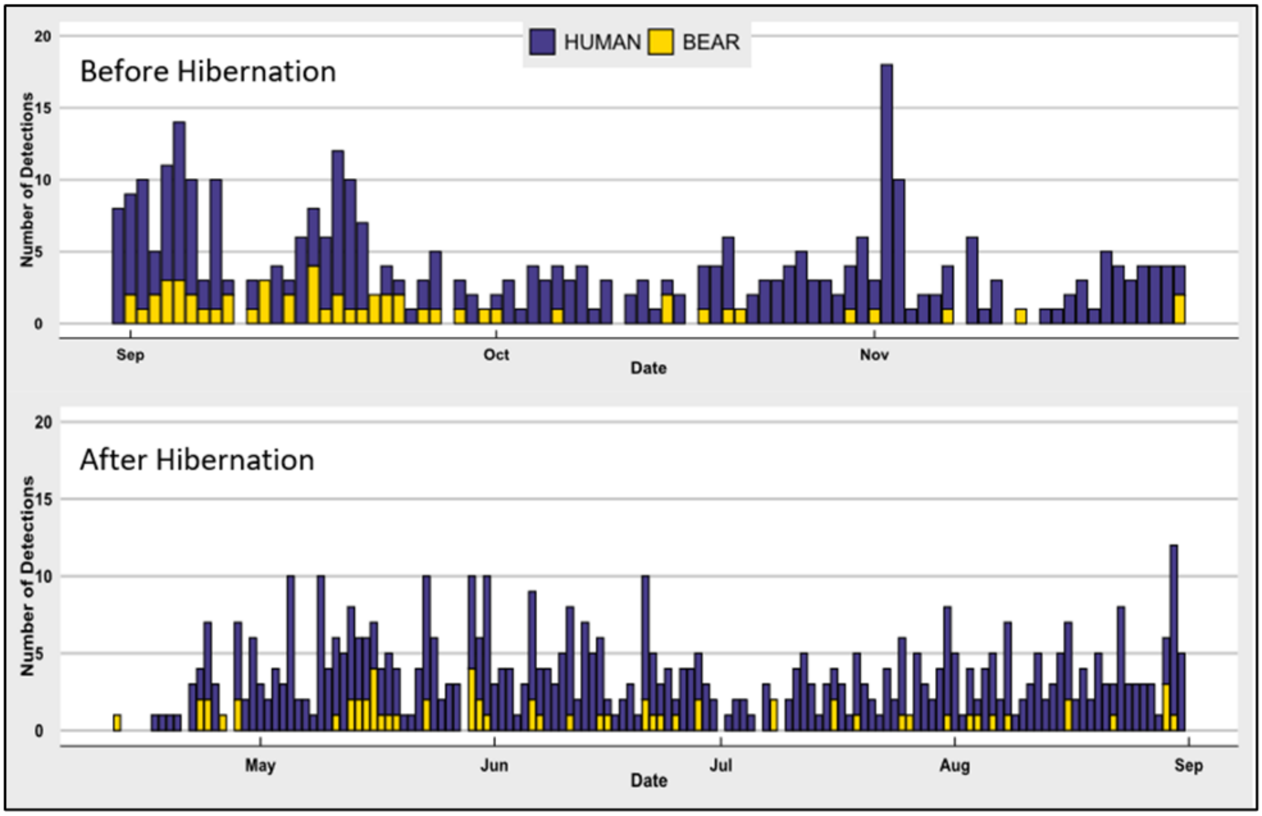

Figure 1.2 | Summary of when black bear and human detections were recorded throughout study period and further broken down into before hibernation (top), and after hibernation (bottom).

4.1 Temporal Activity

Comparing before and after hibernation temporal activity in the American black bear, I observed an increase in activity during diurnal hours by over 30% after hibernation (Before: 42.5%; After: 78.4%) with an overlap estimate of 0.661 (Fig. 1.2). Diurnal time boundaries were determined by calculating the average sunrise/sunset time from all black bear detections for before and after hibernation. A slight increase in black bear activity level was also observed after hibernation (Before: 0.574; After: 0.641) suggesting they were active for a greater proportion of the day though not statistically significant ($p = 0.560$). Variation in activity was also compared for bears with and without cubs utilizing all detections recorded during the study period. I calculated an overlap estimate of 0.799 with bears having greater diurnal activity without cubs (With: 56.4%; Without: 59.6%) as well as a lower activity level (With: 0.669; Without: 0.594) that was not significantly different from bears with cubs ($p=0.598$). I briefly investigated the relationship between black bear activity and temperature, where I observed a consistent increase in the mean temperature from April (7.1°C) to July (24.1°C), and then a decrease moving into November 0.6°C) as expected. Only two (~0.02%) black bear detections occurred at temperatures below freezing during the month of November.

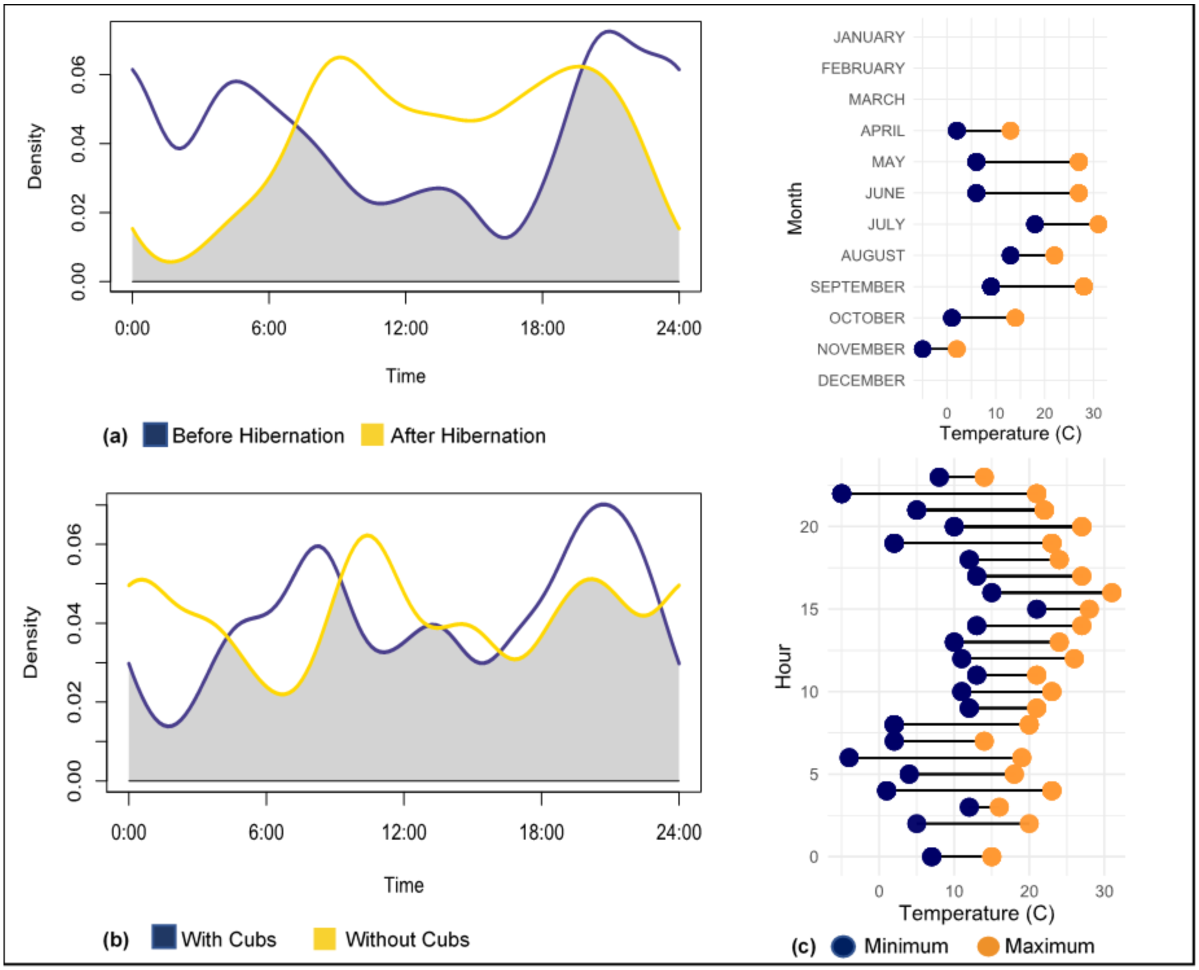

Figure 1.3 | **(a)** Black bear activity before and after hibernation. **(b)** Black bear activity with and without the presence of cubs. The gray area under the curves represents the overlap between the two activity patterns. **(c)** Minimum and maximum temperatures recorded for all black bear detections grouped by month and hour of the day.

Non-motorized human activity (i.e., biking) levels differed significantly before and after hibernation with an increase in the proportion of day they were occurring following black bear hibernation. Human activity consistently had higher overlap with black bear activity after hibernation, which could be a result of the overall increase in human activity observed in the spring. Among the different types of human activity, similar overlap estimates with bear activity were calculated that had no significant differences.

Table 1.3 | Human activity overlap with black bears and activity level estimates before hibernation (BH) and after hibernation (AH).

Human Activity	**BH Overlap Est.**	**AH Overlap Est.**	**BH Activity Level**	**AH Activity Level**
All recreation	0.325	0.621	0.361	0.340
On-foot	0.332	0.635	0.375	0.342
Non-motorized	0.229	0.582	0.209	0.339
Vehicles	0.317	0.573	0.328	0.292

4.2 Occupancy Modeling

Black bear occupancy was driven by human presence, human population density, and changes in seasonality that resulted in greater occupancy before hibernation (i.e., 18 sites occupied) than after hibernation (i.e., 14 sites occupied). My final model showed a near significant negative effect caused by human presence (β = -1.128, ±0.633SE) and human population density (β = -0.159, ±0.605SE) (Fig. 1.3).

The probability of detecting a black bear in my final model was found to be significantly associated with protected areas (β = 1.851, ±0.326SE) and the season (β = - 0.668, ±0.326SE) (Fig. 1.3). Season had a negative effect on black bear detection probability after hibernation, but I suspect this may be influenced by a shorter time period of data collection before hibernation. Protected land areas greatly increased the probability of detecting black bears with a strong positive effect given only 3 sites lie within protected boundaries.

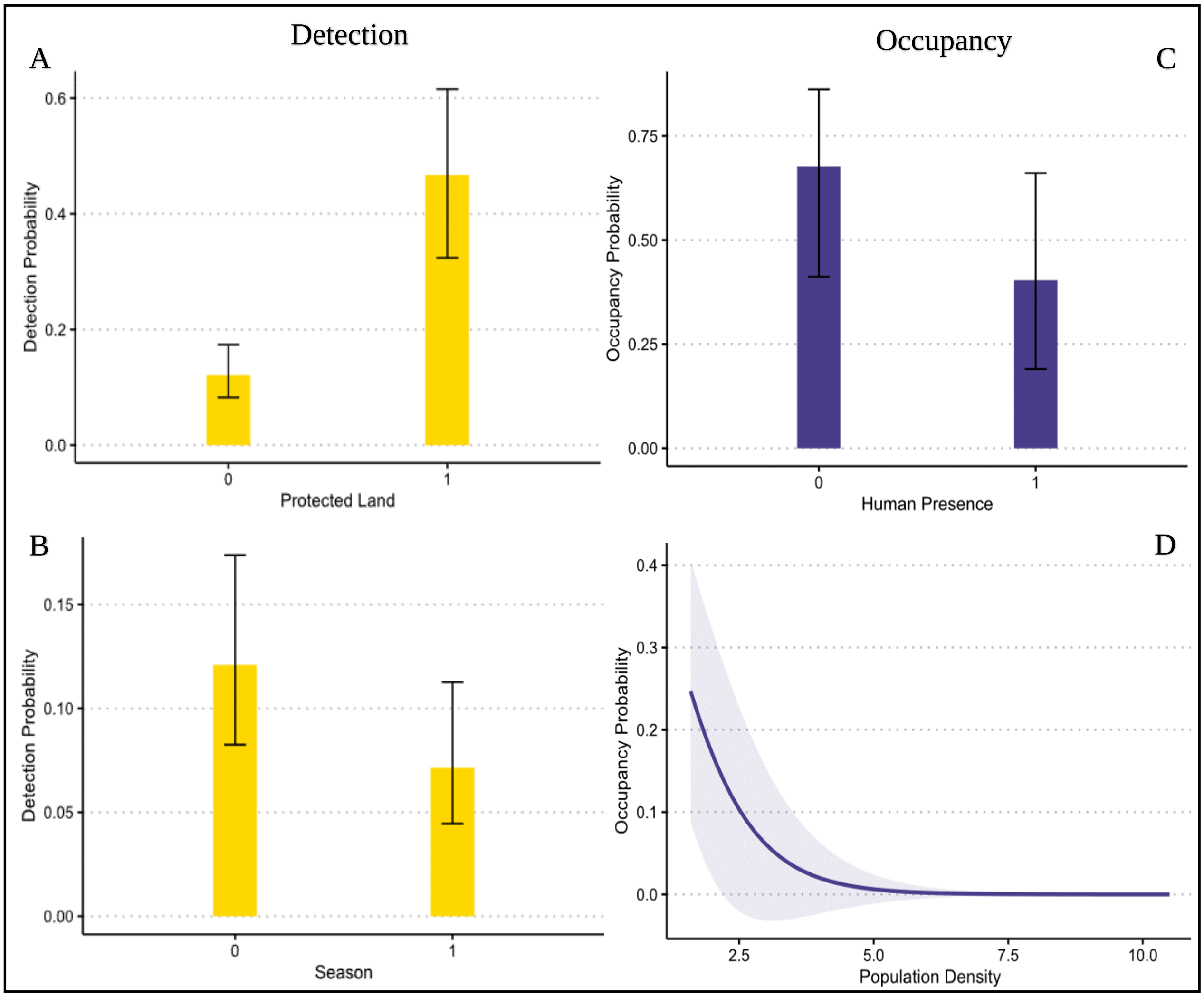

Figure 1.4 | Graphs in left column show the relationship between estimated detection probability and **(A)** protected land [0-unprotected, 1-protected], and **(B)** season [0-before hibernation, 1-after hibernation]. Graphs in right column show the relationship between estimated occupancy probability and **(C)** human presence [0-not present, 1-present], and **(D)** population density. Shaded region represents the standard error.

5. Discussion

My research provides critical insights into the effects that human activity exerts on American black bear activity and occupancy across the urban-wildland interface, thus furthering our knowledge and ability to create better management practices in the region and in areas with recolonizing populations more broadly. Specifically, I investigated how different forms of human activity (i.e., human presence, domestic dogs, vehicles, etc.) and other environmental factors altered black bear occupancy before and after hibernation. My results showed that black bears are significantly affected by human presence across the landscape with variation in activity and occupancy observed before and after hibernation. However, because I found no clear differences in black bear activity based on the different types of human activity and recreation detected, my results suggest black bears might not differentiate among the different types of human activity and recreation occurring in my study area. Similar results have been found in past studies showing that differences in bear activity patterns did not differ between sites with motorized or non-motorized recreation (Ladle et al., 2018).

I used kernel density estimation curves to analyze the temporal activity patterns of black bears finding a consistent trend for increased overlap between bears and humans following hibernation, which I expect is partially due to a substantial rise in outdoor human recreation as a result of COVID-19 restrictions during my study (Blount et al., 2021). This increase was observed for all types of recreation (>38%) after hibernation, thus through further analysis, I concluded that the different types of recreation were highly correlated and human presence captured their effect in a single covariate. Given this, I observed no difference in black bear temporal activity due to variable human activity across the landscape. I also investigated the effect of cub presence on black bear temporal activity, observing a small increase in diurnal activity when cubs were not present. The small sample size of detection with cubs present prevented me from analyzing before and after hibernation data separately, which may have limited my ability to detect an effect, though I do not expect black bear cub activity to vary substantially across seasons. I observed an increase in cub detections in the spring as expected, yet I would also expect the birthing of new cubs to increase the activity level and demand for resources by black bears after hibernation forcing them to spend greater time searching for and consuming food. Similarly, before hibernation I would expect to observe a high demand for resources that are becoming scarcer, forcing black bears to travel and search greater distances to support the energy costs of entering and sustaining hibernation. As such, having a larger dataset might provide greater evidence to support black bear activity being driven by the energy demands of hyperphagia before hibernation and the need for larger quantities of food and nutrients to support cubs following hibernation.

To explore the spatial scale of black bear activity, I used occupancy models and an array of human and environmental covariates. I found black bears to be negatively associated with human presence and human population density. Further, my results indicate that black bears are influenced strongly by human activity across the landscape, with little to no impact from the environmental factors that I measured (Table S1.1). Due to my small dataset for some human activity covariates, I think further investigation into specific types of recreation is necessary to fully understand black bear occurrence on the landscape. For example, my study only included a total of 13 detections where a hunter with a gun was clearly identified. I expected hunters to have a greater effect on black bear occupancy than the average human (i.e., hiker), but my sample size for this covariate was too small to provide meaningful insight. Moreover, I did observe a significant effect on black bear occupancy due to the season (i.e., before or after hibernation), yet a negative effect on occupancy was observed after hibernation, which does not correlate with hunting season. A possible explanation for this observation may be due to high resource needs before hibernation, driving bears to move greater distances in search of food that is becoming more limited moving into winter. The risk of finding food that allows for successful hibernation may outweigh the risk associated with human activity during the hunting season. Further, I found that protected areas had a strong positive association with black bear occupancy. Given only 3 sites (10%) were located within protected lands, no hunting zone or protected areas could also play a key role in determining how black bears use the landscape during hunting seasons. Finally, the increased amount of nocturnal activity displayed by black bears in the fall could substantially increase their chance of avoiding hunters across the landscape due to legal hunting hours beginning 30 mins before sunrise and continuing 30 mins after sunset in the state of Michigan (Michigan DNR, 2021).

American black bears play important functional roles across variable ecosystems of North America, having critical life history traits that can be highly influenced by variation in human activity, weather, and resource availability across the landscape (Johnson et al. 2018). As such, ensuring black bear populations can meet their hibernation requirements should be a primary consideration for wildlife managers, which may influence hunting regulations and the number of tags made available each season for bear harvest. I observed the highest number of black bear detections throughout the months of September and October, which takes place during hunting season and the time when black bears are preparing for hibernation. Although the U.P. has had an active hunting season for many years, continuous monitoring of the population is a necessity to keep a stable population and will provide knowledge for wildlife managers in areas where hunting seasons may need to be established in the future. Moreover, increasing our knowledge of how human hunting activity affects black bear temporal and spatial patterns is critical for understanding the impact that humans have on successful hyperphagia in black bears.

American black bears are a well-known and a frequently studied large carnivore that has been recolonizing and expanding their range across much of North America. Although highly impacted by human presence and population density across the landscape, black bears have the capacity to coexist in human impacted landscapes and even thrive in these altered systems (Evans et al., 2017). Investigating black bear temporal and spatial activity patterns in the U.P. where wildland is abundant yet easily accessible by humans could provide substantial information to inform management practices associated with recolonizing populations across North America.

CHAPTER TWO: HUMANS OVERRIDE ENVIRONMENTAL DRIVERS OF CARNIVORE INTERACTIONS

1. Introduction

Large apex mammalian carnivores often play complex and sometimes keystone roles in structuring terrestrial ecosystems by driving trophic cascades that link predators to prey and prey to plant communities (2015; Miller et al., 2018; Suraci et al., 2019; Dröge et al., 2016; Clinchy et al., 2016). Yet, most carnivores are considered neither large nor apex, but instead are mesocarnivores, which are small to medium in size (i.e., <15kg). Given their smaller size and adaptability to varying environmental and anthropogenic conditions, mesocarnivores far outnumber large carnivores and are more diverse in their ecology and behavior (Roemer et al., 2009). Consequently, mammalian carnivore guilds have emerged as exciting ecological models for examining the many ways in which intraguild interactions (e.g., resource competition, intraguild predation) reverberate across trophic levels to affect and even mediate ecological processes (Lombardi et al., 2020; Gompper et al., 2016; López-Bao et al., 2016; Green et al., 2018). Intraguild interactions can facilitate or limit species' coexistence by driving carnivore temporal and spatial distributions (Miller et al., 2018), mediating carnivore and prey densities, and influencing species' behavior (Gompper et al., 2016; Grassel et al., 2015). Thus, understanding the drivers of spatial and temporal dynamics as well as species co-occurrence among carnivore guild members across heterogeneous landscapes can provide novel insights into intraguild structure.

Wildlife communities can be influenced strongly by competition between interacting carnivore species, and changes in the population density of even a single carnivore species can have significant ecological effects throughout an ecosystem (Miller et al., 2018; Suraci et al., 2019; Dröge et al., 2016; Clinchy et al., 2016). In fact, large carnivores have the potential to initiate top-down effects that influence mesocarnivores' behavior, abundance, and distribution through both consumptive and non-consumptive pathways (Shores et al., 2019; Dellinger et al., 2018). For example, following the reintroduction of gray wolves (*Canis lupus*) on Isle Royale (Michigan, U.S.A.) in 1958, coyotes (*Canis latrans*) were driven to near extirpation (Linnell & Strand, 2000). In contrast, coyote population growth and range expansion across much of North America following historical wolf extirpation in conjunction with the remarkable adaptability of coyotes to urban environments resulted in population changes for several smaller carnivore species such as kit fox (*Vulpes macrotis*), black-footed ferrets (*Mustela nigripes*), and swift fox (*Vulpes velox*) (Linnell & Strand, 2000), especially as coyotes began to fulfill the role of a *de facto* apex predator.

Multiple behavioral mechanisms are essential for carnivore coexistence: temporal partitioning, habitat segregation (López-Bao et al., 2016; Dröge et al., 2016), and the ability of subordinate species to adopt strategies (e.g., active avoidance [Ruiz-Villar et al., 2021], prey-switching [Ghoddousi et al., 2017]) to avoid or reduce competition with dominant sympatric species. However, carnivore community structure is also mediated by environmental factors (e.g., temperature, climate, vegetation), and varying levels of human disturbance (e.g., urbanization, roads, recreation). Environmental factors play a key role in carnivores' associations with distinct land cover characteristics (Gompper et al., 2016), wherein traits related to resource use are critical for carnivore co-occurrence and moderating conflict within the guild (Davies et al., 2007; Green et al., 2018). Further, carnivores are highly sensitive to human disturbance that can increase species spatiotemporal overlap (Murphy et al. 2021) due to their large home range requirements, high metabolic demands associated with large body size (Ripple et al., 2014), and direct persecution via hunting (Smith et al., 2015; Kays et al., 2017). Human disturbance and subsequent landscape transformation can also affect carnivores indirectly by impeding species movement, shifting when and where encounters occur (Murphy et al. 2021), and further diverting time and energy to risk avoidance behaviors (i.e., vigilance, fleeing [Breck et al., 2019]).

The bobcat (*Lynx rufus*), a widespread mesocarnivore that serves as a *de facto* top predator in many ecosystems across their North American range, can mediate the structure of wildlife communities, and influence ecosystem functions (Roberts & Crimmins, 2010). Like many mesocarnivores, bobcat populations across much of the continental United States suffered from landscape transformation associated with human development (Rose et al., 2020) and overexploitation for pelts (Johnson et al., 2010). However, since the early 1990s, many bobcat populations have recovered and are increasing (Roberts & Crimmins, 2010). Still, many mesocarnivores, including bobcats, are still viewed as harvestable resources or pests that require active management (Roemer et al., 2009). Despite exploitation, bobcat populations have shown remarkable resilience with their capacity to respond and adapt to such anthropogenic pressures, as indicated by an expanding geographic range into peri-urban spaces and the exploitation of new niches (Young et al., 2019; Johnson et al., 2010). Thus, bobcats serve as an excellent ecological model to investigate predators that operate at two functional levels (e.g., apex, subordinate) in the carnivore hierarchy depending on local community structure as well as habitat characteristics (Roemer et al., 2009). Further, understanding how bobcats coexist with potentially dominant (e.g., puma [*Puma concolor*], gray wolf, red wolf [*Canis rufus*], coyote) and subordinate (e.g., red fox [*Vulpes vulpes*], gray fox [*Urocyon cinereoargenteus*]) sympatric carnivores can provide new insights for understanding carnivore guild dynamics and implementing effective carnivore conservation and management strategies in a world increasingly impacted by humans (Robert & Crimmins, 2010).

To investigate species co-occurrence and the drivers of bobcat spatiotemporal activity within the carnivore guild of the United States (U.S.), we used the Snapshot USA camera trap dataset (Cove et al., 2021), using bobcats as a focal species. We explored variation in bobcat spatiotemporal activity and assessed carnivore co-occurrence by constructing diel activity density curves (Lashley et al., 2018), applying multispecies occupancy models (Rota et al., 2016), and calculating attraction-avoidance ratios (AARs – Parsons et al., 2016). We tested three hypotheses: **(1)** bobcat spatial and temporal activity would vary based on the presence or absence of dominant carnivores among the communities represented across the U.S., **(2)** bobcats, as a *de facto* apex predator, would influence subordinate mesocarnivores in the absences of dominant predators, and **(3)** environmental variability and human disturbance (i.e., human intensity) would influence bobcat spatiotemporal activity differently depending on which species are present in the carnivore community. We predicted that bobcats would reduce temporal overlap with dominant carnivores (i.e., pumas, gray wolves, red wolves) and avoid sites previously visited by both dominant and subordinate carnivores. Bobcats will also avoid sites previously visited by a dominant carnivore for a longer period of time than a subordinate carnivore, reflecting a greater avoidance response. Our research findings provide novel insights into carnivore co-occurrence and community structure across a diverse range of ecosystems that can aid future management of expanding bobcat populations across the U.S.A.

2. Materials and Methods

2.1 Study Area

This study was conducted across the contiguous lower 48 states of the U.S.A. (Fig. 1). The 48 states extend across a vast latitudinal range of 25.17° to 46.07° and consist of varying levels of elevation and climates resulting in a variety of land cover types and vegetation communities that comprise 10 unique ecoregions and highlight the major ecological areas of the U.S.A. (EPA, 2016; Cove et al., 2021). Further, each U.S.A. state contained at least one camera array that could be categorized by land cover type (i.e., forest, grassland, wetland, etc.) and presence along the urban-wildland gradient (i.e., urban, suburban, wildland). The myriad lands of the U.S.A. support abundant medium to large-sized predators and prey (e.g., >500 g) commonly captured on camera traps (i.e., ~192 mammal species – [Cove et al., 2021]). Members of the carnivore guild make up a substantial portion of these numbers including species such as coyote, bobcat, puma, and several foxes; some exhibit extensive ranges reaching coast to coast that experience considerable variation in environmental conditions, hunting practices, and management strategies.

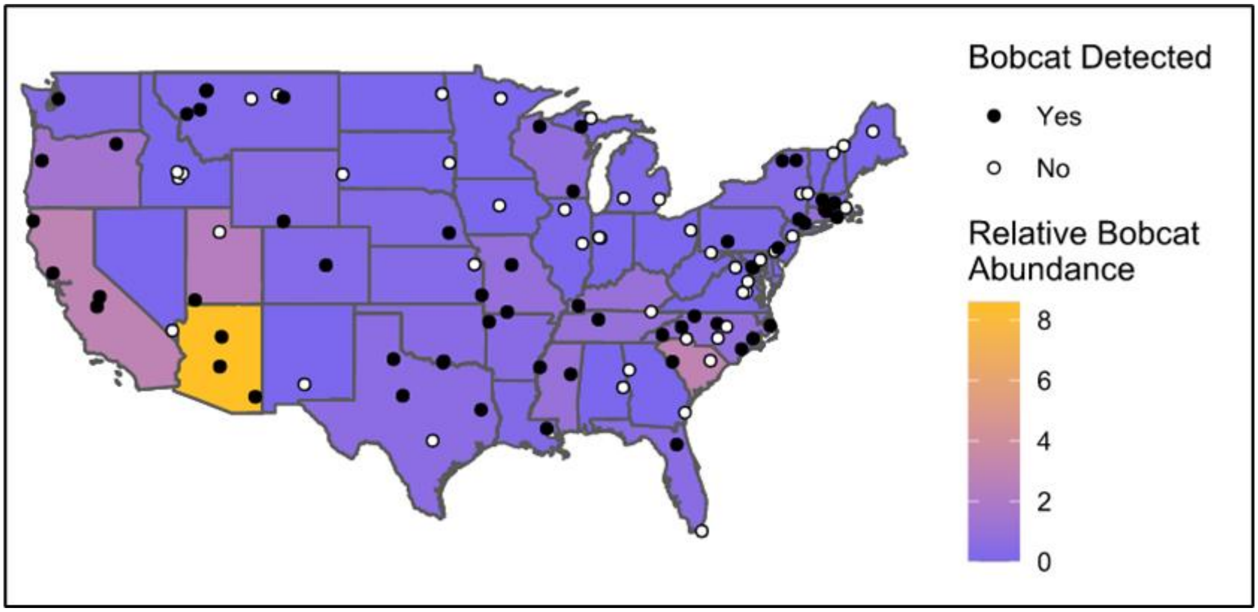

Figure 2.1 | Map of study area consisting of the 48 contiguous United States with the color of each state representing the relative abundance of bobcats inferred from camera trap detections across camera trap arrays. Dots signify whether bobcats were detected (i.e., solid) or not detected (i.e., open) at an array.

2.2 Data Acquisition

We used the Snapshot USA 2019 dataset, generated through a highly collaborative nation-wide camera-trapping initiative (Cove et al., 2021) that resulted in the first systematic effort to document annual trends and distributions of mammal communities across the United States. Snapshot USA uses the eMammal platform, a data management system and archive for camera trap research projects, to identify and store image information (McShea, 2016 - https://emammal.si.edu/snapshot-usa). A full description of Snapshot USA 2019 methods and full dataset are available at (https://doi.org/10.1002/ecy.3353).

We queried Snapshot USA 2019 data by selecting all detections from nine carnivore species (i.e., American badger [*Taxidea taxus*], bobcat, coyote, fisher [*Pekania pennanti*], gray fox, gray wolf, red fox, red wolf, and puma) that exhibit primarily carnivorous diets and appropriate sample sizes. Previous research demonstrates that 30-50 detections can provide acceptable diel pattern estimates when investigating rare species such as carnivores (Lashley et al., 2018), and we included carnivores that had at least 30 detections, as well as puma with only 29 detections because puma are expected to elicit a strong effect on bobcat activity. Our query resulted in 108 camera trap arrays from all 48 contiguous states. We defined an independent event as a single eMammal aggregated sequence, grouped as (a) consecutive images with individuals of the same or different species, and (b) images that were taken within one minute of the previous image. We calculated the relative abundance (RAB) of each carnivore species to summarize relative abundance of carnivores across ecoregions at the individual camera level using the following formula:

$$\text{RAB} = \text{events (per species)} / \text{total trap nights} \times 100$$

Due to the difficulty of estimating true abundance of species at a national scale, RAB offers a simple method for estimation, but does not account for potential bias arising from imperfect detection (Palmer et al., 2018). To accommodate these limitations, I averaged the RAB across species, ecoregions, and states and included an offset term to account for variation in survey effort across camera trap arrays (Fig 2.1).

2.3 Statistical Analyses

Statistical tests and models for all temporal and spatial analyses were implemented in RStudio version 1.3.1073 (RStudio Team, 2020).

2.3.1 Temporal Activity

We determined diel activity patterns using detection times for nine carnivore species across four different U.S.A. time zones. We anchored times to sunrise and sunset events using NOAA calculations in a Microsoft Excel VBA translation (https://peltiertech.com/ 2021). We converted sunrise and sunset times to radians via the ‘transtime’ function in the package ‘activity’ (Rowcliffe, 2021) to express detection times relative to the two solar events. We constructed 95% kernel density estimation curves using the package ‘overlap’ (Meredith & Ridout, 2020) and the estimator Δ_1 when the smaller sample was less than 50 and Δ_4 when the smaller sample was greater than 50 (Ridout and Linkie, 2009). We then estimated the mean temporal overlap coefficient (Δ;scaled from 0 to 1), and calculated confidence intervals using a bias-corrected logit-scale bootstrap of 10,000 resampled estimates for each species-species pair to determine if the two species have exclusionary ($\Delta=0$) or complete overlap ($\Delta=1$) (Ridout & Linkie, 2009; Schmid & Schmidt, 2006; Miller et al., 2018). We then performed a Watson’s Two-Sample Test of Homogeneity (Rao & SenGupta, 2001) in the package ‘circular’ (Agostinelli & Lund, 2017) to determine if times of detection for each species differed significantly from each other, as well as a Wald Test bootstrapped 1,000 times to compare activity level estimates among species. Activity level is an ecological metric that refers to the proportion of time that an animal spends active, providing an index for energy expended, foraging effort, and even vulnerability to risk (Rowcliffe et al., 2014). Finally, we repeated this process using only bobcat detections to determine whether bobcat activity patterns showed any significant differences across ecoregions, and areas of various harvest management (Elbroch, 2017) or population status (e.g., furbearer, threatened) (Roberts & Crimmins, 2010).

2.3.2 Multispecies and Single-species Occupancy Models

We created binary detection history matrices (1 = detected, 0 = not detected) using the start and end date for each camera array in the package ‘camtrapR’ version 2.0.3 (Niedballa et al., 2016), for 6 of the 9 carnivore species. We excluded badger and fisher from the occupancy analyses because these species occupy distinct ranges in the U.S.A., as well as coyotes due to the species occurring at almost every site where bobcats were detected resulting in a strong positive correlation between bobcat and coyote. Further, we combined red wolf and gray wolf into a single category, ‘wolf’, given that we expect similar responses from bobcat to both species. For our analysis, we summarized detection events at the camera array level by aggregating data across all deployments within each array. We accounted for imperfect detection by using weekly sampling occasions that included data for 8 weeks of collection, which reduced the number of observations where the count of detections is zero (Naidoo & Burton, 2020). Although this excluded data from analysis, we determined that adding additional weeks had little to no effect on improving our probability estimates given that few sites collected data longer than eight weeks, and no additional array captured a bobcat that had not been detected in the previous eight weeks. We developed two independent hypotheses: **(1)** Dominant Hypothesis: both wolf and puma will have top-down effects on bobcat spatiotemporal behavior, and **(2)** Subordinate Hypothesis: bobcat will elicit top-down effects on red and gray fox spatiotemporal behavior.

To develop our multi-species models (Rota et al., 2016), we scaled all numerical covariates (Table 2.1) and checked for correlations between all covariate pairs using the package corrplot (Wei & Simko, 2017), with a threshold of 0.7 (Dormann et al., 2013) to indicate a high correlation and a need to remove one of the correlated covariates. The only covariates that were highly correlated were minimum and maximum temperature (0.87), as well as minimum and maximum temperature with average latitude (-0.8, -0.86), thus we used latitude to account for temperature variation. We then evaluated a select group of covariates including survey days and latitude independently on the detection probability of bobcats (Table S2.2), finding that only latitude exceeded the null model. Next, we generated single-species occupancy models that included one independent covariate on occupancy probability to determine the environmental and anthropogenic factors that impact bobcat occupancy most based on AIC values (Burnham & Anderson, 2002). After investigating each covariate's effect on bobcat occupancy, we created two additive impact models: **(1)** Human Impact Model (i.e., human intensity and human population density [Table 2.1]) and **(2)** Environmental Impact Model (i.e., precipitation and gross primary production [Table 2.1]).

determine the main driver of interactions among bobcats and the two carnivore groups.

Table 2.1 | Descriptive statistics of environmental, human, and sampling covariates included in GLMMs and Occupancy models for the detections of 9 carnivore species across 108 camera trap arrays in the U.S. AIC value was calculated by running single-species occupancy models and bolded if ranked above the null model. Starred (*) Indicated inclusion in final model.

Model/Covariate	**Description**	**Max**	**Min**	**AIC Value**
Human Impact Model				
Sum of buildings	# of buildings within 500m	9071.00	0	639.16
Nearest building	average distance to nearest building (m)	5289.19	28.32	643.62
***Human population**	human pop. density (GPW) at 1km sq.	8084.00	0	643.99
***Human intensity**	# of individual human detections	6142.00	0	641.63
Cultivated land	average cultivated land at 1km sq.	0.49	0	645.18
Bobcat harvest status	protected, harvested	NA	NA	644.91
Environmental Impact Model				
Max Temperature	max temp. from nearest NOAA station (F)	31.16	8.41	644.41
Min Temperature	min temp. from nearest NOAA station (F)	25.05	-4.47	645.66
*Precipitation	3-hour avg. accumulation of precipitation	0.61	0	645.50
*GPP	average cumulative GPP at 1km sq.	25318.50	1567.99	644.32
Ecoregion	given ecoregion based on EPA Level I	NA	NA	653.40
Sampling Covariates				
Survey Days	total # of survey days	1674.00	94.00	644.90
Latitude	average latitude by array	48.12	25.23	642.82
Bobcat Pop. Status	decreasing, stable, increasing, unknown	NA	NA	648.77
Coyote Detection Rate	coyote detections per array/survey days	0.44	0	627.59

Additionally, we included a covariate for coyote detection rate in a second pair of our impact models for the dominant carnivores due to the strong association between coyote and bobcat occupancy (Table 2.1). Finally, we implemented species detection histories into multispecies occupancy models for both our dominant and subordinate hypotheses to investigate the influence of two or more interacting species (Rota et al., 2016). Each model identified the probability that two or more species would occupy the same site as a function of our selected model covariates (Rota et al., 2016).

2.3.3 Spatiotemporal Avoidance

We used detection data from 5 species (puma, coyote, gray fox, red fox, and bobcat) that had large enough sample sizes across the 108 arrays to test the relative attraction and/or avoidance of a site by bobcat after the previous visitation by another carnivore, as well as the relative attraction and/or avoidance of a site by another carnivore after a visitation by a bobcat (Parsons et al., 2016). This approach estimates spatiotemporal avoidance, or to what extent a site visited by species A is influenced by visitations of species B (Niedballa et al., 2019). We carried over our top-down effect hypotheses from our occupancy models, thus we continued to use a dominant and subordinate group of carnivores for our analyses. We used Avoidance Attraction Ratios (AARs) (Parsons et al., 2016) where odds ratios (i.e., odds of detecting species B in the absences of species A relative to the odds of detecting species B directly after an observation of species A) were calculated holding bobcat as both our species A and species B (Niedballa et al., 2019). We created AARs by converting detection times to Julian Hours, then comparing the time interval after/before a bobcat and another carnivore visited a site, referred to as the T2/T1 ratio, and then the time interval with/without the visitation of a bobcat or another carnivore, referred to as the T4/T3 ratio (Parsons et al., 2016).

Following AAR calculations, we performed three analyses using log-transformed ratios: **(1)** We used T4/T3 ratios, which are influenced solely by avoidance, to run two-tail t-tests to determine if bobcat avoided or were attracted to a site after visitation from another species, and vice versa. A mean greater than zero indicates species avoidance, whereas a mean less than 0 indicates species attraction. **(2)** We also used T4/T3 ratios to run an analysis of variance

(ANOVA) to determine (a) if bobcat are avoiding any carnivore species more than another, and (b) if any species are avoiding bobcat more than another. If we found significant effects based on an $\alpha = 0.05$, we performed a *post-hoc* Tukey-Pairwise Comparison to determine which pair of carnivores was displaying a significant relationship, as well as the magnitude difference between that pair. And **(3)** using General Linear Mixed Models (GLMMs) and the T2/T1 ratios that include effects of both attraction and avoidance, we investigated whether human or environmental variables had a significant effect on bobcat response to dominant (i.e., coyote) or subordinate (i.e., foxes) carnivores based on our previously developed impact models (Table 1). An AAR value greater than 0 suggests nonrandom movement between the species, indicating that species A is avoiding the area following visitation by species B. An AAR value less than 0 suggests random movement, meaning species A is showing less avoidance/attraction of an area after the passage of species B (Parsons et al., 2016). We ran two impact models and a null model for the dominant and subordinate groups and used the package AICcmodavg (Mazerolle, 2020) to compare the strength of the model effects on bobcat avoidance and attraction.

3. Results

With data from 108 independent camera arrays across the contiguous U.S.A., I recorded a total of 4,645 detections of my nine target carnivore species (i.e., American badger, bobcat, coyote, fisher, gray fox, gray wolf, red fox, red wolf, puma). Bobcats were captured 417 times and occurred at 52 different camera arrays (Fig. 2.1). Seven other carnivore species were captured with greater than 30 detections, with coyotes having the largest sample size (2,405 detections) and making up almost half of the total detections (Table 2.3).

Coyotes had the highest nationwide RAB (4.61) and were the only carnivore detected in the Tropical Wet Forests ecoregion, which was unsurprising given that coyotes were detected at

>90% of sites. Red fox was also highly prevalent nationwide with a total RAB of 3.68. At the ecoregion level, bobcats were most prevalent in the southern semi-arid highlands, but this ecoregion consisted of only one independent site. Further, the Mediterranean ecoregion consisted of multiple sites and hosts the highest RAB for both coyote (19.79) and gray fox (18.79), along with the second highest for bobcat (4.03). In addition, I observed increasing coyote RAB with increasing bobcat RAB across all ecoregions (Table 2.2).

Table 2.2 | Summary of RAB values for each carnivore species at the national level and ecoregion level. Bolded values represent the highest RAB value for each species. (N = northern, E.T.=eastern temperate, N.W.F.M.=northwestern forested mountains, S.S.=southern semiarid, T.W.=tropical wet).

Group	***A. Badger***	***Bobcat***	***Coyote***	***Fisher***	***G. Wolf***	***G. Fox***	***Puma***	***R. Fox***	***R. Wolf***
Nationwide	0.09	0.78	4.61	0.17	0.05	0.95	0.05	3.68	0.04
Ecoregions									
Marine	0.00	0.79	4.40	0.26	0.00	1.34	0.18	0.00	0.00
Desert	**0.70**	1.63	7.61	0.00	0.00	0.14	0.00	**13.08**	0.00
Great Plains	0.28	0.25	5.32	0.00	0.01	0.04	0.03	0.01	0.00
Mediterranean	0.00	4.03	**19.79**	0.00	0.00	**18.79**	0.00	0.00	0.00
N. Forests	0.02	0.24	1.96	**0.47**	**0.31**	0.17	0.00	0.49	0.00
Temp. Sierra	0.68	2.61	7.85	0.00	0.00	2.61	0.33	0.00	0.00
E.T. Forest	0.00	0.45	3.47	0.21	0.01	0.45	0.00	4.37	**0.12**
N.W.F.M.	0.02	0.60	3.69	0.02	0.21	2.96	**0.49**	2.84	0.00
T.W. Forest	0.00	0.00	0.48	0.00	0.00	0.00	0.00	0.00	0.00
S.S. Highlands	0.42	**13.57**	7.52	0.00	0.00	2.61	0.33	0.00	0.00

3.1 Temporal Overlap

All carnivores showed primarily nocturnal activity patterns (Fig. 2.2), with the percent of time being active during nocturnal hours (i.e., between sunset and sunrise) being over 50% for eight out of the nine species, with the exception being the fisher with 48% nocturnal activity (Table 2.3). The bobcat had the third lowest percent nocturnality at 65%, while the red wolf had the highest percent of nocturnal activity at 93%. Daily activity peaks occurred before sunrise and after sunset for all species except for fisher and gray wolf, which have a large peak following sunrise. Temporal activity overlaps between bobcat and each carnivore species varied from 0.69 to 0.90 with the coyote showing the highest overlap and the red wolf showing the lowest (Table 2.3).

Table 2.3 | Summary of detections, overlap estimates, overlap confidence intervals, and activity level estimates for bobcat and 8 carnivore species at the national scale. Percent nocturnal includes all detection occurring outside the approximate bounds of sunrise and sunset throughout the study period.

Species	*Sample Size*	*OverlapEst*	*Overlap CI*	*Activity Level Est.*	*% Nocturnal*
Bobcat	417	------------	-------------------	0.640	65%
Coyote	2405	0.9046	0.8519 – 0.9344	0.632	68%
Fisher	75	0.7674	0.6335 – 0.8501	0.444	48%
Gray Fox	466	0.7383	0.6637 – 0.7735	0.464	85%
Gray Wolf	32	0.8061	0.6828 – 0.9098	0.475	50%
Red Fox	1570	0.8102	0.6932 – 0.9173	0.463	81%
A. Badger	37	0.8391	0.7351 – 0.9234	0.508	74%
Red Wolf	31	0.6942	0.5847 – 0.7781	0.340	93%
Puma	29	0.7583	0.2248 – 0.9961	0.431	85%

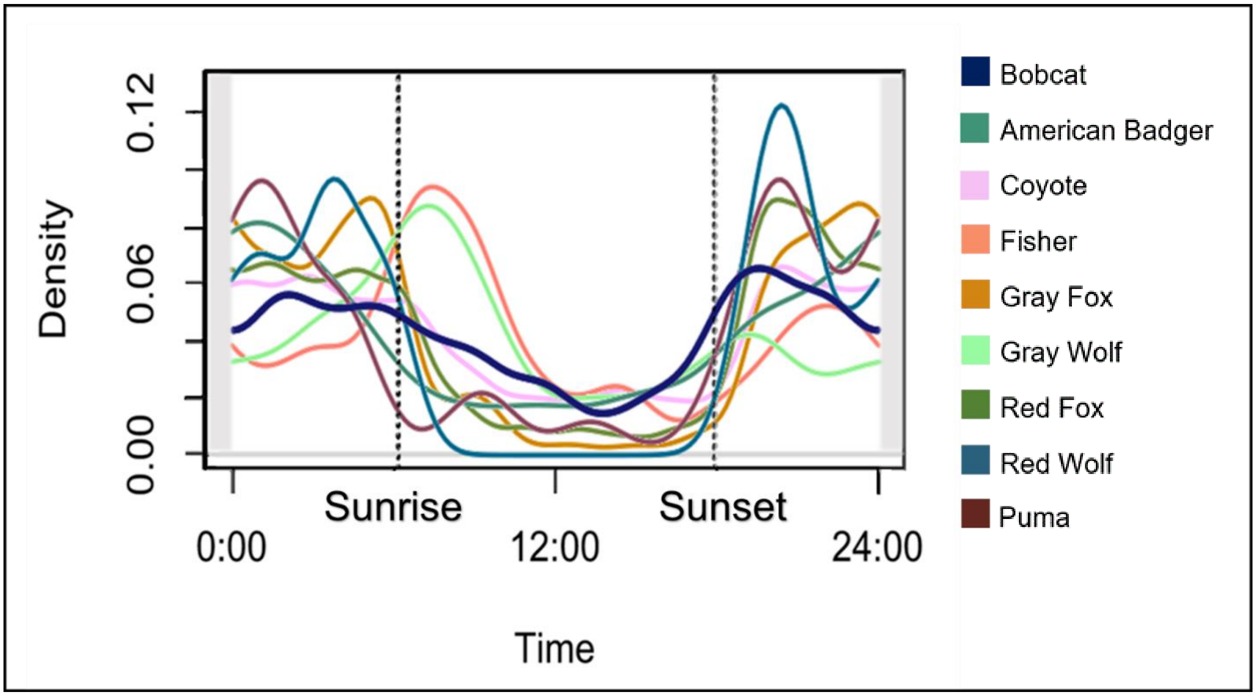

Figure 2.2 | The kernel density graph displays the temporal activity patterns of all nine carnivores using nationwide detections. Vertical black lines indicate sunrise and sunset.

Activity level estimates reveal that bobcats spend the greatest proportion of the day active (0.640), followed by coyote (0.632), both spending greater than 10% more time active than the other seven carnivore species examined. When further comparing activity level estimates, the bobcat had a significantly higher activity level than the fisher, gray fox, red fox, red wolf, and puma (Table 2.4). Distribution of bobcat temporal activity was significantly different from all eight carnivores considered, with the greatest variation between the bobcat and gray fox (U^2 test = 1.717) (Table 2.4). No significant differences for activity distribution were found between harvest status and population status, but activity level estimates were significantly different for regions where the bobcat population was increasing (act = 0.616) vs. decreasing (act = 0.375). The decreasing populations' activity plot shows little to no activity in the afternoon but then a strong peak nearing midnight, while the increasing populations' have a steadier activity pattern throughout the day (Figure S2.1). Two pairings of ecoregions returned significant values when comparing the activity distribution (Northern Forests-Eastern Temperate Forests [U^2 test = 0.194]; Southern Semiarid Highlands-Eastern Temperate Forests [U^2 test = 0.229]) (Table S2.4 and Table S2.5). Several paired ecoregions also displayed significant differences in bobcat activity level (Table S2.5), which could be a result of different carnivore community make-up as you move across the U.S.

Table 2.4 | Displays a matrix using two statistical tests to compare the temporal activity of nine carnivore species. I set my alpha value at 0.05 and all significant differences between species are bolded. **Top Right:** Watson's non-parametric two sample U^2 test to determine if samples of two species differ significantly. Test statistic is significant when >0.187. **Lower Left:** Wald test with 1000 bootstraps to statistically compare activity level estimates for fitted activity distributions between two species. Wald statistic is provided.

	Bobcat	**Coyote**	**Fisher**	**Gray Fox**	**Gray Wolf**	**Red Fox**	**Red Wolf**	**Badger**	**Puma**
Bobcat		**0.299**	**0.343**	**1.717**	**0.191**	**1.291**	**0.291**	**0.139**	**0.234**
Coyote	0.022		**0.428**	**1.506**	**0.243**	**1.441**	0.180	0.080	**0.166**
Fisher	**4.759**	**2.117**		**1.035**	0.028	**0.839**	**0.462**	**0.308**	**0.364**
G. Fox	**8.821**	**21.713**	0.011		**0.594**	**0.492**	0.053	0.072	0.097
G. Wolf	2.008	2.165	0	0.011		**0.484**	**0.438**	**0.238**	**0.355**
R. Fox	**9.605**	**27.376**	0.013	0	0.013		0.071	0.059	0.077
R. Wolf	**12.619**	**17.289**	1.188	2.964	1.208	3.080		0.056	0.036
Badger	1.836	2.099	0.059	0.250	0.059	0.268	2.507		0.039
Puma	**6.034**	**8.009**	0.127	0.207	0.129	0.208	0.927	0.520	

3.2 Occupancy Modelling

3.2.1 *Single-species Occupancy Modeling*

The highest ranked single-species models for bobcat included only human-related covariates, latitude, and coyote detection rate, but no environmental covariates. Latitude was excluded from our final models despite its significance as there was no biological reason to include it, and given that our dataset had an eight-week cumulative detection probability of ~99% when bobcats were present. Further, bobcat were detected across the entire north-south range of the study area and their detection rate was not correlated with latitude. Sum of buildings was also excluded despite its significance, which was attributed to the idea that human population density would capture the same information as buildings despite them not being highly correlated, as well as complicating the "Human Impact Models" and minimizing effects of other covariates.

3.2.2 Multispecies Occupancy Modeling

Dominant Hypothesis | The ‘Human Impact’ model with the addition of coyote detection rate as a covariate was the top ranked model for investigating top-down effects of wolves and pumas on bobcats (Table S2.6). Bobcat occupancy was negatively affected by human population (β = -0.054, ±0.393SE) and human presence (β = -3.604, ±1.891SE), but a positive association with coyote detection rate (β = 1.932, ±0.520SE) was observed. Human population had a strong negative association with interactions between the bobcat and wolves (β = -4.588, ±8.537SE), as well as between bobcat and puma (β = -3.557, ±7.274SE). Increasing human intensity β = 0.062, ±4.454SE) and increased coyote rate (β = 0.006, ±0.357SE) both had a positive effect on the interaction between pumas and bobcats but for wolves these effects were negative (Table S2.7).

Subordinate Hypothesis | The ‘Environmental Impact’ model was the top-ranked model for the top-down effects that bobcats have on red and gray foxes (Table S2.8). Bobcat occupancy showed a positive relationship with both gross primary production (β = 0.073, ±0.266SE) and precipitation (β = 0.398, ±0.245SE). Interactions between the red fox and bobcat were also positively correlated and increased with gross primary production (β = 0.452, ±0.341SE) and precipitation (β = 0.136, ±0.297SE), but a different trend was observed for the gray fox (Figure S2.2). The interaction between bobcats and gray foxes were positively associated with increased gross primary production (β = 0.186, ±0.314SE), but precipitation was found to have a significant negative association (β = -1.348, ±0.469SE) with the species interactions (Table S2.9).

3.3 Spatiotemporal Avoidance

T-Tests | Due to the low sample size for multiple carnivores, AARs were only calculated for the coyote and foxes (i.e., gray fox and red fox) when performing t-tests. When holding the bobcat as species A, the bobcat displayed avoidance of coyotes (T-test: meanT4/T3 = 0.815, t = 6.199, p = 1.256e-06) as well as avoidance of foxes (T-test: meanT4/T3 = 0.677, t = 3.481, p = 0.006). When holding bobcat as species B, coyote (T-test: meanT4/T3 = -0.184, t = -2.807, p = 0.007) displayed attraction to bobcats while foxes (T-test: meanT4/T3 = 0.036, t = 0.147, p = 0.885) avoided bobcats (Table S2.10).

Analysis of Variance (ANOVA) | I used one-way ANOVA to **(a)** determine if bobcats were avoiding any species more than another, and **(b)** determine if any species was avoiding bobcats more than another species. For this analysis, I included all species that had multiple AAR values, even with low sample sizes (i.e., red fox [4], puma [4]). Bobcats were found to avoid species differently (F = 2.843, df = 3, p = 0.050) (Table S2.11), but there was only one significant pairing in which bobcats avoided pumas more than coyotes (Tukey Pairwise Comparison, mean diff = -1.058, CI [-2.034, -0.082]). Further, no carnivore species were found to avoid bobcats significantly more than another (F = 0.688, df = 4, p = 0.603) (Table S2.12).

General Linear Mixed Models | Linear mixed effects models were run to determine what effect covariates have on the avoidance or attraction of bobcats to other carnivores using the two impact models as well as a null model for comparison.

Dominant | The dominant model held bobcat as species A and the dominant carnivores as species B. The 3 models were compared using AIC weights, but neither impact model had a greater model weight than the null model (AICc = 0.70; Table S2.13 and Table S2.14).

Subordinate |The subordinate models held subordinate carnivores as species A and the bobcat as species B. Comparing the 3 models using AIC weights, the human impact model ranked highest with the greatest model weight (AICc = 0.80, $R^2 = 0.400$). Human intensity showed a near significant positive effect ($\beta = 0.164$; $p = 0.059$) and population density had a significant negative effect ($\beta = -0.204$; $p = 0.024$) (Table S2.14). Although population density was found to be significant, this strong relationship was primarily driven by two values that were extreme outliers following an outlier test using percentiles (97.5 percentile < 2760.456) (Fig. 2.3). However, I did not exclude these data from my analysis as it still reflected real-world data that could potentially reveal an important relationship if I were to add additional data to the model.

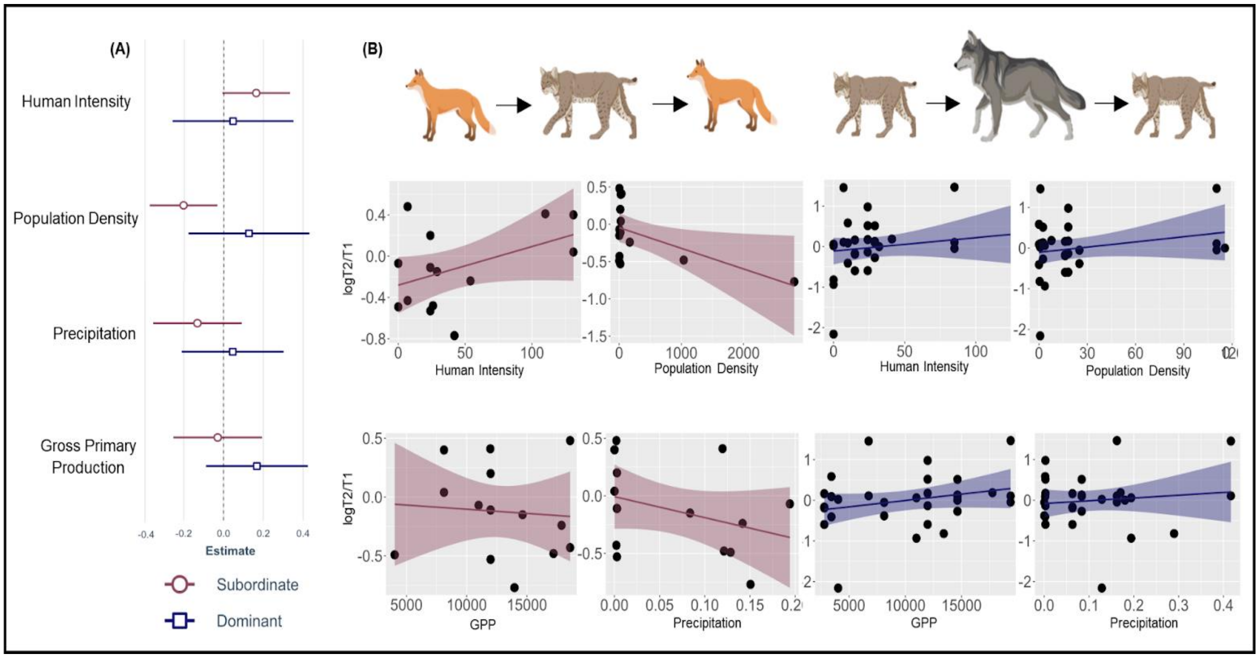

Figure 2.3 | (A) Displays the covariate effects and 95% confidence interval for all 'impact model' covariates for both dominant and subordinate carnivores. **(B)** Displays the relationship between each model covariate and the logT2/T1 ratio for dominant (i.e., blue) and subordinate (i.e., red) carnivores with bands representing 95% confidence intervals.

4. Discussion

Many studies have investigated the spatiotemporal behavior of carnivores across a single habitat type or region, yet few have encompassed a study area as large and diverse in both ecosystem structure and carnivore diversity as the contiguous United States. My large-scale survey of carnivore activity included nine species including my focal species (i.e., bobcat). The bobcat was found to show a consistent distribution of temporal activity across the variable U.S. landscape, with some variation seen among ecoregions providing evidence that the bobcat can persist and possibly adapt to many different types of ecosystems with variable environmental factors. However, I found the distribution of activity to be significantly different from each of the eight other carnivore species. Furthermore, I found evidence that bobcats respond differently on a large spatial scale to dominant carnivores (i.e., wolves, puma) and subordinate carnivores (i.e., foxes), with fluctuating impacts mediated by human and environmental factors. Based on my 'Human Impact' model, I determined that bobcats displayed a weaker random avoidance response to dominant carnivores when there was an increase in human intensity, but a stronger nonrandom avoidance response to subordinate carnivores (Fig. 2.3). This could support the human-shield hypothesis (Clinchy et al., 2016), which would suggest that bobcats are using humans to shield themselves from potential interactions with dominant carnivores. Thus, when human intensity is high, I found bobcats seemingly paying less attention to avoiding dominant carnivores. Finally, my multispecies occupancy models provided evidence that the relationships between bobcats and either dominant or subordinate carnivores are primarily influenced by different types of variability. Dominant carnivores were observed to be strongly impacted by human-related factors, while subordinate carnivores were affected more by environmental factors. My findings suggest that across the bobcats' range their responses to dominant and subordinate carnivores vary, as well as what types of factors drive these responses. Given that the 'Human Impact' model best explained the dominant carnivores' effects on bobcat occupancy and that bobcats themselves were primarily impacted by anthropogenic factors, these results suggest that bobcats may act in a dominant or apex capacity in the absence of wolves and pumas.

Throughout this study, I addressed the differing effects that both dominant and subordinate carnivores had on the temporal and spatial activity of bobcats. My findings indicate that bobcats had the highest detected activity level of the species I evaluated, suggesting that bobcats may be able to mediate competition through increased behavioral plasticity allowing for a flexible temporal activity pattern (Frey et al., 2017). Greater plasticity in temporal behavior can allow bobcats to adjust their daily activity and respond to the presence or absence of potential competitors, as well as avoid being constrained by accessibility to prey by utilizing time periods when many common prey species (i.e., squirrels chipmunks) are most active (Monterroso et al., 2014). Spatiotemporally, I found a similar trend. Bobcats showed avoidance of all species tested (Stable S2.10), while no carnivore avoided bobcats more than another. However, I found that the small subordinate foxes (i.e., red and gray) did avoid bobcats (Table S2.10), although not significant, still suggests bobcats being dominant over foxes, especially in more urban areas (Suraci et al., 2017).

My multispecies occupancy models revealed differing trends for what factors impacted and affected relationships among carnivore community members. Dominant carnivores and their relationship with bobcats were highly associated with human factors (i.e., population density, human presence), but varying effects were observed for wolves and pumas. Human factors negatively affected bobcat-wolf interactions, which may be a result of wolves commonly utilizing man-made features such as low-use roads and trails to traverse the landscape (Lesmerises et al., 2013), a trend not observed in bobcats. On the other hand, human intensity resulted in a positive effect on bobcat-puma interactions as well as coyote detection rate. Although these positive interactions were weak, these results provide an example of how humans may act as shields (Clinchy et al., 2016) against pumas (Table S2.7), and how coyotes adapt, associate, and can be rewarded by living in urban environments (Breck et al., 2019; Cove et al., 2012). The relationship between bobcats and the fox species was most supported by environmental factors (i.e., GPP, precipitation), with increased GPP having an overall positive effect for increasing interactions (Stable S2.8). Increased GPP could result in areas with more vegetative growth and land cover that could be beneficial for these smaller species to hide and avoid potential threats. Interactions between the bobcat and gray fox were strongly driven by precipitation, with an increase in average 3-hour precipitation throughout the study period decreasing the interactions of the two species. This negative effect was not observed for the red fox, thus precipitation is affecting the two foxes differently. Increased average precipitation could serve as an index for vegetative growth, which could have an additive effect with GPP making certain environments less suitable for gray foxes which are present across many rocky, grassland areas. The differences in how the red and gray fox respond to environmental variables may allow them to spatial partition themselves across the landscape and avoid direct competition.

The relationship between bobcats and coyotes was found to be different than that of bobcats and any other carnivores. Specifically, coyotes were recorded at nearly every site bobcats were captured, were the only species to show an attraction to bobcats, and to have ~90% temporal overlap with bobcats (Table 2.3). Given the high correlation between these two species that share both time and space, I would expect to find differences in their diet that allow them to coexist at such a high level (Hutchinson, 1957). For example, bobcats are strictly carnivorous, whereas coyotes are highly adaptable and omnivorous allowing them to be ubiquitous across the U.S. and feed on a variety of food sources (Breck et al., 2019; Drake et al., 2021). The differences in diet may allow these two species to coexist so closely in space and time, but coyotes being attracted to bobcats could potentially be a result of coyotes seizing opportunities to locate bobcat kills that they may be able to scavenge (Allen et al., 2015). Finally, coyotes had a strong influence on the effect of human intensity when running the single-species occupancy models. When predicting the interaction between human intensity and the detection rate of coyotes on bobcat occupancy, I observed a rapid decrease in occupancy as human intensity increased. Given that coyotes have been found to adapt and utilize human-modified habitats (Breck et al., 2019) and bobcats are known to exhibit a preference to avoid coyotes spatially, and the interaction of these two factors greatly increased the negative effect of human intensity on bobcat occupancy. Based on my findings there is a strong correlation between bobcat and coyote site use, but bobcats display higher sensitivity to human factors which is observed in the negative effect from human intensity across the landscape.

The Snapshot USA data used for analyses was the result of a highly collaborative effort by researchers across the country, giving us the first ever nationwide camera trapping dataset, yet for many carnivores that are considered rare, more data is still needed to produce robust results that allow us to fully understand the complex carnivore community across the U.S. My findings revealed that the bobcat is an adaptable predator that coexists with several dominant and subordinate carnivores across the U.S., showing variation in activity and occupancy based on the community structure, environmental and anthropogenic factors. Bobcats have the potential to act in different capacities among the Carnivora, driven by the presence of dominant carnivores such as wolves and pumas. Furthermore, my results provide evidence that bobcats may help facilitate a behavioral cascade among dominant carnivores (i.e., wolves, puma) and subordinate carnivores (i.e., foxes), but more research must be conducted to assess whether these findings hold across the U.S. (Shores et al., 2019). Addressing the relationships within diverse carnivore communities such as the one found in the U.S. is essential for understanding how anthropogenic change will continue to influence wildlife communities.

SUMMARY AND CONCLUSIONS

I investigated intraguild interactions among members of the U.S. carnivore guild, which can be mediated by a variety of anthropogenic and environmental factors that influence species' temporal and spatial patterns. For example, I found that human activity is the primary driver of large carnivore temporal and spatial activity across the landscape, with different types of human recreation resulting in similar effects. I was also able to discern variation in factors that drive interactions among dominant and subordinate carnivores within the U.S. carnivore community using a well-established mesocarnivore that inhabits a variety of ecosystems across the country as a focal species.

My research addresses relationships within a diverse carnivore community and how it can be strongly influenced by guild make-up and human activity ranging from urbanization to human recreation. My findings help to better understand intraguild interactions among members of the carnivore community and how their differing activity patterns support carnivore coexistence, and how anthropogenic change can influence entire wildlife communities by driving top-town effects. As such, my work will inform wildlife managers and policy makers on decisions to reduce the negative impact of recreational activities on sensitive and recolonizing wildlife, as well as educate the public on the importance of preserving protected spaces to benefit species of conservation and management concern.

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APPENDIX A

SUPPLEMENTARY 1: CHAPTER 1 TABLES

Table S1.1 | Detection history of American black bears. Locations 1-30 represent detections before hibernation. Locations 31-60 represent detections after hibernation.

Location	o1	o2	o3	o4	o5	o6	o7	o8	o9	o10	o11	o12	o13	o14	o15	o16	o17	o18
Camera 1	1	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 2	1	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 3	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 4	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 5	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 6	0	0	0	1	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 7	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 8	1	1	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 9	1	1	1	0	1	0	1	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 10	1	1	1	1	1	0	1	1	1	0	0	0	0	NA	NA	NA	NA	NA
Camera 11	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 12	0	1	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 13	0	1	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 14	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 15	1	0	1	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 16	0	0	1	1	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 17	0	0	1	1	0	0	0	0	0	0	0	0	1	NA	NA	NA	NA	NA
Camera 18	1	1	0	0	0	0	0	0	0	0	1	0	0	NA	NA	NA	NA	NA
Camera 19	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 20	0	0	0	0	0	1	0	0	0	1	0	0	0	NA	NA	NA	NA	NA
Camera 21	0	1	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 22	0	1	1	1	0	0	0	1	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 23	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 24	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 25	1	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 26	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 27	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 28	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA

Camera 29	0	0	0	0	1	0	0	1	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 30	0	0	0	0	0	0	0	0	0	0	0	0	0	NA	NA	NA	NA	NA
Camera 31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 33	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0
Camera 34	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
Camera 35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 40	1	1	1	0	1	1	1	1	1	0	1	1	0	0	0	0	0	0
Camera 41	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Camera 42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 43	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Camera 44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 45	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	1	0
Camera 46	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
Camera 47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 48	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Camera 49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Camera 50	0	0	0	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0
Camera 51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 53	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 57	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Camera 58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Camera 59	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Camera 60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table S1.2 | Results for all single-species single factor models on detection probability of black bears in order of weighted AIC.

Model Group	Covariate	AIC	ΔAIC	Model Weight
Human Impact	Protected Land	458.27	0.00	1.00
-------------------------------	Null	483.14	24.88	<0.01
Environmental Impact	Season	483.67	25.40	<0.01

Table S1.3 | Results for all single-species single factor models on occupancy probability of black bears in order of weighted AIC. Detection covariates included in all models.

Model Group	Covariate	AIC	ΔAIC	Model Weight
Human Impact	Population Density	454.65	0.00	0.144
Human Impact	Human Presence	455.06	0.41	0.117
Human Impact	Human Count	455.61	0.96	0.089
Human Impact	Human On-Foot	455.90	1.25	0.077
Human Impact	Domestic Dog Present	456.09	1.44	0.065
Human Impact	Human Non-motorized	456.25	1.60	0.065
Human Impact	Passenger Vehicle Present	456.39	1.74	0.060
Human Impact	Sum of Human Impact	456.64	1.99	0.053
-------------------------------	Null Model	457.00	2.35	0.044
Human Impact	Number of Dogs	457.22	2.57	0.040
Human Impact	Recreation Vehicle Present	457.46	2.81	0.039
Human Impact	Distance to Road	457.46	2.81	0.035
Environmental Impact	Season	458.34	3.69	0.023
Environmental Impact	Elevation	458.52	3.87	0.021
Human Impact	Gun Present	458.68	4.03	0.019
Human Impact	Utility Vehicle Present	458.68	4.04	0.019
Environmental Impact	Landcover Type	458.79	4.15	0.018
Human Impact	Protected Land	458.95	4.30	0.017
Environmental Impact	Nearest Water Source	458.99	4.34	0.016
Human Impact	Number of Vehicles	459.00	4.35	0.016
Human Impact	Land Ownership	459.18	4.53	1.015

APPENDIX B

SUPPLEMENTARY 2: CHAPTER 2 FIGURES

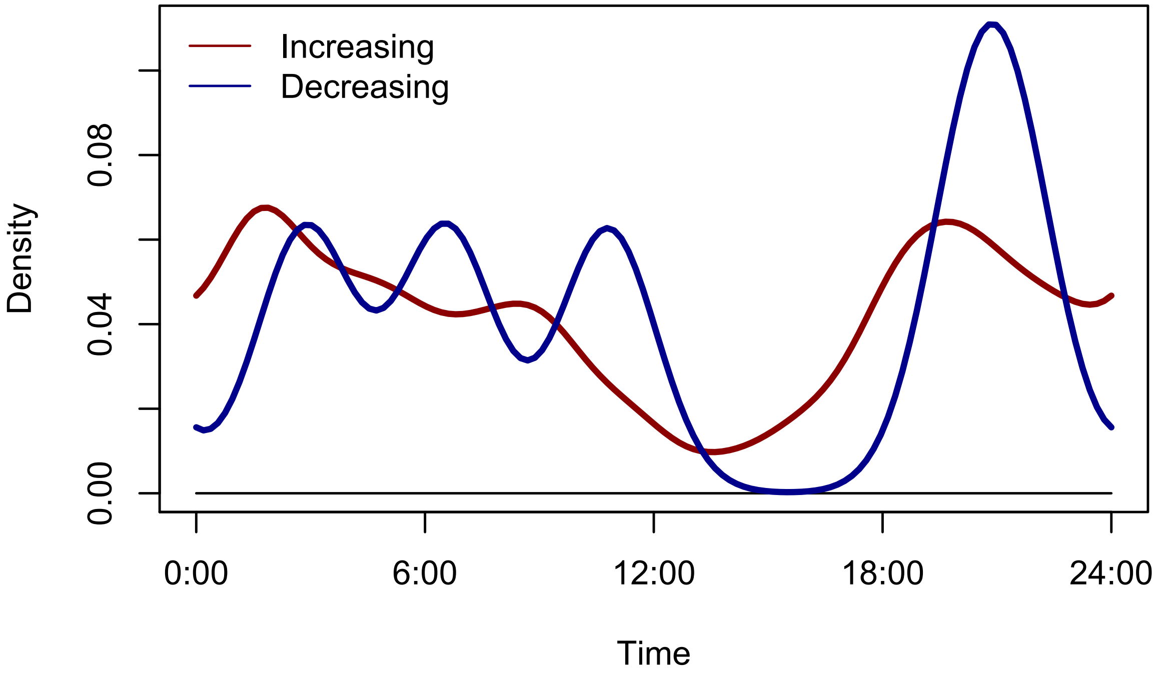

Figure S2.1 | Displays bobcat activity in states with increasing (red) vs decreasing (blue) populations.

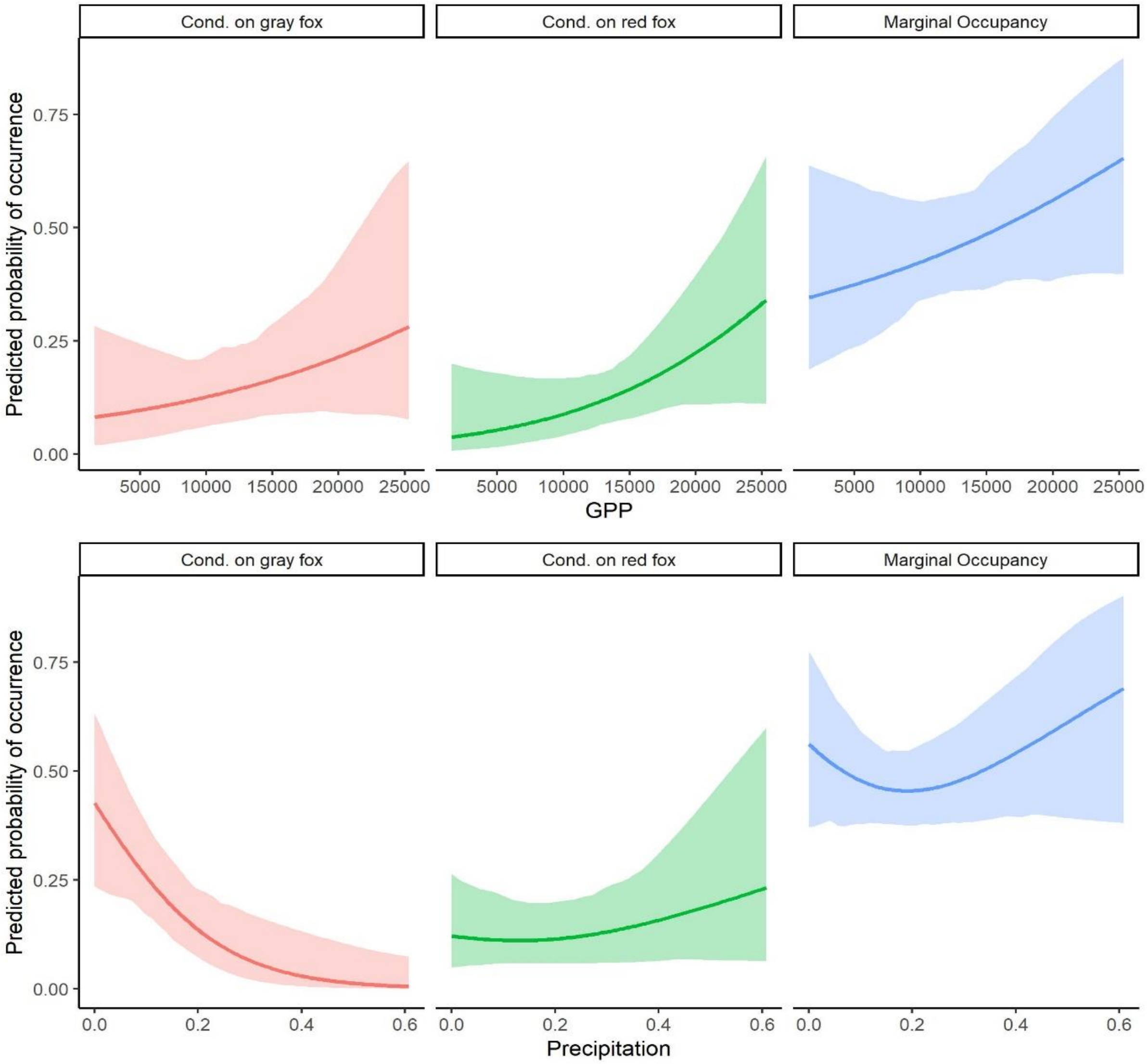

Figure S2.2 | Displays the effects of selected environmental covariates (i.e., precipitation and gross primary production) on the subordinate carnivores (i.e., red and gray fox).

APPENDIX C

SUPPLEMENTAL 3: CHAPTER TWO TABLES

Table S2.1 | Bobcat detection history across all 108 arrays for 8 weeks.

o1	o2	o3	o4	o5	o6	o7	o8
0	0	0	0	NA	NA	NA	NA
0	0	0	0	0	1	0	NA
1	1	1	1	1	1	1	1
0	0	0	1	1	1	1	1
1	0	1	1	0	1	0	0
0	0	0	0	0	0	0	0
1	1	1	1	0	1	0	0
1	1	1	1	1	1	1	1
0	0	1	1	1	1	1	0
0	0	1	0	0	1	0	0
0	0	0	0	0	0	0	NA
1	0	1	0	0	1	NA	NA
0	1	0	NA	NA	NA	NA	NA
0	0	0	0	NA	NA	NA	NA
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
1	1	1	1	1	0	NA	NA
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	NA	NA
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0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	NA	NA	NA
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0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
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1	1	0	0	NA	NA	NA	NA
1	0	0	0	0	0	0	NA
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0	0	0	0	0	0	0	0

0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0
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1	1	0	1	1	0	0	NA
0	0	0	0	0	0	0	NA
0	0	0	0	0	1	1	0
1	0	0	0	1	1	1	0
0	0	0	1	0	0	0	NA
0	0	0	0	0	0	0	NA
1	0	0	0	1	1	0	NA
0	0	0	0	NA	NA	NA	NA
1	1	0	0	0	0	0	NA
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0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	NA	NA	NA
0	1	1	1	0	1	1	0
0	0	0	0	0	NA	NA	NA
0	1	0	0	0	0	0	0
0	0	1	0	0	0	NA	NA
0	0	0	0	0	0	0	1

0	0	0	0	0	0	0	0
1	0	0	NA	NA	NA	NA	NA
0	0	1	NA	NA	NA	NA	NA
0	1	1	0	1	1	0	NA
1	1	1	1	0	0	NA	NA
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0	0	0	0	0	0	0	NA
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1	1	0	1	1	1	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	NA	NA	NA
1	0	0	0	0	0	0	1

Table S2.2 | Results for selected single factor detection covariate models on probability of detecting a bobcat in order of weighted AIC.

Model Group	Covariate	AIC	ΔAIC	Model Weight
Sampling	Latitude	638.98	0.00	0.891
------------------------------	Null	643.84	4.86	0.078
Sampling	Survey Days	645.73	6.75	0.030

Table S2.3 | Results for all single-species single factor models on occupancy probability of bobcats in order of weighted AIC. No detection covariates included.

Model Group	Covariate	AIC	ΔAIC	Model Weight
Sampling	Coyote Detection Rate	627.59	0.00	0.99
Human Impact	Human Presence	639.16	11.57	<0.01
Human Impact	Human Population Density	641.63	14.05	<0.01
Sampling	Latitude	642.82	15.23	<0.01
Human Impact	Sum of Buildings	643.62	16.03	<0.01
------------------------------	Null	643.84	16.26	<0.01
Human Impact	Nearest Building	643.99	16.40	<0.01
Environmental Impact	Gross Primary Production	644.32	16.73	<0.01
Environmental Impact	Maximum Temperature	644.41	16.82	<0.01
Sampling	Survey Days	644.90	17.31	<0.01
Human Impact	Hunting Status	644.91	17.32	<0.01
Human Impact	Cultivated Land	645.18	17.60	<0.01
Environmental Impact	Precipitation	645.50	17.91	<0.01
Environmental Impact	Minimum Temperature	645.66	18.08	<0.01
Sampling	Population Status	648.77	21.19	<0.01
Environmental Impact	Ecoregion	654.40	25.81	<0.01

Table S2.4 | Results for bobcat activity level estimates by ecoregion, harvest status, and population status.

Ecoregion	Activity Level Est.	Population Status	Activity Level Est.	Hunting Status	Activity Level Est.
Southern Semiarid Highlands	0.503	increasing	0.616	hunted	0.583
Temperate Sierras	0.184	decreasing	0.375	protected	0.576
Northwestern Forested Mtns.	0.419	stable	0.605		
Marine West Coast Forest	0.411				
Northern Forests	0.423				
Great Plains	0.452				
Mediterranean	0.184				
North American Deserts	0.584				
Eastern Temperate Forest	0.601				

Table S2.5 | Results for temporal analysis comparing bobcat harvest status categories, bobcat population status categories, and ecoregions to determine if times of detections differed for the between any pairings. Significance level 0.05. Critical value = 0.187. Near Significant 0.05< p-value<0.10.

Marine = Marine West Coast Forest; Plains = Great Plains; N. Forest = Northern Forests; E.T. Forests = Eastern Temperate Forests; Desert = North American Deserts; Sierras = Temperate Sierras; N.W.F.M. = Northwestern Forested Mountains; Mediterranean = Mediterranean California; S.S. Highlands = Southern Semiarid Highlands.

Categories	**Wald U^2**	**Significance**	**Wald Statistic**	**Significance**
Hunt/Harvest Status				
Protected – Harvested	0.137	---------	0.004	---------
Population Status				
Increasing – Decreasing	0.027	----------	4.118	Significant
Stable – Increasing	0.105	----------	0.013	----------
Decreasing – Stable	0.037	----------	3.294	----------
Ecoregions				
Marine – Plains	0.050	----------	0.074	----------
Marine – N.W.F.M.	0.047	----------	0.003	----------
Marine – Sierras	0.086	----------	3.008	Near Significant
Marine – N. Forests	0.108	----------	0.005	----------
Marine – Desert	0.063	----------	1.759	----------
Marine – Mediterranean	0.086	----------	3.033	Near Significant
Marine – Highlands	0.091	----------	0.471	----------

Marine – E.T. Forests	0.045	----------	2.406	----------
Plains – N.W.F.M.	0.062	----------	0.055	----------
Plains – Sierras	0.140	----------	4.409	Significant
Plains – N. Forests	0.073	----------	0.037	----------
Plains – Desert	0.045	----------	1.086	----------
Plains – Mediterranean	0.140	----------	4.447	Significant
Plains – Highlands	0.063	----------	0.154	----------
Plains – E.T. Forests	0.046	----------	1.581	----------
Desert – N.W.F.M.	0.078	----------	1.913	----------
Desert – Sierras	0.125	----------	14.841	Significant
Desert – N. Forests	0.107	----------	1.477	----------
Desert – Mediterranean	0.125	----------	15.035	Significant
Desert – Highlands	0.052	----------	0.578	----------
Desert – E.T. Forests	0.142	----------	0.035	----------
Sierras – N.W.F.M.	0.179	Near Significant	3.826	Near Significant
Sierras – N. Forests	0.102	----------	3.186	Near Significant
Sierras – Mediterranean	0.023	----------	0.000	----------
Sierras – Highlands	0.107	----------	8.759	Significant
Sierras – E.T. Forests	0.142	----------	19.701	Significant
N. Forests – N.W. F. M.	0.175	Near Significant	0.001	----------
N. Forests – Mediterranean	0.102	----------	3.211	Near Significant
N. Forests – Highlands	0.058	----------	0.349	----------
N. Forests – E.T. Forests	0.194	Significant	2.035	----------
Highlands – Mediterranean	0.107	----------	8.865	Significant
Highlands – N.W.F.M.	0.113	----------	0.467	----------
Highlands – E.T. Forests	0.229	Significant	1.027	----------
N.W.F.M. – Mediterranean	0.179	Near Significant	3.863	Significant
N.W.F.M – E.T. Forests	0.056	----------	2.706	Near Significant
Mediterranean – E.T. Forests	0.142	----------	20.015	Significant

Table S2.6 | Model selection results from multispecies occupancy models for dominant carnivores.

Model	AIC	ΔAIC	Model Weight
Human Impact w/ Coyote	881.23	0.00	0.87
Environmental Impact w/ Coyote	885.10	3.87	1.00
Human Impact	900.54	19.31	1.00
Environmental Impact	905.95	24.72	1.00

Table S2.7 | Full results for top human and top environmental impact occupancy models for dominant carnivores.

Model	Interaction	Covariate	Estimate	SE	P-value
Human Impact w/ Coyote	bobcat	Human Population Density	-0.054	0.393	8.91e-01
Human Impact w/ Coyote	bobcat	Human Presence	-3.604	1.8191	5.67e-02
Human Impact w/ Coyote	bobcat	Coyote Detection Rate	1.932	0.520	2.05e-04
Human Impact w/ Coyote	bobcat	Intercept	-0.502	0.395	2.04e-01
Human Impact w/ Coyote	wolves	Intercept	-2.425	0.547	9.22e-06
Human Impact w/ Coyote	puma	Intercept	-2.730	0.629	1.43e-05
Human Impact w/ Coyote	bobcat:wolves	Human Population Density	-4.588	8.537	5.91e-01
Human Impact w/ Coyote	bobcat:wolves	Human Presence	-0.409	6.673	9.51e-01
Human Impact w/ Coyote	bobcat:wolves	Coyote Detection Rate	-1.066	0.907	2.40e-01
Human Impact w/ Coyote	bobcat:wolves	Intercept	-0.999	2.993	9.51e-01
Human Impact w/ Coyote	bobcat:puma	Human Population Density	-3.557	7.274	6.25e-01
Human Impact w/ Coyote	bobcat:puma	Human Presence	0.062	4.454	9.89e-01
Human Impact w/ Coyote	bobcat:puma	Coyote Detection Rate	0.006	0.357	9.86e-01
Human Impact w/ Coyote	bobcat:puma	Intercept	-0.117	2.503	9.63e-01
Environ. Impact w/ Coyote	bobcat	Gross Primary Production	0.719	0.284	1.15e-02
Environ. Impact w/ Coyote	bobcat	Precipitation	0.216	0.303	4.75e-01
Environ. Impact w/ Coyote	bobcat	Coyote Detection Rate	1.991	0.590	7.36e-04
Environ. Impact w/ Coyote	bobcat	Intercept	0.005	0.295	9.87e-01
Environ. Impact w/ Coyote	wolves	Intercept	-2.415	0.547	1.02e-05
Environ. Impact w/ Coyote	puma	Intercept	-2.703	0.618	1.21e-05
Environ. Impact w/ Coyote	bobcat:wolves	Gross Primary Production	-0.679	0.627	2.78e-01

Environ. Impact w/ Coyote	bobcat:wolves	Precipitation	0.567	0.481	2.38e-01
Environ. Impact w/ Coyote	bobcat:wolves	Coyote Detection Rate	-1.301	0.979	1.84e-01
Environ. Impact w/ Coyote	bobcat:wolves	Intercept	0.228	0.814	7.79e-01
Environ. Impact w/ Coyote	bobcat:puma	Gross Primary Production	-0.498	0.499	2.89e-01
Environ. Impact w/ Coyote	bobcat:puma	Precipitation	0.136	0.412	3.19e-01
Environ. Impact w/ Coyote	bobcat:puma	Coyote Detection Rate	-0.062	0.377	7.41e-01
Environ. Impact w/ Coyote	bobcat:puma	Intercept	0.839	0.791	8.70e-01

Table S2.8 | Model selection results from multispecies occupancy models for subordinate carnivores.

Model	AIC	ΔAIC	Model Weight
Environmental Impact	1571.46	0.00	0.53
Human Impact	1577.17	5.71	1.00

Table S2.9 | Full results for top human and top environmental impact occupancy models for subordinate carnivores.

Model	Interaction	Covariate	Estimate	SE	P-value
Environmental Impact	bobcat	Intercept	0.231	0.317	0.467
Environmental Impact	bobcat	Gross Primary Production	0.073	0.266	0.784
Environmental Impact	bobcat	Precipitation	0.398	0.245	0.104
Environmental Impact	gray fox	Intercept	-1.147	0.333	0.001
Environmental Impact	red fox	Intercept	0.223	0.285	0.436
Environmental Impact	bobcat:grayfox	Intercept	0.385	0.517	0.457
Environmental Impact	bobcat:grayfox	Gross Primary Production	0.186	0.314	0.553
Environmental Impact	bobcat:grayfox	Precipitation	-1.321	0.451	0.004
Environmental Impact	bobcat:redfox	Intercept	-1.321	0.451	0.003
Environmental Impact	bobcat:redfox	Gross Primary Production	0.452	0.341	0.185
Environmental Impact	bobcat:redfox	Precipitation	0.136	0.297	0.647
Human Impact	bobcat	Intercept	0.143	0.374	0.702
Human Impact	bobcat	Human Population Density	-0.778	0.612	0.203
Human Impact	bobcat	Human Presence	-0.934	1.039	0.369
Human Impact	gray fox	Intercept	-1.117	0.336	0.001
Human Impact	red fox	Intercept	0.237	0.289	0.412
Human Impact	bobcat:grayfox	Intercept	0.585	1.057	0.291
Human Impact	bobcat:grayfox	Human Population Density	-0.431	0.837	0.606
Human Impact	bobcat:grayfox	Human Presence	0.631	1.426	0.658
Human Impact	bobcat:redfox	Intercept	-1.258	0.601	0.036
Human Impact	bobcat:redfox	Human Population Density	0.837	0.647	0.195
Human Impact	bobcat:redfox	Human Presence	-0.866	2.097	0.680

Table S2.10 | Results for all two-tail t-tests analyzing spatiotemporal avoidance using AARs (T4/T3).

Species A	Species B	mean	t	Df	95% CI	p-value
bobcat	coyote	0.815	6.199	27	0.545 – 1.085	1.256e-06
bobcat	gray & red fox	0.677	3.481	10	0.244 – 1.110	0.006
coyote	bobcat	-0.184	-2.807	51	-0.316 - -0.0525	0.007
gray & red fox	bobcat	0.036	0.147	14	-0.492 – 0.565	0.885

Table S2.11 | Results for ANOVAs analyzing spatiotemporal avoidance using AARs (T4/T3). **(1)** Bobcats avoiding one carnivore more than another, and **(2)** carnivore avoiding bobcat more than another.

ANOVA	Group	df	Sum Sq	Mean Sq	F value	p-value
1	Species	3	3.947	1.316	2.843	0.050
1	Residuals	39	18.047	0.463	------	------------
2	Species	4	1.057	0.264	0.688	0.603
2	Residuals	65	24.987	0.384	------	------------

Table S2.12 | Results for Tukey Pairwise Comparison for ANOVA 1 that resulted in a significant p-value.

Species 1	Species 2	diff	lwr	upr	p adj
gray fox	coyote	-0.155	-0.827	0.518	0.926
puma	coyote	-1.058	-2.034	-0.082	0.029
red fox	coyote	0.025	-1.833	1.883	0.999
puma	gray fox	-0.903	-1.983	0.177	0.129
red fox	gray fox	0.180	-1.735	2.094	0.994
red fox	puma	1.083	-0.958	3.124	0.493

Table S2.13 | Model selection results from linear models analyzing spatiotemporal avoidance (AARs) for subordinate and dominant carnivores.

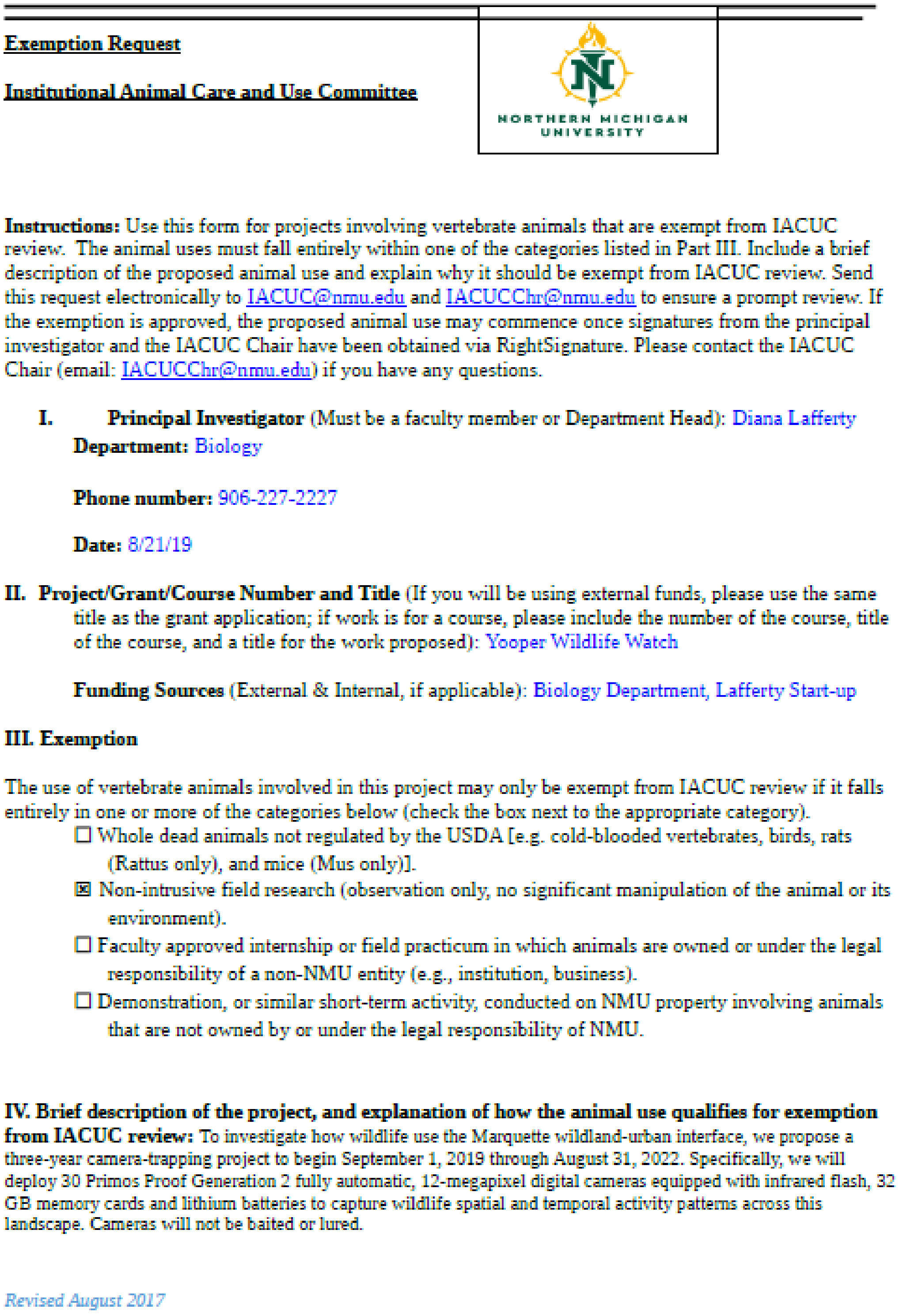
Hypothesis	Model	AIC	ΔAIC	R^2	Model Weight
Subordinate	Human Impact	14.46	0.00	0.400	0.80
Subordinate	Null	17.43	2.96	---------	0.18
Subordinate	Environmental Impact	22.41	7.95	-0.020	0.02
Dominant	Null	67.05	0.00	---------	0.70
Dominant	Environmental Impact	69.82	2.77	0.007	0.17
Dominant	Human Impact	70.42	3.37	-0.013	0.13

Table S2.14 | Results for linear models analyzing spatiotemporal avoidance with the effects of anthropogenic and environmental factors using AARs (T2/T1).

Model	Hypothesis	Covariate	Estimate	Std. Error	t-value	p-value
Human Impact	Subordinate	Intercept	-0.201	0.110	-1.825	0.093
Human Impact	Subordinate	Human Presence	0.004	0.002	2.086	0.0590
Human Impact	Subordinate	Population Density	-0.0002	0.0001	-2.593	0.024
Human Impact	Dominant	Intercept	-0.129	0.164	-0.789	0.437
Human Impact	Dominant	Human Presence	0.001	0.004	0.311	0.758
Human Impact	Dominant	Population Density	0.004	0.004	0.851	0.402
Environmental Impact	Subordinate	Intercept	8.212e-02	3.406e-01	0.241	0.814
Environmental Impact	Subordinate	GPP	-6.972e-06	2.448e-05	-0.285	0.781
Environmental Impact	Subordinate	Precipitation	-1.825e+00	1.425e+00	-1.281	0.224
Environmental Impact	Dominant	Intercept	-3.473e-01	2.588e-01	-1.342	0.190
Environmental Impact	Dominant	GPP	4.103e-01	1.108e+00	0.370	0.714
Environmental Impact	Dominant	Precipitation	2.979e-05	2.217e-05	1.344	0.190

APPENDIX D

SUPPLEMENTAL 3: IACUC EXEMPTION DOCUMENT



Exemption Request

Institutional Animal Care and Use Committee

NORTHERN MICHIGAN UNIVERSITY

Instructions: Use this form for projects involving vertebrate animals that are exempt from IACUC review. The animal uses must fall entirely within one of the categories listed in Part III. Include a brief description of the proposed animal use and explain why it should be exempt from IACUC review. Send this request electronically to IACUC@nmu.edu and IACUCChr@nmu.edu to ensure a prompt review. If the exemption is approved, the proposed animal use may commence once signatures from the principal investigator and the IACUC Chair have been obtained via RightSignature. Please contact the IACUC Chair (email: IACUCChr@nmu.edu) if you have any questions.

I. **Principal Investigator** (Must be a faculty member or Department Head): Diana Lafferty

Department: Biology

Phone number: 906-227-2227

Date: 8/21/19

II. **Project/Grant/Course Number and Title** (If you will be using external funds, please use the same title as the grant application; if work is for a course, please include the number of the course, title of the course, and a title for the work proposed): Yooper Wildlife Watch

Funding Sources (External & Internal, if applicable): Biology Department, Lafferty Start-up

III. Exemption

The use of vertebrate animals involved in this project may only be exempt from IACUC review if it falls entirely in one or more of the categories below (check the box next to the appropriate category).

☐ Whole dead animals not regulated by the USDA [e.g. cold-blooded vertebrates, birds, rats (Rattus only), and mice (Mus only)].

☒ Non-intrusive field research (observation only, no significant manipulation of the animal or its environment).

☐ Faculty approved internship or field practicum in which animals are owned or under the legal responsibility of a non-NMU entity (e.g., institution, business).

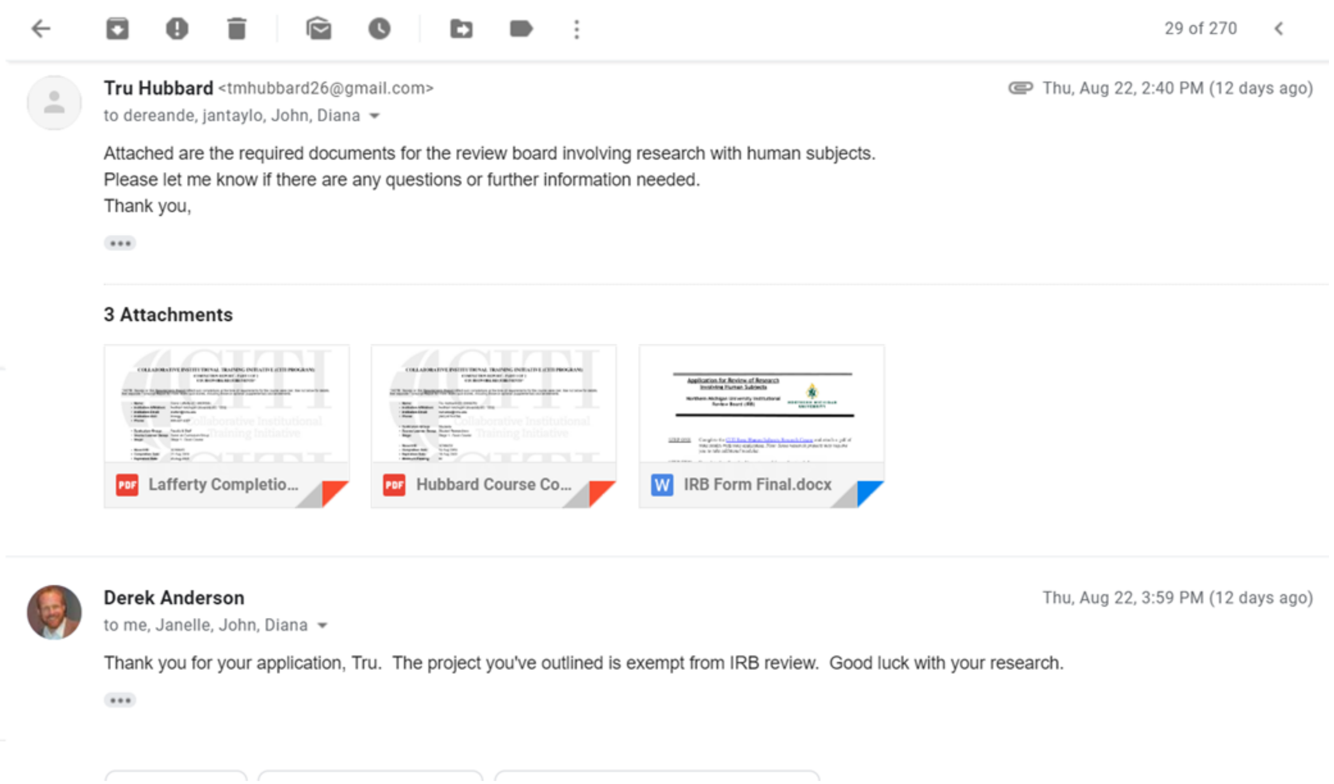
☐ Demonstration, or similar short-term activity, conducted on NMU property involving animals that are not owned by or under the legal responsibility of NMU.

IV. Brief description of the project, and explanation of how the animal use qualifies for exemption from IACUC review: To investigate how wildlife use the Marquette wildland-urban interface, we propose a three-year camera-trapping project to begin September 1, 2019 through August 31, 2022. Specifically, we will deploy 30 Primos Proof Generation 2 fully automatic, 12-megapixel digital cameras equipped with infrared flash, 32 GB memory cards and lithium batteries to capture wildlife spatial and temporal activity patterns across this landscape. Cameras will not be baited or lured.

Revised August 2017

APPENDIX E

SUPPLEMENTAL 4: IRB EXEMPTION DOCUMENT



Tru Hubbard <tmhubbard26@gmail.com>

Thu, Aug 22, 2:40 PM (12 days ago)

to dereande, jantaylo, John, Diana

Attached are the required documents for the review board involving research with human subjects.
Please let me know if there are any questions or further information needed.
Thank you,

Derek Anderson

Thu, Aug 22, 3:59 PM (12 days ago)

to me, Janelle, John, Diana

Thank you for your application, Tru. The project you've outlined is exempt from IRB review. Good luck with your research.

APPENDIX F

SUPPLEMENTAL 5: R SCRIPT FOR CHAPTER 1 ANALYSIS

```
######American black bear Supplemental Temporal Activity Code for Analysis in R##########


##Set working directory
setwd("C:/Users/truhubba/Documents/Research Project/Manuscripts/American Black Bear/")
##Install packages
install.packages(c("ggplot2", "dplyr", "gridExtra", "lubridate", "ggthemes", "readr", "hrbrthemes", "circular"))
##Load packages
library(circular)
library(ggplot2)
library(dplyr)
library(lubridate)
library(gridExtra)
library(ggthemes)
library(readr)
library(hrbrthemes)
library(overlap)
library(chron)
library(activity)
###########################ONLYBEAR######################################
##Read in csv with only bear detections for entire study period
bear <- read.csv("only_bear.csv")
View(bear)
############################################################

###Format time data
bear_de<-60 * 24 * as.numeric(times(bear$time))
bear_de2<-(bear_de/1440)
View(bear_de2)
range(bear_de2)
timeRad<-(bear_de2*2*pi)

###Create dataset for before and after hibernation
bear_detB<- timeRad[bear$period =="before"]
bear_detA <- timeRad[bear$period=="after"]
```

```
########Graph Detections throughout study period (before [b1] or after [d1])################
###############################################################################
bear2<-read.csv("after_BH.csv")
bear2$date<-as.Date(bear2$date,"%m/%d/%Y")
bear2$choice<-factor(bear2$choice, levels=rev(levels(bear2$choice)))
ggplot(bear2,aes(x=date, fill=choice, order=-as.numeric(choice)))+
  geom_bar(mapping = aes(),colour="black")+
  scale_fill_manual("Legend", values = c("HUMAN"="darkslateblue", "BEAR"="gold1"))+
  theme_economist_white()+
  theme(plot.title=element_text(hjust=0.5))+
  theme(axis.title.x = element_text(face="bold", size=12))+
  theme(axis.title.y = element_text(face="bold", size=12))+
  theme(axis.text.y =element_text(size=8, face="bold"))+
  theme(axis.text.x = element_text(size=8, face="bold"))+
  ggtitle("Total American Black Bear Detections Across Study Time Period")+
  theme(plot.title = element_text(hjust = 0.5, face= "bold",size=16))+
  xlab("Date")+
  ylab("Number of Detections")
d1
b1
grid.arrange(b1,d1, nrow=1)

###############BLACK BEAR OVERLAP ESTIMATES####################
######################################################################
##Create overlap plot for before and after hibernation
overlapPlot(bear_detB, bear_detA)
overlapPlot(bear_detB, bear_detA, xcenter="noon", main=" Bear Before & After Hibernation",
linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"), linewidth=c(3,3),lty=3)
legend("bottom",c("Before","After"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue"))

######Percent of activity between sunrise and sunset (% Nocturnal or % Diurnal)############
###before hibernation
beforeden<-densityPlot(bear_detB, rug = TRUE)
wanted <- beforeden$x > 6+57/60 & beforeden$x <20+36/60
wanted
mean(beforeden$y[wanted]) *14  # probability mass for the 14 hr period.

###aftern hibernation
afterden<-densityPlot(bear_detA, rug = TRUE)
wanted <- afterden$x > 5+20/60 & afterden$x <20+20/60
wanted
mean(afterden$y[wanted]) *15  # probability mass for the 14 hr period.

########################OVERLAP CALCULATIONS#############################
###Check sample sizes to determine which estimate to use
length(bear_detB)
```

```
length(bear_detA)

## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1
################################################################################
###Calculate Estimates of Overlap####################################################
(Dhats <- overlapEst(bear_detB, bear_detA, type="Dhat4"))
###Bootstrap for confidence intervals
bsA <- resample(bear_detB, 1000)
bsAA <- resample(bear_detA, 1000)

###Analyse with bootEst, estimating with proper Dhat
bs <- bootEst(bsA, bsAA, type = "Dhat4")
###Find the mean
mean(bs)
##Get Confidence Intervals
bootCI(Dhats,bs, conf = 0.95)
bootCIlogit(Dhats,bs, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).

#######WITH/WITHOUT CUBS (before and after hibernation combined)#################
cub_time<-60 * 24 * as.numeric(times(bear$time))
cub_time2<-(cub_time/1440)
View(cub_time2)
range(cub_time2)
timeRad<-(cub_time2*2*pi)

no_cub <- timeRad[bear$cub_present =="N"]#NO CUBS PRESENT
cub <- timeRad[bear$cub_present=="Y"]#CUBS PRESENT

densityPlot(no_cub,extend=NULL,lwd=2,ylim=c(0,0.08),col='plum1',main="Cubs")+lty=3
overlapPlot(no_cub, cub)
overlapPlot(no_cub,cub,xcenter="noon",main="CubAcitivity",linetype=c("solid","solid"),linecol
=c("mediumorchid4","darkorange2"),linewidth=c(3,3),lty=3)

legend("bottom",c("WithoutCubs","WithCubs"),lty=c(1,1),bty='n',
col=c("mediumorchid4","darkorange2"))
par(bg="gray97")

##############################################################

###########OVERLAP ESTIMATE BETWEEN CUBS AND NO CUBS#################
(Dhats <- overlapEst(no_cub, cub, type="Dhat1"))
```

```
#########################################################################################
###PROPORTION OF DAY SPENT ACTIVE WITH AND WITHOUT CUBS################
cubden<-densityPlot(cub, rug = TRUE)
wanted <- cubden$x > 5+57/60 & cubden$x <19+36/60
wanted
mean(cubden$y[wanted]) *14  #probability mass for the 14 hr period.

nocubden<-densityPlot(no_cub, rug = TRUE)
wanted <- nocubden$x > 5+57/60 & nocubden$x <19+36/60
wanted
mean(nocubden$y[wanted]) *14  #probability mass for the 14 hr period.
#########################################################################################
###ACTIVITY LEVEL WITH AND WITHOUT CUBS#####################################
f_cub <- fitact(cub, sample="data", reps=1000)
f_nocub <- fitact(no_cub, sample="data", reps=1000)
f_cub@act
f_nocub@act
compareAct(list(f_cub,f_nocub))

#########################################################################################
#########################################################################################
#########################ONLY HUMAN DATA#########################################

human<-read.csv("human.csv")
####################################################################
####before/after hibernation########################
hums<-60 * 24 * as.numeric(times(human$time))
hums2<-(hums/1440)
View(hums2)
range(hums2)
timeRad<-(hums2*2*pi)
hum_before <- timeRad[human$period =="before"]
hum_after <- timeRad[human$period=="after"]
#########################################################################################

###OVERLAP ESTIMATES- BEFORE HIBERNATION- HUMAN AND BEAR#############
###Check Sample Sizes
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1
length(bear_detA)
length(bear_detB)
(Dhats <- overlapEst(hum_before,bear_detB, type="Dhat4"))
(Dhats <- overlapEst(hum_after,bear_detA, type="Dhat4"))
###PROPORTION OF DAY SPENT ACTIVE
humbden<-densityPlot(hum_before, rug = TRUE)
wanted <- humbden$x > 5+57/60 & humbden$x <19+36/60
```

```
wanted
mean(humbden$y[wanted]) *14  # probability mass for the 6 hr period.

humaden<-densityPlot(hum_after, rug = TRUE)
wanted <- humaden$x > 5+57/60 & humaden$x <19+36/60
wanted
mean(humaden$y[wanted]) *14  # probability mass for the 14 hr period.

###################################################################################
###ACTIVITY LEVEL BEFORE AND AFTER##########################################
f_before <- fitact(hum_before, sample="data", reps=1000)
f_after <- fitact(hum_after, sample="data", reps=1000)
f_before@act
f_after@act
compareAct(list(f_before,f_after))
###################################################################################
#########SORTING BY TYPE OF RECREATION (on foot activity)########################

###sort and set data into radians
human2<-subset(human, period=="before")
human_b<-60 * 24 * as.numeric(times(human2$time))
human_b<-(human_b/1440)
timeRad<-(human_b*2*pi)
hum_foot_before <- timeRad[human2$on_foot=="TRUE"]

human3<-subset(human, period=="after")
human_a<-60 * 24 * as.numeric(times(human3$time))
human_a<-(human_a/1440)
timeRad<-(human_a*2*pi)
hum_foot_after <- timeRad[human3$on_foot=="TRUE"]


###################################################################################
###OVERLAP ESTIMATE BETWEEN BEFORE AND AFTER HIBERNATION
###Check Sample Sizes
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1
length(bear_detA)
length(bear_detB)
(Dhats <- overlapEst(hum_foot_before,bear_detB, type="Dhat4"))
(Dhats <- overlapEst(hum_foot_after,bear_detA, type="Dhat4"))
###PROPORTION OF DAY SPENT ACTIVE
humbden<-densityPlot(hum_foot_before, rug = TRUE)
wanted <- humbden$x > 5+57/60 & humbden$x <19+36/60
wanted
mean(humbden$y[wanted]) *14  # probability mass for the 14 hr period.
```

```
humaden<-densityPlot(hum_foot_after, rug = TRUE)
wanted <- humaden$x > 5+57/60 & humaden$x <19+36/60
wanted
mean(humaden$y[wanted]) *14  # probability mass for the 14 hr period.

############################################################################################
###ACTIVITY LEVEL BEFORE AND AFTER##############################################
f_before <- fitact(hum_foot_before, sample="data", reps=1000)
f_after <- fitact(hum_foot_after, sample="data", reps=1000)
f_before@act
f_after@act
compareAct(list(f_before,f_after))
############################################################################################
########SORTING BY TYPE OF RECREATION (Non-motorized activity)################

human2<-subset(human, period=="before")
human_b<-60 * 24 * as.numeric(times(human2$time))
human_b<-(human_b/1440)
timeRad<-(human_b*2*pi)
hum_non_before <- timeRad[human2$non_motorized=="TRUE"]

human3<-subset(human, period=="after")
human_a<-60 * 24 * as.numeric(times(human3$time))
human_a<-(human_a/1440)
timeRad<-(human_a*2*pi)
hum_non_after <- timeRad[human3$non_motorized=="TRUE"]


############################################################################################
###OVERLAP ESTIMATE BETWEEN BEFORE AND AFTER HIBERNATION###########
###Check Sample Sizes
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1
length(bear_detA)
length(bear_detB)
(Dhats <- overlapEst(hum_non_before,bear_detB, type="Dhat4"))
(Dhats <- overlapEst(hum_non_after,bear_detA, type="Dhat4"))
###PROPORTION OF DAY SPENT ACTIVE
humbden<-densityPlot(hum_non_before, rug = TRUE)
wanted <- humbden$x > 5+57/60 & humbden$x <19+36/60
wanted
mean(humbden$y[wanted]) *14  # probability mass for the 6 hr period.

humaden<-densityPlot(hum_non_after, rug = TRUE)
wanted <- humaden$x > 5+57/60 & humaden$x <19+36/60
```

```
wanted
mean(humaden$y[wanted]) *14  # probability mass for the 14 hr period.

######################################################################################
###ACTIVITY LEVEL BEFORE AND AFTER###########################################
f_before <- fitact(hum_non_before, sample="data", reps=1000)
f_after <- fitact(hum_non_after, sample="data", reps=1000)
f_before@act
f_after@act
compareAct(list(f_before,f_after))


######################################################################################
######################################################################################
###COMPARE ACTIVITY OF VEHICLES BEFORE AND AFTER HIBERNATION########
######################################################################################
##read in csv
veh<-read.csv("vehichle_data.csv")
##convert times and compare
veh2<-subset(veh, time.period=="before")
veh_b<-60 * 24 * as.numeric(times(veh2$time))
veh_b<-(veh_b/1440)
veh_b<-timeRad<-(veh_b*2*pi)

veh3<-subset(veh, time.period=="after")
veh_a<-60 * 24 * as.numeric(times(veh3$time))
veh_a<-(veh_a/1440)
veh_a<-timeRad<-(veh_a*2*pi)

######################################################################################
###PROPORTION OF DAY SPENT ACTIVE############################################
humbden<-densityPlot(veh_b, rug = TRUE)
wanted <- humbden$x > 5+57/60 & humbden$x <19+36/60
wanted
mean(humbden$y[wanted]) *14  # probability mass for the 14 hr period.

humaden<-densityPlot(veh_a, rug = TRUE)
wanted <- humaden$x > 5+57/60 & humaden$x <19+36/60
wanted
mean(humaden$y[wanted]) *14  # probability mass for the 14 hr period.

######################################################################################
###ACTIVITY LEVEL BEFORE AND AFTER###########################################
f_before <- fitact(veh_b, sample="data", reps=1000)
f_after <- fitact(veh_a, sample="data", reps=1000)
f_before@act
f_after@act
```

```
compareAct(list(f_before,f_after))

#################################################################################
###OVERLAP ESTIMATE BETWEEN BEARS AND VEHICLES######################
###Check Sample Sizes
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1
length(veh_a)
length(veh_b)
(Dhats <- overlapEst(veh_b,bear_detB, type="Dhat4"))
(Dhats <- overlapEst(veh_a,bear_detA, type="Dhat1"))
#################################################################################
#################################################################################



##########American black bear Supplemental Occupancy Modeling Code for Analysis in R###
library(unmarked)
library(AICcmodavg)
library(ggplot2)
library(ggthemes)
library(hrbrthemes)
library(jtools)
setwd("C:/Users/truhubba/Documents/ResearchProject/Manuscripts/AmericanBlack
Bear/Occupancy/")

########################BlackbearSingle-SpeciesModels#################

##load in Detection csv and covariate csv
bear<-read.csv("combined_bear_occ.csv")
covs<-read.csv("final_covariates.csv")
View(bear)
View(covs)
head(covs)
###################################################################
##Format the data for unmarked. Use ?unmarkedMultFrame? and
#specify the number of primary periods
siteCovs<-
(covs[,c("number_humans","number_human_on_foot","landowner","number_dogs","number
_vehicles","Sum_of_human_impact","hum_pop","elevation","m_watsource","m_road","land_
cover","human_present","human_present_foot","dog_present","protected","cubs_present","n_
vehicle","rec_vehicle","u_vehicle","non_motor_human","gun_present"
"number_non_motor_human","season")])

###Create unmarked object#####
bearumk<-
unmarkedFrameOccu(y=bear,siteCovs=data.frame(nnomotor=scale(covs$number_non_motor
```

```
_human),nhuman=scale(covs$number_humans),nhumfoot=scale(covs$number_human_on_f
oot),nveh=scale(covs$number_vehicles),land=factor(covs$landowner),ndog=scale(covs$numb
er_dogs),humP=scale(covs$human_present),season=factor(covs$season),pro=factor(covs$pro
tected),lcover=factor(covs$land_cover),hum=scale(covs$Sum_of_human_impact),
wat=scale(covs$m_watsource),passveh=factor(covs$n_vehicle),recveh=factor(covs$rec_vehicl
e),uveh=factor(covs$u_vehicle),dog=factor(covs$dog_present),gun=factor(covs$gun_present),
pop=scale(covs$hum_pop),elv=scale(covs$elevation),
road=scale(covs$m_road),cub=factor(covs$cubs_present)))
summary(bearumk)

# occu(~detection ~occupancy)
####################################################################
############DETECTION PROBABILITY MODELS##########################

null<-occu(~1 ~1, bearumk) #null
det1<-occu(~cub ~1, bearumk )#cubs---excluded
det2<-occu(~season ~1, bearumk) #season
det3<-occu(~pro ~1, bearumk) #protected areas

fl2<-fitList(null,det1,det2,det3)
modSel(fl2)
summary()

####################################################################
#############OCCUPANCY PROBILITY MODELS##########################

occ1 <- occu( ~season+pro ~1, bearumk)  #Null
occseason<-occu(~season+pro ~season, bearumk) #season
occhuman<- occu(~season+pro ~nhuman, bearumk) #number of total humans
occhumfoot<-occu(~season+pro ~nhumfoot, bearumk) #number of humans on foot
occpop<- occu(~season+pro ~pop, bearumk) #population density
occndog<- occu( ~season+pro ~ndog, bearumk) #number of dogs
occpro<- occu( ~season+pro ~pro, bearumk) #protected areas
occhum<- occu( ~season+pro ~hum, bearumk) #sum of human impact
occrecveh<- occu( ~season+pro ~recveh, bearumk) #recreation vehicle
occelv<- occu( ~season+pro ~elv, bearumk) #elevation
occwat<- occu( ~season+pro ~wat, bearumk) #water source
occroad<- occu( ~season+pro ~road, bearumk) #road
occdog<- occu( ~season+pro ~dog, bearumk) #dog present
occlcover<- occu( ~season+pro ~lcover, bearumk) #landcover
occnveh<- occu( ~season+pro ~nveh, bearumk) #nubmer of vehicles
occland<- occu( ~season+pro ~land, bearumk) #land ownership
occpveh<- occu( ~season+pro ~passveh, bearumk) #passenger vehicle
occnnomotor<- occu( ~season+pro ~nnomotor, bearumk) #number of non-motorized
occgun<- occu( ~season+pro ~gun, bearumk) #gun
occuveh<-occu(~season+pro ~uveh, bearumk) #utility vehicle
occhumP<-occu(~season+pro ~humP, bearumk) #human presence
```

```
####Compare single factor models####

fl<-fitList(occ1, occseason,occgun,occnnomotor,occpveh, occnveh, occpop, occlcover, occdog,
occroad,occhum,occpro,occwat,occelv,occuveh,occland,occrecveh,occndog,occhumfoot,occhum
an,occhumP)
modSel(fl)

####Create additive models to test for final occupancy model####
occbear<-occu(~season+pro ~)
summary()

##Compare additive models####
fl2<-fitList()
modSel(fl2)


##check confidence intervals
##Non-overlapping with zero! That suggests the covariate is a strong predictor!
##Overlaps with zero then this is a weak predictor
confint( , type="state")
confint( ,type="det")
####################################################################################
####################################################################################

##########################Plot Occupancy Model Predictions############################
PLOTTING COMBINED DETECTION AND OCCUPANCY COVARIATES###############
```

```
occbear<-occu(~pro+season ~pop+humP, bearumk)
summary(occbear)

pop.data <- data.frame(pop=seq(from=1.60, to= 10.50, length=60), humP=rep(0, 60),
season=rep(0,60), pro=rep(0,60))
predictions <- predict(occbear, type='state', newdata=pop.data, appendData=TRUE)
View(predictions)
ggplot(data=predictions, aes(x=pop, y=Predicted,ymin=Predicted-SE, ymax=Predicted+SE))+
  geom_ribbon(fill="darkslateblue", alpha=0.1)+
  geom_line(color="darkslateblue", size=1)+
  labs(x="Population Density", y = "Occupancy Probability")+
  theme_clean()


human.data <- data.frame(pop=rep(0,60), humP=seq(from=0, to=1, length=60),
season=rep(0,60), pro=rep(0,60))
predictions2 <- predict(occbear, type='state', newdata=human.data, appendData=TRUE)
View(predictions2)

human<-read.csv("humP.csv")
```

```
ggplot(data=human, aes(x=humP, y=Predicted))+
  geom_col(fill="darkslateblue", width = 0.2, alpha=1)+
  scale_x_discrete(limits = c(0,1))+
  geom_errorbar(aes(ymin=min, ymax=max), width=0.1)+
  labs(x="Human Presence", y = "Occupancy Probability")+
  theme_clean()

protected<- data.frame(season=rep(0,60), pro=seq(from=0, to=1,
length=60),pop=rep(0,60),humP=rep(0, 60))
prediction3 <- predict(occbear, type='det', newdata=protected, appendData=TRUE)
View(prediction3)
protect<-read.csv("protected.csv")
ggplot(data=protect, aes(x=protected, y=Predicted))+
  geom_col(fill="gold1", width=0.2, alpha=1)+
  geom_errorbar(aes(ymin=min, ymax=max), width=0.1)+
  scale_x_discrete(limits = c(0,1))+
  labs(x="Protected Land", y = "Detection Probability")+
  theme_clean()

sea<- data.frame(season=seq(from=0, to=1, length=60),pop=rep(0,60),humP=rep(0, 60),
pro=rep(0,60))
prediction <- predict(occbear, type='det', newdata=sea, appendData=TRUE)
View(prediction)

season<-read.csv("season.csv")
ggplot(data=season, aes(x=season, y=Predicted))+
  geom_col(fill="gold1", width=0.2, alpha=1)+
  geom_errorbar(aes(ymin=min, ymax=max), width=0.1)+
  scale_x_discrete(limits =c(0,1))+
  labs(x="Season", y = "Detection Probability")+
  theme_clean()
```

APPENDIX G

SUPPLEMENTAL 6: R SCRIPT FOR CHAPTER 2 ANALYSIS

```
######Carnivore Supplemental Temporal Activity Code for Analysis in R##########


setwd("C:/Users/truhubba/Documents/ResearchProject/Manuscripts/Snapshot-Carnivore
Community/")
library(activity)
library(dplyr)
library(lubridate)
library(chron)
library(overlap)
library(ggplot2)
####################################################################################
####################################################################################

###Anchoring by sunrise and Sunset Test on small dataset
###read in dataset####uses small subset of random detections to test code
snapshot<-read.csv("Anchor-Test.csv")
View(snapshot)

snapshot2<-mutate(snapshot, rawtimes=60 * 24 * as.numeric(times(snapshot$Time))/1440*2*pi)
##convert time to radians

snapshot3<-mutate(snapshot2, sunrise=60 * 24 *
as.numeric(times(snapshot2$sunrise))/1440*2*pi)  ##convert sunrise time to radians

snapshot4<-mutate(snapshot3, sunset=60 * 24 * as.numeric(times(snapshot3$sunset))/1440*2*pi)
##convert sunset time to radians
View(snapshot4)

##create object with the original detectition times after being converted to radians
dat<-snapshot2$rawtimes
View(dat)

##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(snapshot4$sunrise, snapshot4$sunset)
View(anchor)

##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
```

```
eqntimes<-transtime(dat, anchor, type = "equinoctial")
View(eqntimes)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqntimes)
plot(rawAct)
plot(eqnAct)
#############################################################################################
#############################################################################################
###############USE FULL SNAPSHOT CARNIVORE DATASET######################

###read in dataset
snapshot<-read.csv("snapshot_data_carnivores.csv")
View(snapshot)

snapshot2<-mutate(snapshot, rawtimes=60 * 24 * as.numeric(times(snapshot$Time))/1440*2*pi)
##convert time to radians
snapshot3<-mutate(snapshot2,sunrise=60*24* as.numeric(times(snapshot2$sunrise))/1440*2*pi)
##convert sunrise time to radians
snapshot4<-mutate(snapshot3, sunset=60 * 24 * as.numeric(times(snapshot3$sunset))/1440*2*pi)
##convert sunset time to radians
View(snapshot4)


##create object with the original detection times after being converted to radians
dat<-snapshot4$rawtimes
View(dat)

##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(snapshot4$sunrise, snapshot4$sunset)
View(anchor)

##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqntimes<-transtime(dat, anchor, type = "equinoctial")
View(eqntimes)

##plot and compare including all species in data set
rawAct<-fitact(dat)
eqnAct<-fitact(eqntimes)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
#############################################################################################
#############################################################################################

#############Create Density Curves##########################################################
```

```
###subset for specific species
subcoy<-subset(snapshot4, Common.Name=="Coyote")##coyote
View(subcoy)
##create object with the original detectition times after being converted to radians
dat<-subcoy$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subcoy$sunrise, subcoy$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqncoyote<-transtime(dat, anchor, type = "equinoctial")
View(eqncoyote)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqncoyote)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))

##density curve
densityPlot(eqncoyote,extend=NULL,col='purple',main="CoyoteActivity")+
abline(v=c(6+31/60, 19+26/60), lty=3)
#####################################################################################
#####################################################################################

###subset for specific species
subbob<-subset(snapshot4, Common.Name=="Bobcat")##bobcat
View(subbob)
##create object with the original detectition times after being converted to radians
dat<-subbob$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subbob$sunrise, subbob$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqnbobcat<-transtime(dat, anchor, type = "equinoctial")
View(eqnbobcat)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqnbobcat)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))

##density curve
```

```
densityPlot(eqnbobcat,extend=NULL,col='purple',main="BobcatActivity")+
abline(v=c(6+31/60, 19+26/60), lty=3)
#################################################################################

##overlap plot of coyote and bobcat

overlapPlot(eqnbobcat, eqncoyote, xcenter="noon", main="Acitivity Overlap Bobcat vs. Coyote",
linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)

legend("bottomleft",c("Bobcat","Coyote"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue")
)

par(bg="gray97")

################################Calculate Overlap ################################

###Check Sample Sizes
length(eqnbobcat)
length(eqncoyote)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1

(Dhats <- overlapEst(eqnbobcat, eqncoyote, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsCOY <- resample(eqncoyote, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBC <- bootEst(bsBOB, bsCOY, type = "Dhat4")
mean(bsBC)

##Get Confidence Intervals
bootCI(Dhats,bsBC, conf = 0.95)
bootCIlogit(Dhats,bsBC, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).
#################################################################################
#################################################################################
###subset for specific species
subfish<-subset(snapshot4, Common.Name=="Fisher")##fisher
View(subfish)
##create object with the original detectition times after being converted to radians
dat<-subfish$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
```

```
anchor<-cbind(subfish$sunrise, subfish$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqnfisher<-transtime(dat, anchor, type = "equinoctial")
View(eqnfisher)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqnfisher)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
densityPlot(eqnfisher,extend= NULL, col='purple',main="Fisher Activity")+
abline(v=c(6+31/60, 19+26/60), lty=3)

##overlap plot of fisher and bobcat

overlapPlot(eqnbobcat, eqnfisher, xcenter="noon", main="Acitivity Overlap Bobcat vs. Fisher",
linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)

legend("bottomleft",c("Bobcat","Fisher"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue"))

par(bg="gray97")

#################################Calculate Overlap################################

###Check Sample Sizes
length(eqnbobcat)
length(eqnfisher)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1


(Dhats <- overlapEst(eqnbobcat, eqnfisher, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsFISH <- resample(eqnfisher, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBF <- bootEst(bsBOB, bsFISH, type = "Dhat4")
mean(bsBF)

##Get Confidence Intervals
bootCI(Dhats,bsBF, conf = 0.95)
bootCIlogit(Dhats,bsBF, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
```

```
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).
################################################################################
################################################################################

###subset for specific species
subgfox<-subset(snapshot4, Common.Name=="Grey Fox")##greyfox
View(subgfox)
##create object with the original detectition times after being converted to radians
dat<-subgfox$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subgfox$sunrise, subgfox$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqngreyfox<-transtime(dat, anchor, type = "equinoctial")
View(eqngreyfox)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqngreyfox)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
densityPlot(eqngreyfox, extend = NULL, col='purple',main="Grey Fox Activity")+
abline(v=c(6+31/60, 19+26/60), lty=3)
lines(eqnbobcat, col="red")


##overlap plot of greyfox and bobcat
overlapPlot(eqnbobcat, eqngreyfox, xcenter="noon", main="Acitivity Overlap Bobcat vs. Grey
Fox",linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)
legend("bottomleft",c("Bobcat","GreyFox"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue
"))
par(bg="gray97")
#################################Calculate Overlap################################

###Check Sample Sizes
length(eqnbobcat)
length(eqngreyfox)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1

(Dhats <- overlapEst(eqnbobcat, eqngreyfox, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
```

```
bsBOB <- resample(eqnbobcat, 10000)
bsGF <- resample(eqngreyfox, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBGF <- bootEst(bsBOB, bsGF, type = "Dhat4")
mean(bsBGF)

##Get Confidence Intervals
bootCI(Dhats,bsBGF, conf = 0.95)
bootCIlogit(Dhats,bsBGF, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).
##################################################################################
##################################################################################

###subset for specific species
subgw<-subset(snapshot4, Common.Name=="Gray Wolf")##graywolf
View(subgw)
##create object with the original detectition times after being converted to radians
dat<-subgw$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subgw$sunrise, subgw$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqngraywolf<-transtime(dat, anchor, type = "equinoctial")
View(eqngraywolf)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqngraywolf)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
densityPlot(eqngraywolf,extend=NULL,col='purple',main="GrayWolfActivity")+
abline(v=c(6+31/60, 19+26/60), lty=3)

##overlap plot with bobcat
overlapPlot(eqnbobcat, eqngraywolf, xcenter="noon", main="Acitivity Overlap Bobcat vs. Gray
Wolf", linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)
legend("bottomleft",c("Bobcat","GrayWolf"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue"))
par(bg="gray97")
```

```
################################Calculate Overlap##############################

###Check Sample Sizes
length(eqnbobcat)
length(eqngraywolf)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1

(Dhats <- overlapEst(eqnbobcat, eqngraywolf, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsGW <- resample(eqngraywolf, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBGW <- bootEst(bsBOB, bsGW, type = "Dhat4")
mean(bsBGW)

##Get Confidence Intervals
bootCI(Dhats,bsBGW, conf = 0.95)
bootCIlogit(Dhats,bsBGW, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).

#############################################################################
###subset for specific species
subpuma<-subset(snapshot4, Common.Name=="Puma")##puma
View(subpuma)
##create object with the original detectition times after being converted to radians
dat<-subpuma$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subpuma$sunrise, subpuma$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqnpuma<-transtime(dat, anchor, type = "equinoctial")
View(eqnpuma)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqnpuma)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
```

```
densityPlot(eqnpuma,extend=NULL,col='maroon',main="GrayWolfActivity")+
abline(v=c(6+31/60, 19+26/60), lty=3)

##overlap plot with bobcat
overlapPlot(eqnbobcat, eqnpuma, xcenter="noon", main="Acitivity Overlap Bobcat vs. Puma",
linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)
legend("bottomleft",c("Bobcat","Puma"),lty=c(1,1),bty='n', col=c("darkgoldenrod1","darkblue"))
par(bg="gray97")

###############################CalculateOverlap###############################
###Check Sample Sizes
length(eqnbobcat)
length(eqnpuma)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1

(Dhats <- overlapEst(eqnbobcat, eqnpuma, type="Dhat1"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsGW <- resample(eqnpuma, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBP <- bootEst(bsBOB, bsP, type = "Dhat4")
mean(bsBP)

##Get Confidence Intervals
bootCI(Dhats,bsBP, conf = 0.95)
bootCIlogit(Dhats,bsBP, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).

#############################################################################
###subset for specific species
subab<-subset(snapshot4, Common.Name=="American Badger")##american badger
View(subab)
##create object with the original detectition times after being converted to radians
dat<-subab$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subab$sunrise, subab$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
```

```
eqnab<-transtime(dat, anchor, type = "equinoctial")
View(eqnab)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqnab)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
densityPlot(eqnab,extend=NULL,col='teal',main="AmericanBadgerActivity")+
abline(v=c(6+31/60, 19+26/60), lty=3)

##overlap plot with bobcat
overlapPlot(eqnbobcat, eqnab, xcenter="noon", main="Acitivity Overlap Bobcat vs. American
Badger", linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)
legend("bottomleft",c("Bobcat","GrayWolf"),lty=c(1,1),bty='n',
col=c("darkgoldenrod1","darkblue"))
par(bg="gray97")

################################CalculateOverlap################################
###Check Sample Sizes
length(eqnbobcat)
length(eqnab)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1

(Dhats <- overlapEst(eqnbobcat, eqnab, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsGW <- resample(eqnab, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBGW <- bootEst(bsBOB, bsAB, type = "Dhat4")
mean(bsBAB)

##Get Confidence Intervals
bootCI(Dhats,bsBAB, conf = 0.95)
bootCIlogit(Dhats,bsBAB, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).

##############################################################################
```

```
###subset for specific species
subrf<-subset(snapshot4, Common.Name=="Red Fox")##red fox
View(subrf)
##create object with the original detectition times after being converted to radians
dat<-subrf$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subrf$sunrise, subrf$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqnrf<-transtime(dat, anchor, type = "equinoctial")
View(eqnrf)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqnrf)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
densityPlot(eqnrf, extend = NULL, col='green',main="Red Fox Activity")+ abline(v=c(6+31/60,
19+26/60), lty=3)

##overlap plot with bobcat
overlapPlot(eqnbobcat, eqngraywolf, xcenter="noon", main="Acitivity Overlap Bobcat vs. Red
Fox",linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3),
olapcol="white",)
legend("bottomleft",c("Bobcat","RedFox"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue"
))
par(bg="gray97")
################################CalculateOverlap################################
###Check Sample Sizes
length(eqnbobcat)
length(eqnrf)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1

(Dhats <- overlapEst(eqnbobcat, eqnrf, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsGW <- resample(eqnrf, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBRF <- bootEst(bsBOB, bsRF, type = "Dhat4")
mean(bsBRF)
```

```
##Get Confidence Intervals
bootCI(Dhats,bsBRF, conf = 0.95)
bootCIlogit(Dhats,bsBRF, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary. However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).

####################################################################################
###subset for specific species
subrw<-subset(snapshot4, Common.Name=="Red Wolf")##red fox
View(subrw)
##create object with the original detectition times after being converted to radians
dat<-subrw$rawtimes
View(dat)
##create a two coloumn vector with radians of sunrise and sunset
anchor<-cbind(subrw$sunrise, subrw$sunset)
View(anchor)
##run transtimes to express time expressed relative to the two solar events (i.e., sunrise, sunset)
eqnrw<-transtime(dat, anchor, type = "equinoctial")
View(eqnrw)

##plot and compare
rawAct<-fitact(dat)
eqnAct<-fitact(eqnrw)
plot(rawAct)
plot(eqnAct)
plot(eqnAct, add=TRUE, data="n", tline=list(col="magenta"))
densityPlot(eqnrw,extend = NULL, col='green',main="Red Wolf Activity")+ abline(v=c(6+31/60, 19+26/60), lty=3)

##overlap plot with bobcat
overlapPlot(eqnbobcat, eqnrw, xcenter="noon", main="Acitivity Overlap Bobcat vs. Red Wolf", linetype=c("solid","solid"),linecol=c("darkgoldenrod1","darkblue"),linewidth=c(3,3), olapcol="white",)
legend("bottomleft",c("Bobcat","RedWolf"),lty=c(1,1),bty='n',col=c("darkgoldenrod1","darkblue"))
par(bg="gray97")
#################################CalculateOverlap#################################
###Check Sample Sizes
length(eqnbobcat)
length(eqnrw)
## If the smaller sample is less than 50, Dhat1 gives the best estimates, together with
## confidence intervals from a smoothed bootstrap with norm0 or basic0 confidence interval.
## Dhat4 is recommended if both samples are larger then 50, otherwise use Dhat1
```

```
(Dhats <- overlapEst(eqnbobcat, eqnrw, type="Dhat4"))
###Bootstrap for confidence intervals (999 datasets)
bsBOB <- resample(eqnbobcat, 10000)
bsGW <- resample(eqnrw, 10000)

###Analyse with bootEst, estimating with proper Dhat
bsBRW <- bootEst(bsBOB, bsRW, type = "Dhat4")
mean(bsBRW)

##Get Confidence Intervals
bootCI(Dhats,bsBRW, conf = 0.95)
bootCIlogit(Dhats,bsBRW, conf = 0.95)
###The percentiles CI, "perc", gives quantiles of the bootstrap values, interpolated if necessary.
However, in general, the bootstrap estimates are biased, so "perc" should be corrected.
###"basic" is a bias-corrected version of "perc", analogous to t1: 2 x t0 - perc.
###"norm" gives tail cutoffs for a normal distribution with  = t1 and sd = sd(bt).

###############################################################################
###############################################################################


#############COMPARING ACTIVITY BETWEEN ECOREGIONS####################
#########################BOBCAT############################################

###Set up data
bobcat<-subset(snapshot4, Common.Name=="Bobcat")
setwd("C:/Users/truhubba/Documents/ResearchProject/Manuscripts/Snapshot-Carnivore
Community/AAR/")
covs<-read.csv("Site_Detection_Covariates.csv")
view(covs)
View(snapshot4)
###Combine activity data and covariate data
bob2<-full_join(covs, bobcat, by= "Array", stringAsFactors=FALSE)%>%
  na.omit()
View(bob2)

####Sorting Data by Ecoregion######################################
subnorth<-subset(bob2, Ecoregion=="Northern Forests")
dat<-subnorth$rawtimes
anchor<-cbind(subnorth$sunrise, subnorth$sunset)
eqnnorth<-transtime(dat, anchor, type = "equinoctial")

subdesert<-subset(bob2, Ecoregion=="North American Deserts")
dat<-subdesert$rawtimes
anchor<-cbind(subdesert$sunrise, subdesert$sunset)
eqndesert<-transtime(dat, anchor, type = "equinoctial")
```

```
submed<-subset(bob2, Ecoregion=="Mediterranean California")
dat<-submed$rawtimes
anchor<-cbind(submed$sunrise, submed$sunset)
eqnmed<-transtime(dat, anchor, type = "equinoctial")

subeast<-subset(bob2, Ecoregion=="Eastern Temperate Forest")
dat<-subeast$rawtimes
anchor<-cbind(subeast$sunrise, subeast$sunset)
eqneast<-transtime(dat, anchor, type = "equinoctial")

subarid<-subset(bob2, Ecoregion=="Southern Semiarid Highlands")
dat<-subarid$rawtimes
anchor<-cbind(subarid$sunrise, subarid$sunset)
eqnarid<-transtime(dat, anchor, type = "equinoctial")

subsierra<-subset(bob2, Ecoregion=="Temperate Sierras")
dat<-subsierra$rawtimes
anchor<-cbind(subsierra$sunrise, subsierra$sunset)
eqnsierra<-transtime(dat, anchor, type = "equinoctial")

submtn<-subset(bob2, Ecoregion=="Northwestern Forested Mountains")
dat<-submtn$rawtimes
anchor<-cbind(submtn$sunrise, submtn$sunset)
eqnmtn<-transtime(dat, anchor, type = "equinoctial")

subplain<-subset(bob2, Ecoregion=="Great Plains")
dat<-subplain$rawtimes
anchor<-cbind(subplain$sunrise, subplain$sunset)
eqnplain<-transtime(dat, anchor, type = "equinoctial")

submarine<-subset(bob2, Ecoregion=="Marine West Coast Forest")
dat<-submarine$rawtimes
anchor<-cbind(submarine$sunrise, submarine$sunset)
eqnmarine<-transtime(dat, anchor, type = "equinoctial")

####Sort Data by Hunting Status##############################################
subprotected<-subset(bob2, Hunting.Status=="protected")
dat<-subprotected$rawtimes
anchor<-cbind(subprotected$sunrise, subprotected$sunset)
eqnprotected<-transtime(dat, anchor, type = "equinoctial")

subhunt<-subset(bob2, Hunting.Status=="hunted")
dat<-subhunt$rawtimes
anchor<-cbind(subhunt$sunrise, subhunt$sunset)
eqnhunt<-transtime(dat, anchor, type = "equinoctial")
```

```
#########Sort Data by Pop Status########################################
subin<-subset(bob2, Population.Status=="increasing")
dat<-subin$rawtimes
anchor<-cbind(subin$sunrise, subin$sunset)
eqnin<-transtime(dat, anchor, type = "equinoctial")

substable<-subset(bob2, Population.Status=="stable")
dat<-substable$rawtimes
anchor<-cbind(substable$sunrise, substable$sunset)
eqnstable<-transtime(dat, anchor, type = "equinoctial")

subde<-subset(bob2, Population.Status=="decreasing")
dat<-subde$rawtimes
anchor<-cbind(subde$sunrise, subde$sunset)
eqnde<-transtime(dat, anchor, type = "equinoctial")

##############RUN WATSON U2 TESTS-ACTIVITY DISTRIBUTION################
library(circular)
watson.two.test(eqnmed,eqneast)
#############################################################################
##############RUN WALD TEST-ACTIVTY LEVEL##############################
###Wald Test: statistical difference between two or more activity level estimates...is the difference
between estimates 1 and 2 significantly different from 0
#Bootstrap reps

###Hunting Status######
f_hunt <- fitact(eqnhunt, sample="data", reps=1000)
f_pro <- fitact(eqnprotected, sample="data", reps=1000)
f_hunt@act
f_pro@act
compareAct(list(f_pro,f_hunt)) ###Ho is no difference between estimates of activity level

###Population Status####
f_in <- fitact(eqnin, sample="data", reps=1000)
f_de <- fitact(eqnde, sample="data", reps=1000)
f_stable <- fitact(eqnstable, sample="data", reps=1000)
f_in@act
f_de@act
f_stable@act
compareAct(list(f_stable,f_in)) ###Ho is no difference between estimates of activity level

###Ecoregions#######
f_desert <- fitact(eqndesert, sample="data", reps=1000)
f_mtn <- fitact(eqnmtn, sample="data", reps=1000)
f_north <- fitact(eqnnorth, sample="data", reps=1000)
```

```
f_east <- fitact(eqneast, sample="data", reps=1000)
f_plain <- fitact(eqnplain, sample="data", reps=1000)
f_med <- fitact(eqnmed, sample="data", reps=1000)
f_marine <- fitact(eqnmarine, sample="data", reps=1000)
f_sierra <- fitact(eqnsierra, sample="data", reps=1000)
f_arid <- fitact(eqnarid, sample="data", reps=1000)
f_arid@act
f_sierra@act
f_mtn@act
f_marine@act
f_north@act
f_east@act
f_plain@act
f_med@act
f_desert@act
compareAct(list(f_marine,f_east)) ###Ho is no difference between estimates of activity level
###################################################################################
###################################################################################
```

```
##########Bobcat Supplemental Single-species Occupancy Code for Analysis in R##########

library(unmarked)
library(AICcmodavg)
library(ggplot2)
library(scales)
setwd("C:/Users/truhubba/Documents/Research Project/Manuscripts/Snapshot-Carnivore
Community/Occupancy/")

##load in Detection csv and covariate csv
bob<-read.csv("Bobcat_weekly_history.csv")
covs<-read.csv("Site_Detection_Covariates.csv")
View(bob)
View(covs)

##Format the data for unmarked. Use ?unmarkedMultFrame? and
#specify the number of primary periods
siteCovs<-(covs[,c("Sum.of.survey_days", "Average.of.Latitude", "Hunting.Status",
"Population.Status", "Ecoregion", "Average.of.cultiv1km","Average.of.nearest_building_m",
"Sum.of.n_buildings_500m", "Average.of.gpw_v4_pop", "Average.of.GPP_VAR1km",
"Average.of.daily.TMAX", "Average.of.daily.TMIN",
"Sum.of.Human.Presence","Average.of.3hr_precip", "Average.of.CUM_GPP1km",
"coyote_rate")])
```

```
bobumk<-unmarkedFrameOccu(y=bob,
siteCovs=data.frame(nbuild=scale(covs$Average.of.nearest_building_m),
pop=scale(covs$Average.of.gpw_v4_pop),days=scale(covs$Sum.of.survey_days),
lat=scale(covs$Average.of.Latitude), hunt=factor(covs$Hunting.Status),
popstat=factor(covs$Population.Status), cult=scale(covs$Average.of.cultiv1km),
gpp=scale(covs$Average.of.CUM_GPP1km),hum=scale(covs$Sum.of.Human.Presence),
hum2=scale(covs$Sum.of.Human.Presence),
precip=scale(covs$Average.of.3hr_precip), maxt=scale(covs$Average.of.daily.TMAX),
mint=scale(covs$Average.of.daily.TMIN),
eco=factor(covs$Ecoregion),sbuild=scale(covs$Sum.of.n_buildings_500m),
coy=scale(covs$coyote_rate)))
summary(bobumk)

View(siteCovs)
###can run individual correlation checks between covariates
cor(covs$coyote_rate,covs$Sum.of.Human.Presence)

#############################################################################
# occu(~detection ~occupancy)
#####Detection Models#########################################################
det1 <- occu( ~days ~1, bobumk) #survey days affect on bobcat detection when site is occupied
det2 <- occu (~lat ~1, bobumk) # latitude
detnull<-occu(~1~1, bobumk) #null

fl <- fitList(det1,detnull, det2)
ms_det <- modSel(fl)  #Model Selection of detection covariates
ms_det
summary(det1)

######Bobcat Occupancy models##################################################
occ1 <- occu( ~1 ~1, bobumk)  #Null
occbuild<- occu(~1 ~nbuild, bobumk) #nearest of buildings
occsbuild<-occu(~1 ~sbuild, bobumk) #sum of buildings
occpop<- occu(~1 ~pop, bobumk) #population
occlat<- occu( ~1 ~lat, bobumk) #latitude
occdays<-occu(~1 ~days, bobumk) #survery days
occcult<- occu( ~1 ~cult, bobumk) #cultivated land
occgpp<- occu( ~1 ~gpp, bobumk) #gross primary production
occhum<- occu( ~1 ~hum, bobumk) #human presence
occprecip<- occu( ~1 ~precip, bobumk) #precipitation
occhunt<- occu( ~1 ~hunt, bobumk) #harvest/hunt status
occpopstat<- occu( ~1 ~popstat, bobumk) #population status
```

```
occeco<- occu( ~1 ~eco, bobumk) #ecoregion
occmaxt<- occu( ~1 ~maxt, bobumk) #max temp
occmint<- occu( ~1 ~mint, bobumk) #min temp
occcoy<- occu(~1 ~coy, bobumk) #coyote detection rate

fl<-fitList(occcoy,occdays,occ1,occsbuild,occmaxt,occmint, occbuild, occpop, occlat, occcult,
occgpp, occhum, occprecip, occhunt, occpopstat, occeco)
modSel(fl)

###Final Models with Coyote###################################
occbobhumancoy<-occu(~1 ~pop+hum+coy, bobumk)##human
occbobenvironmentcoy<-occu(~1 ~gpp+precip+coy, bobumk)##environment

###Final Models without Coyote######################################
occbobhuman<-occu(~1 ~pop+hum+lat, bobumk)##human
occbobenvironment<-occu(~1 ~gpp+precip+lat, bobumk)#environment

fl<-fitList(occbobenvironment,occbobenvironmentcoy,occbobhuman,occbobhumancoy,occbob3)
modSel(fl)
###############################################################################
###############################################################################
```

```
###############3Carnivore Supplemental AAR Code for Analysis in R###################


#set working directory
setwd("C:/Users/truhubba/Documents/Research Project/Manuscripts/Snapshot-Carnivore
Community/AAR/")

#read in AAR files
bobcatA<-read.csv("BobcatA.csv")#use for dominant species with covs
bobcatB<-read.csv("BobcatB.csv")#use for subordinate species with covs
View(bobcatB)

#load required packages
library(dplyr)
library(ggplot2)
library(ggpubr)
library(tidyverse)
library(AICcmodavg)
library(lme4)
library(brms)
```

```
library(lattice)
library(rstan)
library(rstanarm)
library(lmerTest)
library(jtools)

######################################################################################
####PART 1: TWO TAIL T-TESTS TO DETERMINE ATTRACTION OR AVOIDANCE BY
THE BOBCAT#######################################################################
####Are bobcats attracted to or avoiding other species?
######################################################################################
##USING T2/T1 RATIOS (includes avoidance and attraction)
##Check normality
coyote<-subset(bobcatA, Species=="Coyote")###COYOTE
hist(coyote$T2.T1)
# One-sample t-test
coyoteAAR <- t.test(coyote$T2.T1, mu=0)
# Printing the results
coyoteAAR
######################################################################################
##Check normality
badger<-subset(bobcatA, Species=="American Badger")###AMERICAN BADGER
hist(badger$T2.T1)
# One-sample t-test
badgerAAR <- t.test(badger$T2.T1, mu=0)
badgerAAR
######################################################################################
redfox<-subset(bobcatA, Species=="Red Fox")###RED FOX
hist(redfox$T2.T1)
# One-sample t-test
redfoxAAR <- t.test(redfox$T2.T1, mu=0)
redfoxAAR
######################################################################################
greyfox<-subset(bobcatA, Species=="Grey Fox")###GRAY FOX
hist(greyfox$T2.T1)
# One-sample t-test
greyfoxAAR <- t.test(greyfox$T2.T1, mu=0)
greyfoxAAR
######################################################################################
puma<-subset(bobcatA, Species=="Puma")###PUMA
hist(puma$T2.T1)
# One-sample t-test
pumaAAR <- t.test(puma$T2.T1, mu=0)
```

```
pumaAAR
######################################################################################

######################################################################################
##USING T4/T3 RATIOS (only accounts for avoidance)
coyote<-subset(bobcatA, Species=="Coyote")##COYOTE
hist(coyote$T4.T3)
# One-sample t-test
coyoteAAR <- t.test(coyote$T4.T3, mu=0)
# Printing the results
coyoteAAR
########################################################################
puma<-subset(bobcatA, Species=="Puma")##PUMA
hist(puma$T4.T3)
# One-sample t-test
pumaAAR <- t.test(puma$T4.T3, mu=0)
pumaAAR
##########################################################################
greyfox<-subset(bobcatA, Species%in% c("Grey Fox","Red Fox"))##FOXES
hist(greyfox$T4.T3)
# One-sample t-test
gfoxAAR <- t.test(greyfox$T4.T3, mu=0)
gfoxAAR
######################################################################################
######################################################################################
####PART 2: REVERSE T-TEST TO INVESTIGATE OTHER CARNIVORES RESPONSE
TO BOBCAT#########################################################################
##Are other carnivores avoiding or attracted to bobcat?
#####################################################################################
##Check normality
coyote<-subset(bobcatB, Species=="Coyote")##COYOTE T2/T1
hist(coyote$T2.T1)
# One-sample t-test
coyoteAAR <- t.test(coyote$T2.T1, mu=0)
# Printing the results
coyoteAAR
######################################################################################
coyote<-subset(bobcatB, Species=="Coyote")##COYOTE T4/T3
hist(coyote$T4.T3)
# One-sample t-test
coyoteAAR <- t.test(coyote$T4.T3, mu=0)
# Printing the results
coyoteAAR #mean=0.815
```

```
#####################################################################
greyfox<-subset(bobcatB, Species%in%c("Grey Fox", "Red Fox"))##FOXES T4/T3
hist(greyfox$T4.T3)
##############################################################################
##############################################################################
####PART 3: ANOVA TO DETERMINE VARIATION AMONG SPECIES
RESPONSE###################################################################
###Are bobcats avoiding one species more than another?
####Analysis of Variance (ANOVA)################################################

hist(bobcatA$T4.T3)#Normality Test
one.way <- aov(T4.T3 ~ Species, data = bobcatA)
summary(one.way)

##Tukey-Pairwise comparison
tukey.one.way<-TukeyHSD(one.way)
tukey.one.way
##############################################################################
####Is any species avoiding bobcat more than another?

hist(bobcatB$T4.T3)#Normality Test
one.way <- aov(T4.T3 ~ Species, data = bobcatB)
summary(one.way)

##Tukey-Pairwise comparison
tukey.one.way<-TukeyHSD(one.way)
tukey.one.way
##############################################################################
##############################################################################
##PART 4: INVESTIGATING COVARIATE EFFECTS ON DOMINANT AND
SUBORDINATE SPECIES#######################################################
##How do environmental and human variables effect bobcats avoidance of other species?
###########################################
##read in covariate csv
covs<-read.csv("Site_Detection_Covariates.csv")
view(covs)

###Combine AAR data with covariate data (Dominant & Subordinate Hypothesis)
##dominant join
data<-full_join(covs, bobcatA, stringAsFactors=FALSE)%>%
  na.omit()
##subordinate join
data2<-full_join(covs, bobcatB, stringAsFactors=FALSE)%>%
```

```
  na.omit()

###subset data for required species
dataAA<-subset(data, Species%in%c("Gray Wolf", "Red Wolf", "Puma", "Coyote")) #dominant
dataB<-subset(data2, Species%in%c("Grey Fox", "Red Fox")) #subordinate
view(dataB)

##scale numeric covariates
dataB$Average.of.3hr_precip<-scale(dataB$Average.of.3hr_precip)
dataB$Average.of.Latitude<-scale(dataB$Average.of.Latitude)
dataB$Sum.of.survey_days<-scale(dataB$Sum.of.survey_days)
dataB$Average.of.CUM_GPP1km<-scale(dataB$Average.of.CUM_GPP1km)
dataB$Sum.of.Human.Presence<-scale(dataB$Sum.of.Human.Presence)
dataB$Sum.of.n_buildings_500m<-scale(dataB$Sum.of.n_buildings_500m)
dataB$Average.of.gpw_v4_pop<-scale(dataB$Average.of.gpw_v4_pop)

dataAA$Average.of.3hr_precip<-scale(dataAA$Average.of.3hr_precip)
dataAA$Average.of.Latitude<-scale(dataAA$Average.of.Latitude)
dataAA$Sum.of.survey_days<-scale(dataAA$Sum.of.survey_days)
dataAA$Average.of.CUM_GPP1km<-scale(dataAA$Average.of.CUM_GPP1km)
dataAA$Sum.of.Human.Presence<-scale(dataAA$Sum.of.Human.Presence)
dataAA$Sum.of.n_buildings_500m<-scale(dataAA$Sum.of.n_buildings_500m)
dataAA$Average.of.gpw_v4_pop<-scale(dataAA$Average.of.gpw_v4_pop)
#####################################################################################
#RUN GENERALIZED LINEAR MIXED MODELS#####################################
###SUBORDINATE MODELS########################################################

#####HUMAN IMPACT MODEL
model1<-lm(T2.T1~Sum.of.Human.Presence+Average.of.gpw_v4_pop, data = dataB)
summary(model1)

####NULL MODEL
null<-lm(T2.T1~1, data = dataB)

####ENVIRONMENTAL IMPACT MODEL
model2<-lm(T2.T1~Average.of.3hr_precip+Average.of.CUM_GPP1km, data=dataB)
summary(model2)
#####################################################################################
###PLACE MODELS IN LIST TO COMPARE USING AIC VALUES (SUBORDINATE)####
cand.models<-list()
cand.models[[1]]<-lm(T2.T1~Average.of.gpw_v4_pop+Sum.of.Human.Presence, data=dataB)
cand.models[[2]]<-lm(T2.T1~Average.of.3hr_precip+Average.of.CUM_GPP1km, data=dataB)
cand.models[[3]]<-lm(T2.T1~1,data = dataB)
```

```
Modnames<-c("human","environment","null")

#view output
aictab(cand.set=cand.models, modnames = Modnames,sort = TRUE)
summary(cand.models[[3]])
################################################################################
#####DOMINANT MODELS######################################################

###HUMAN IMPACT MODEL
model11<-lm(T2.T1~Sum.of.Human.Presence+Average.of.gpw_v4_pop, data = dataAA)
summary(model11)

####NULL MODEL
null2<-lm(T2.T1~1,data=dataAA)

####ENVIRONMENTAL IMPACT MODEL
model22<-lm(T2.T1~Average.of.3hr_precip+Average.of.CUM_GPP1km, data=dataAA)
summary(model22)
################################################################################
#PLACE MODELS IN LIST TO COMPARE USING AIC VALUES (LARGE CARNIVORES)
cand.modelsb<-list()
cand.modelsb[[1]]<-lm(T2.T1~Average.of.gpw_v4_pop+Sum.of.Human.Presence,data=dataAA)
cand.modelsb[[2]]<-lm(T2.T1~Average.of.3hr_precip+Average.of.CUM_GPP1km,
data=dataAA)
Modnames<-c("human","environment","null")

#view output
aictab(cand.set=cand.modelsb, modnames = Modnames,sort = TRUE)
################################################################################
PLOT FULL MODELS TO COMPARE EFFECTS OF DOMINANT AND
SUBORDINATE#####################################################################
plot_summs(model1,model2, scale=T, model.names = c("Human Impact","Environmental
Impact", "Null"), colors = c("palevioletred4","midnightblue"))
plot_summs(model1,model11, scale=T, model.names = c("Subordinate","Dominant",), colors =
c("palevioletred4","midnightblue"))
plot_summs(model2,model22, scale=T, model.names = c("Subordinate","Dominant"),colors =
c("palevioletred4","midnightblue"))
plot_summs(null,null2, scale=T, model.names =
c("Subordinate","Dominant"),line.thickness=5,colors = c("palevioletred4","midnightblue"))
plot_summs(bigmodel)
################################################################################

################################################################################
```

```
#####VISUALIZING RELATIONSHIPS
###LINEAR MODEL SCATTER PLOTS####################################

#######################################
#A-B SUBORDINATE HUMAN MODEL
#######################################
a<-ggplot(dataB, aes(x=Sum.of.Human.Presence, y=T2.T1))+
  geom_point(size=5)+
  theme(text = element_text(size=26))+
  stat_smooth(method="lm", col="palevioletred4", fill="palevioletred4")
a
b<-ggplot(dataB, aes(x=Average.of.gpw_v4_pop, y=T2.T1))+
  geom_point(size=5)+
  theme(text = element_text(size=26))+
  stat_smooth(method="lm", col="palevioletred4", fill="palevioletred4")
b

###Check Population Outlier
max(covs$Average.of.gpw_v4_pop)

lower_bound <- quantile(covs$Average.of.gpw_v4_pop, 0.025)
lower_bound
upper_bound <- quantile(covs$Average.of.gpw_v4_pop, 0.975)
upper_bound
outlier_ind <- which(covs$Average.of.gpw_v4_pop < lower_bound |
covs$Average.of.gpw_v4_pop > upper_bound)
outlier_ind

###########################################
#C-D SUBORDINATE ENVIRONMENTAL MODEL
###########################################
c<-ggplot(dataB, aes(x=Average.of.CUM_GPP1km, y=T2.T1))+
  geom_point(size=5)+
  theme(text = element_text(size=26))+
  stat_smooth(method="lm", col="palevioletred4", fill="palevioletred4")
c
d<-ggplot(dataB, aes(x=Average.of.3hr_precip, y=T2.T1))+
  geom_point(size=5)+
  theme(text = element_text(size=26))+
  stat_smooth(method="lm", col="palevioletred4", fill="palevioletred4")
d
```