DRIVERS AND MECHANISMS OF CARNIVORE COMMUNITIES ACROSS AN URBAN TO WILDERNESS GRADIENT IN NEW YORK STATE

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ABSTRACT

S.L. Opel. Evaluation of Carnivore Community Responses to Human Disturbance and Forest Characteristics, 105 pages, 6 tables, 25 figures, 2025. Ecology style guide used.

To better understand how the complex landscape dynamics of New York shape carnivore communities, I employed single species occupancy models and daily activity pattern overlaps. In a more novel approach, I utilized a 1m resolution LiDAR imaging canopy height model (CHM) to obtain a higher level of detail to describe forest cover and structure of camera sites. I also employed more traditional landcover and road data to describe human disturbance. Median canopy height, proportion of tall trees and road density proved to be important predictors of carnivore occupancy and temporal activity. The two forest characteristics were variable in their relationship (positive or negative) with individual species predicted occupancy but were found to be highly positive with respect to species' temporal activity overlaps. Road density displayed a highly negative association with species' occupancy, with the exception of raccoons, as well as negatively affecting species' activity overlaps.

Key Words: New York, carnivores, mesocarnivores, mammals, occupancy, activity patterns, conservation, human disturbance

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CHAPTER 1: Background and Introduction

Natural History

The landscape of eastern North America has undergone drastic changes in the last 400 years, shaped largely by European colonization and settlement (Thompson et al. 2013). Pre-colonization, which occurred in the early 1600's, the northeastern United States landscape consisted primarily of forest stewarded by native peoples, but in the 1800's mass deforestation for agricultural purposes removed more than half of the forest cover (Bellemare et al. 2002, Thompson et al. 2013). This shift towards clearing for agriculture resulted in the extirpation of native apex predators, pumas or cougars *(Puma concolor)*, grey wolves *(Canis lupus)*, and Canadian lynx *(Lynx canadensis)* due to habitat loss as well as active hunting for the fur trade and to prevent predation of livestock and injury to people (Gompper et al. 2016). At the turn of the 20th century settlement and agriculture shifted westward resulting in dramatic reforestation of the Northeast in the past 150 years (Bellemare et al. 2002, Thompson et al. 2013) (Figure 1.1 and Figure 1.2). Central New York counties such as Onondaga and Tompkins counties exemplify this dramatic change as they were virtually 100% forested pre-settlement with Onondaga County plummeting to 8% forest cover in 1930 (Hill 1985, Nyland et al. 1986, Flinn et al. 2005) and skyrocketing to 62% forest cover today (NY DEC Forests and the Environment) (Figure 1.3).

Despite the extensive reforestation of the eastern U.S., forests and faunal communities have not returned to their pre-settlement state. While 80% of the Northeast region was found to be forested in 2010, less than 1% of forests consisted of intact old growth, (Thompson et al. 2013) a forest characteristic (proxied by median canopy height and proportion of trees >20m) that my study found to be an important mechanism in facilitating co-existence of native carnivores. The natural reforestation of this region appears to have reached its peak and is slightly declining again due to

increases in development rather than agricultural purposes as it had been in the past (Thompson et al. 2013). Historically native apex predators have not been reintroduced, resulting in fundamental changes to mammal communities. These changes include the resulting mesopredator release (Ritchie and Johnson 2009, Prugh et al. 2009) exemplified by the recent and rapid expansion of coyotes *(Canis latrans)* in the eastern U.S. (Hody and Kays 2018, Bragina et al. 2019) (Figure 1.4) as well as the release of predation pressures of white-tailed deer populations resulting in their overabundance in the Northeast region (Healy et al. 1997, Warren 2011).

Coyote Expansion

The competitive and predation pressure of coyotes on local mammal communities from which the coyotes had been historically absent have been a heavily researched topic since their expansion into the Northeast in the mid-20th century (Fener et al. 2005, Warsen 2012, Hody and Kays 2018, Bragina et al. 2019). Findings show that coyotes do not exert apex predator pressures on white-tailed deer abundance as suspected (and hoped) (Warsen 2012, Bragina et al. 2019, Avrin et al. 2023). However, their competitive pressure on other mesocarnivore species is variable and not well understood (Major and Sherburne 1987, Litvaitis and Harrison 1989, Gompper 2002, LeFlore et al. 2019, Dyck et al. 2022). In aggregate, these results suggest that when habitat and diet overlap of mesocarnivore species with coyotes was high, niche partitioning, particularly temporal partitioning, allowed for the co-existence of existing communities with the invading coyote (Litvaitis and Harrison 1989, Fedriani et al. 2000, Chamberlain and Leopold 2005, Rodríguez-Luna et al. 2023, Cervantes et al. 2023).

With this study, I aimed to better understand the impacts of these dramatic landscape and mammal community changes in New York. I utilized occupancy modeling to address the landscape effects on carnivore species individually and daily activity pattern overlaps to evaluate landscape effects

on the temporal partitioning of these species in an attempt to determine the mechanisms that allow for the persistence and co-existence of these species. Identifying these mechanisms could greatly inform forest management for the conservation of native carnivore species and improve the overall health of the dynamic ecosystems of New York.

Observational Data

My study area consisted of 14 camera trap arrays across New York State (Figure 1.5) that I obtained from open access camera trap data that I accessed via the Wildlife Insights platform. This observational data was primarily provided by Snapshot USA (Rooney et al. 2025), a national collaborative survey of terrestrial wildlife populations using camera traps that follow a standardized protocol (Appendix 1.1). This protocol includes, but is not limited to, a sampling window of September 1 to October 31st with a two-week leeway on either side, a minimum of 400 trap nights, cameras being deployed 200m-5km apart and 50cm from the ground, and the prohibition of bait. I also utilized data collected by Black Rock Forest (LaPoint et al. 2018, Lapoint et al. 2021), a 501(c)(3) not-for-profit organization that maintains a 3,920-acre forest and scientific field station in the Lower Hudson Valley of New York, following a similar protocol. The 14 arrays consist of Black Rock Forest (BRF), the Cary Institute (Cary), a non-profit environmental research organization, Cranberry Lake Biological Station (CLBS), a remote SUNYESF research station/campus located at Cranberry Lake in the Adirondacks, Dyken Pond (Dyken), a recreational area in the Hudson Valley, Heiberg Forest (Heiberg), a research forest owned by SUNYESF located 25 miles south of Syracuse, Mianus River Gorge Preserve (Mianus), a nature preserve in the Hudson Valley, Newburgh, a city just north of BRF in the Hudson Valley, New York City (NYC), the largest populated city in the U.S., Paul Smith's College and St. Lawrence University, two colleges located in the upper Adirondack park. Albany Pine Bush Preserve (PineBush), a nature

preserve located outside of Albany, Skaneateles Conservation Area, a recreational area in Central New York, Syracuse, a city in Central New York where SUNY-ESF and Syracuse University are located, and Wolf Pond, a recreational area in the Hudson Valley.

The availability of open access ecological data has increased substantially since its emergence in the early 1990's (Lal and Lal 2011). Camera trapping is a powerful tool for monitoring wildlife populations non-invasively by enabling scientists to observe wildlife without disturbing or altering their behavior. Camera trapping also provides ample data that can be used to evaluate populations in many different ways. Allowing valuable observational data to be used repeatedly for many different kinds of analysis, allowing for much more information to be extracted from a single data source. The ability to access and compile these data from multiple sources allows for the analysis of larger sample sizes compared to those collected by individual studies, which generally increases the precision of analyses (Stockwell and Peterson 2002). However, utilizing open access data does come with its own challenges. Primarily, data compiled from multiple sources are highly heterogenous due to high variability in study design, collection protocols, and even terminology (Reichman et al. 2011, Salguero-Gómez et al. 2021). This was the most challenging aspect of compiling and preparing Snapshot USA (Rooney et al. 2025) and Black Rock Forest (LaPoint et al. 2018 & 2021) data for use in occupancy modeling. Camera trap arrays varied greatly in terms of data collection effort and design (Figure 1.6 and Appendix 1.2). The Black Rock Forest (BRF) array had the highest sampling effort with 12,904 total trap nights across 7 years while Syracuse (Syr) had the lowest at 224 total trap nights over 1 year. Area and distance between cameras also varied widely among arrays and years with the New York City (NYC) array consistently sampling the largest area (239-427 km^2) and some arrays sampling less than $1km^2$ (Appendix 1.3a. Appendix 1.3b, and Appendix 1.3c).

Camera trap arrays also varied widely in environmental characteristics, which was ideal for differences in effects of these characteristics on carnivore species occurrence and interactions (Figure 1.7, 1.8 and 1.9). Even among the urban-most arrays, NYC, Syracuse, Newburgh, and Albany Pine Bush, which displayed similar environmental characteristics, variability was still present with Newburgh possessing higher proportion of canopy and higher canopy height and Syracuse displaying the highest proportion of open area (Figure 1.7 and 1.8). Variability was high even among the Adirondack region arrays, Paul Smith's College, St. Lawrence University, and Cranberry Lake Biological Station (CLBS), with St. Lawrence displaying canopy height similar to the urban-most sites despite being on the opposite end of the development spectrum (Figure 1.7 and 1.9). The non-urban Hudson Valley region arrays, Black Rock Forest (BRF), Mianus River Gorge, Scenic Hudson Valley (Wolf), and Dyken Pond, displayed the highest overall canopy height and cover, with Mianus and the Heiberg Forest array located in the Central New York Region displaying the two highest mean and median canopy heights and relative proportion of trees >20m tall (Figure 1.7). Mianus, Heiberg and Wolf had the highest proportion of canopy of all arrays, while Dyken had the highest proportion of water by far (Figure 1.8). While the NYC array was of course the most developed overall, Syracuse displayed higher proportion of development due to camera site level characteristics (Figure 1.9). Cameras were placed in parks and forested areas of NYC while Syracuse cameras included more development within the 200m radius.

Ultimately, my goal was to identify fundamental mechanisms of mesocarnivore coexistence, i.e. those spatial and landscape properties (see below) that facilitate occupancy. Thus, in all subsequent modeling I characterize the camera trap arrays broadly, but do not use array itself as either a predictor or a random effect but rather focus on those properties across individual camera sites.

Spatial Data

Each camera site was characterized by several localized spatial covariates, broadly separated into forest characteristics and human disturbance. Uniquely, the forest characteristic and development variables were calculated from canopy height models (CHM) of high-resolution LiDAR imaging (Figure 1.10), a novel approach to describing wildlife habitat. Forest characteristic covariates prepared for use in my study consisted of mean, median, and standard deviation of canopy height, proportion of canopy cover and proportion of trees >20m tall (relative to canopy cover), proportion of open area and proportion of water as well as Moran's I, a measure of spatial autocorrelation, I used to describe landscape heterogeneity (Table.1.1 and Figure 1.11). Covariates intended to describe human disturbance included proportion of area developed and road density (Table 1.1.). Across the wide range of environments represented by the camera arrays, I characterized each camera site with the suite of environmental covariates. When faced with a large set of covariates, it can be useful to characterize the complexity and interactions among the covariates with a dimension reduction technique or ordination. I used Principal Component Decomposition of each camera site with the complete suite of 10 covariates. The decomposition values of arrays are displayed in Figure 1.12, and Figure 1.13 shows a side-by-side comparison of the first and second principal component covariate loadings with principal component 1 (PC1) describing an axis related to greater degrees of "urbanness" (i.e. more developed areas, higher road density, less tree cover), and PC2 where higher values were associated with more water presence and higher complexity of canopy structure. Although the sites were generally distinct with some particularly strong contrasts, (e.g., New York City with positive PC1, low average PC2; Mianus with negative PC1, positive PC2, and Dyken with low PC1 and negative PC2), overall, there was considerable overlap across the sites and considerable variation within sites, which was useful for my goal of identifying the fundamental drivers of coexistence that cut across intrinsic variation among sites.

Modeling Strategies

This thesis consists of this Introduction, two body chapters, and an overarching Conclusion. In Chapter 2 I use occupancy modeling to evaluate the effects of environmental covariates on individual species occurrence to better understand how carnivore communities are structured by the dynamic system of New York landscapes using the unmarked R package (Fiske and Chandler 2011, Kellner et al. 2023, R Core Team 2025). Occupancy models estimate the probability that a species will occupy a given site while incorporating imperfect detection, where an individual might fail to be detected despite being present at that site (MacKenzie et al. 2002). Due to my central scientific questions being related to occupancy and not detection, I focused on using ecologically meaningful covariates to evaluate occupancy and aggregated covariates into principal components for use as detection covariates to avoid confounding predictors of occupancy and detection probabilities. Single-season occupancy models were selected as my observational data occurs during the fall season when no colonization or extinctions are expected to occur (Mackenzie and Royle 2005). I then used Akaike's Information Criterion (AIC) to determine the variables that were the best predictors of occupancy probability for each species individually.

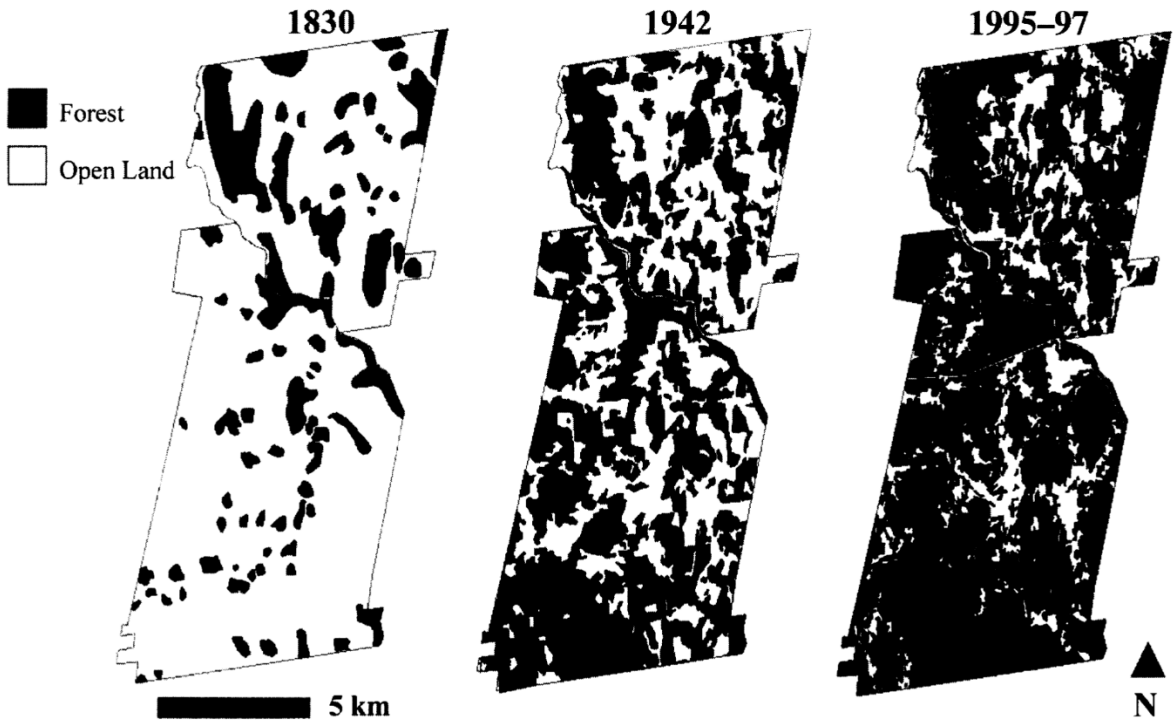
In Chapter 3 I employed daily activity pattern overlaps using the R overlap package which calculates overlaps using kernel density functions (Ridout and Linkie 2009, Meredith et al. 2024, R Core Team 2025) to evaluate the temporal partitioning of species pairs to identify the environmental variables that shape community interactions and niches. I created overlap networks to visually interpret how species activity overlap changes at different covariate intensities. For both these chapters, I use the exact same observational and spatial data described here and consequently refer to these tables and figures as needed.

In the Conclusions I discuss the novelty of my study in comparing carnivore communities across such a large study area and the employment of LiDAR imaging to evaluate wildlife habitat. I also discuss the limitations of this study and suggest improvements and recommendations for future research on this topic including use of additional environmental covariates and observational data to best identify the environmental characteristics that promote the persistence and coexistence of carnivore species to better inform forest management and conservation of these faunal communities.

Table 1.1. Description of covariates and covariate codes used for modelling.

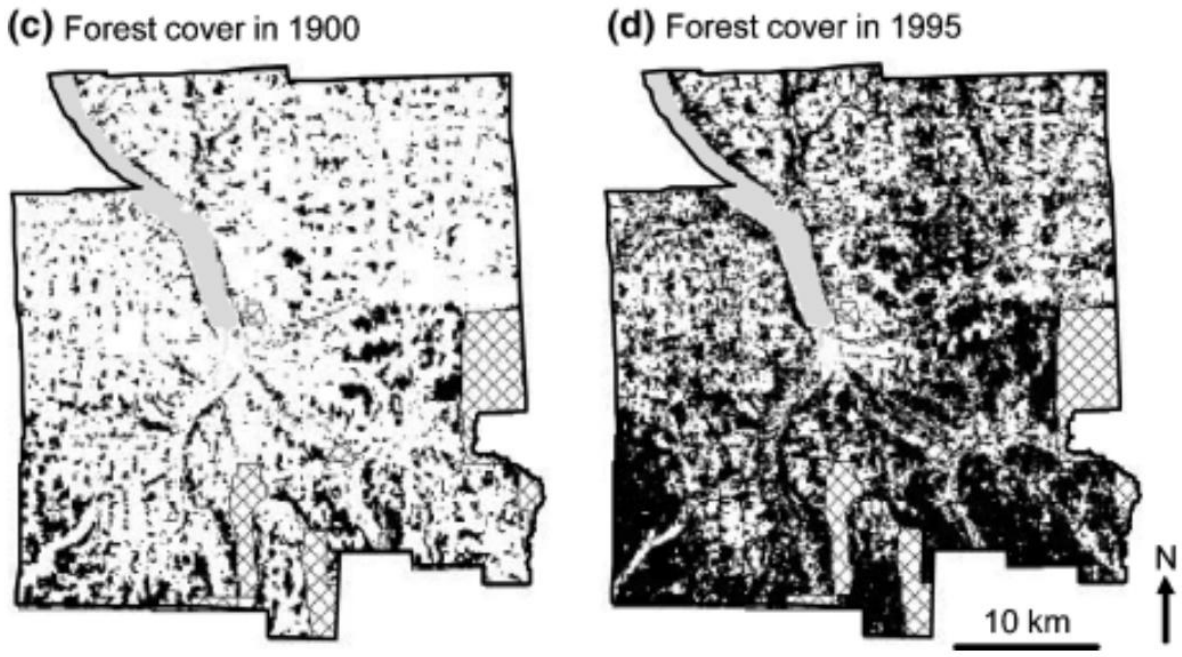
Covariate Modeling Code	**Covariate Description**
median_height	Median canopy height derived from LiDAR canopy height model (CHM).
sd_height	Standard deviation of canopy height derived from LiDAR CHM.
prop_canopy	Proportion of canopy cover derived from LiDAR CHM.
relprop_verytall	Proportion of trees >20m tall relative to canopy cover derived from LiDAR CHM.
prop_open	Proportion of open area calculated as total area – prop_canopy.
prop_water	Proportion of water bodies derived from LiDAR CHM.
MoransI	Moran's I, measuring spatial autocorrelation derived from LiDAR CHM. $I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$ Source: NYS GIS Clearinghouse. 2023. NYS Historic LiDAR Collections. https://gis.ny.gov/lidar.
prop_developed	Proportion of development derived from LiDAR CHM masked with medium and high developed classifications from landcover (NLCD).
road_density	Density of roads derived from USCB's 2024 TIGER/Line Shapefiles.
PC1	Principal component 1 describing an axis related to greater degrees of "urbanness" (i.e. more developed areas, higher road density, less tree cover).
PC2	Principal component 2 describing an axis with with more water presence and higher complexity of canopy structure.

Figure 1.1. Changes in land cover in 1830, 1942, and 1995-97 of two towns in western Massachusetts.



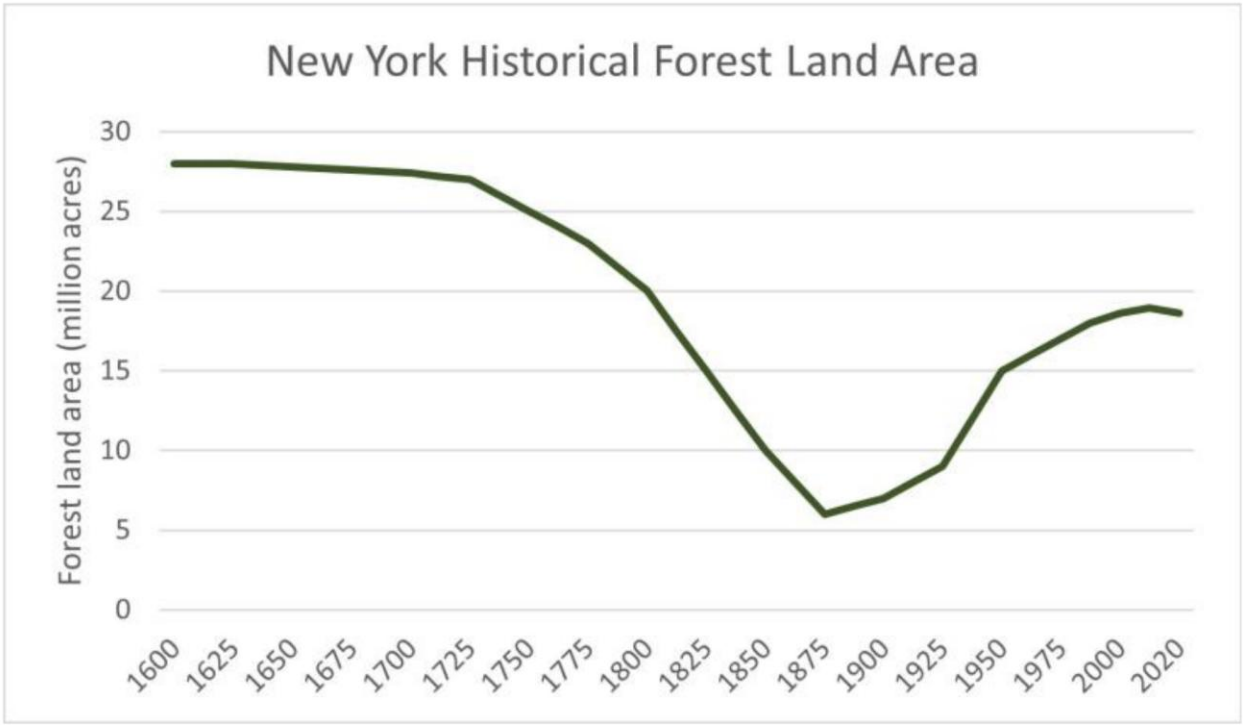
Changes in land cover in 1830, 1942, and 1995-97 of two towns in western Massachusetts showing large increases in forest cover that exemplify the 19th century reforestation of the eastern U.S. Source: Bellemare et al. 2002

Figure 1.2. Maps of Tompkins county New York forest cover between 1900 and 1995.



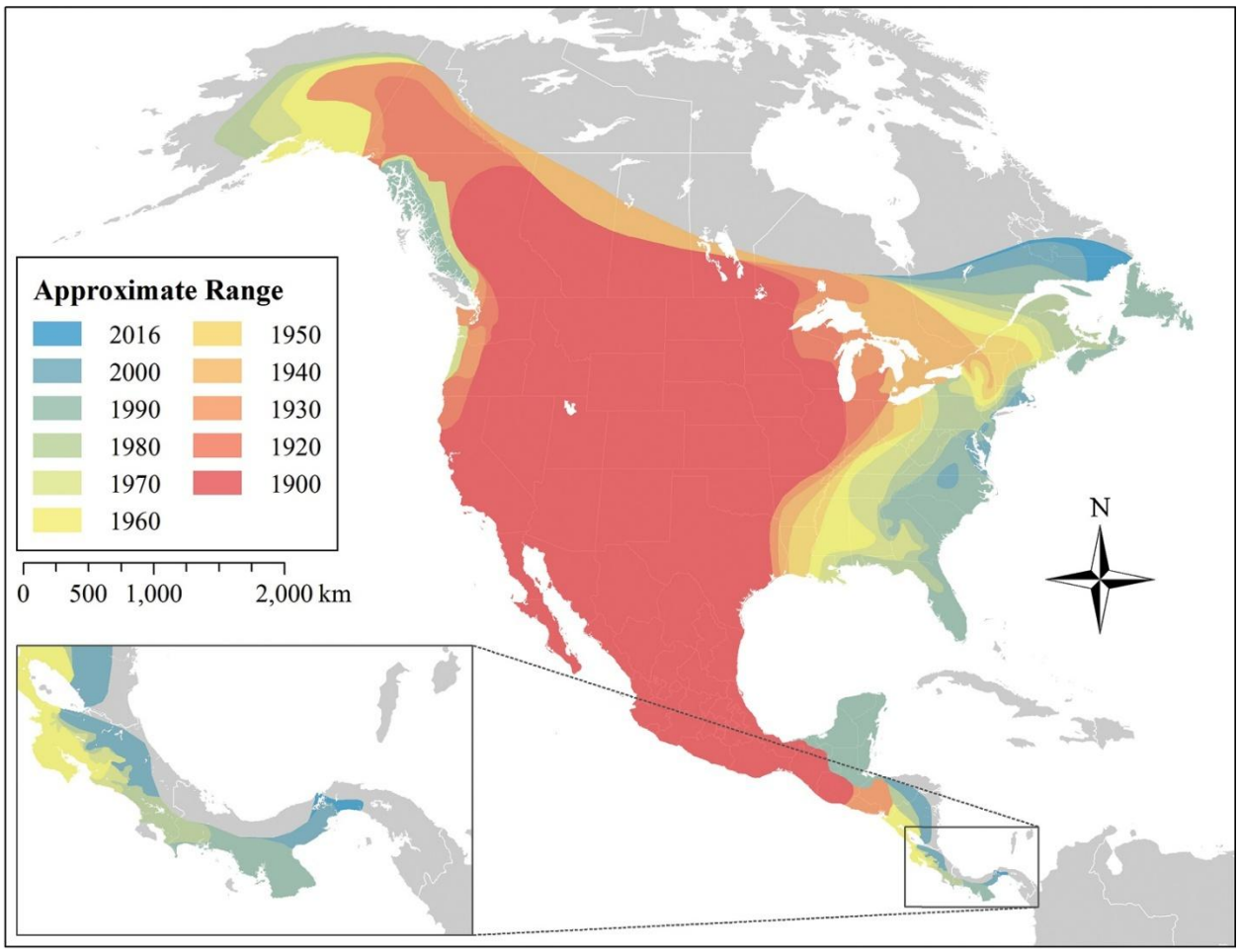
Maps of Tompkins county New York showing increased forest cover between 1900 and 1995. Source: Flinn et al. 2005

Figure 1.3. Graph of historical forested land area in million acres of New York State from 1600 to 2020.



Graph of forested land area in acres of New York State from 1600 to 2020 showing the mass forest clearing by settlers in the 18th and 19th centuries as well as the subsequent reforestation that occurred in the 20th century through 2020. Sourced from NY DEC Forests and the Environment web page. https://dec.ny.gov/nature/forests-trees/forests-and-the-environment

Figure 1.4. Map of coyote range expansion in North America by decade.



Map of coyote range expansion by decade, showing coyote invasion into New York occurred during 1940-1980. Source: (Hody and Kays 2018)

Figure 1.5. Map of study area with deployments color coded by array

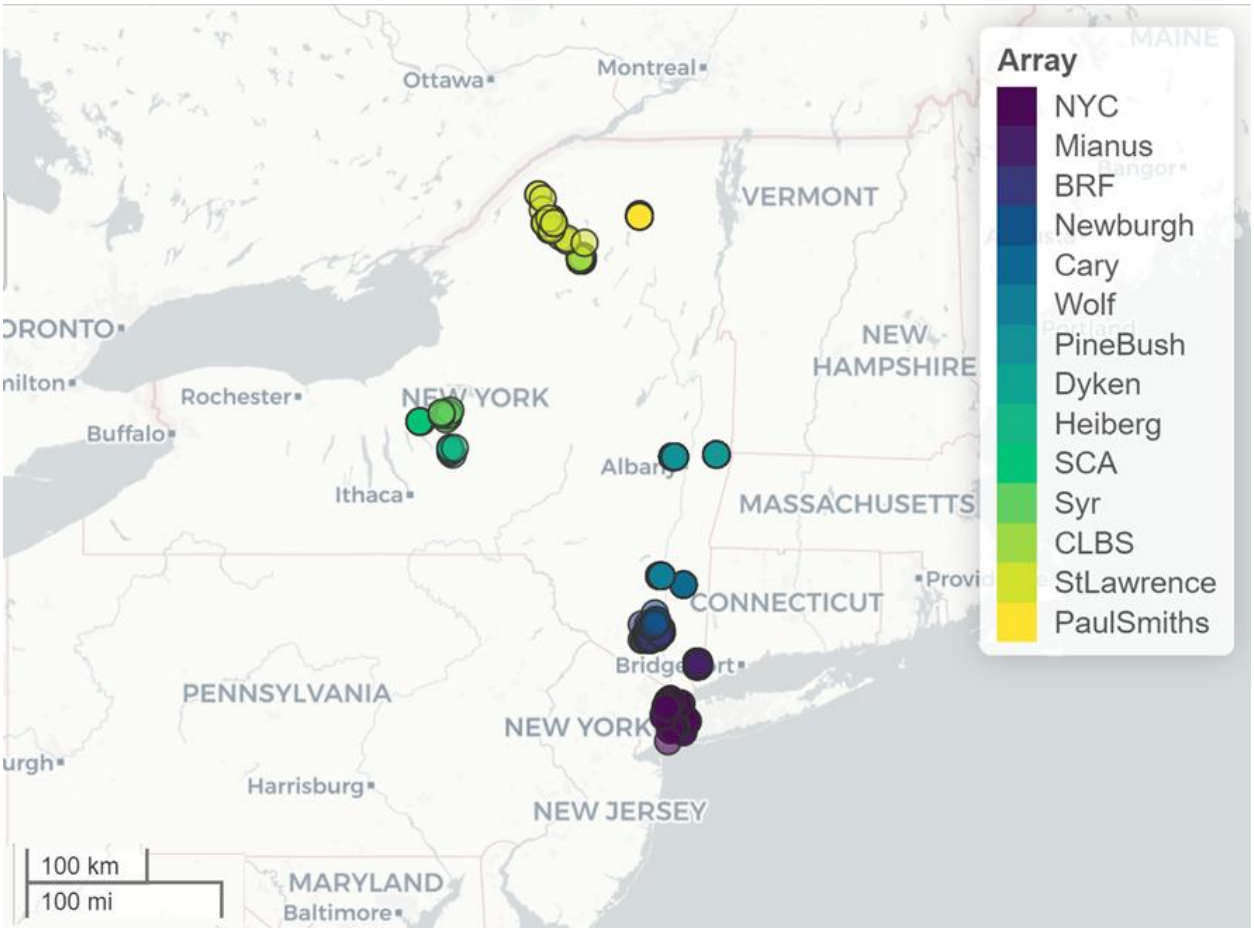


Figure 1.6. Camera trap array sampling effort showing number of cameras and duration for each year sampled.

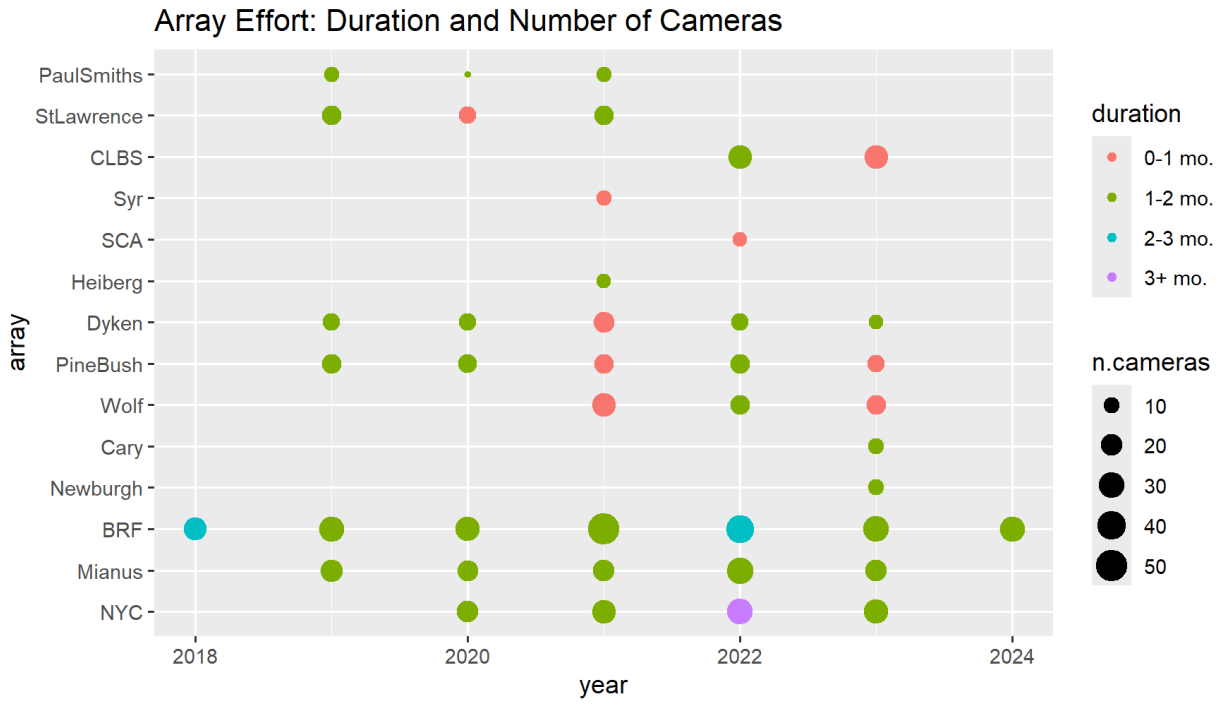


Figure 1.7. Canopy height covariate averages with 95% confidence intervals for camera trap arrays showing high variability of array characteristics.

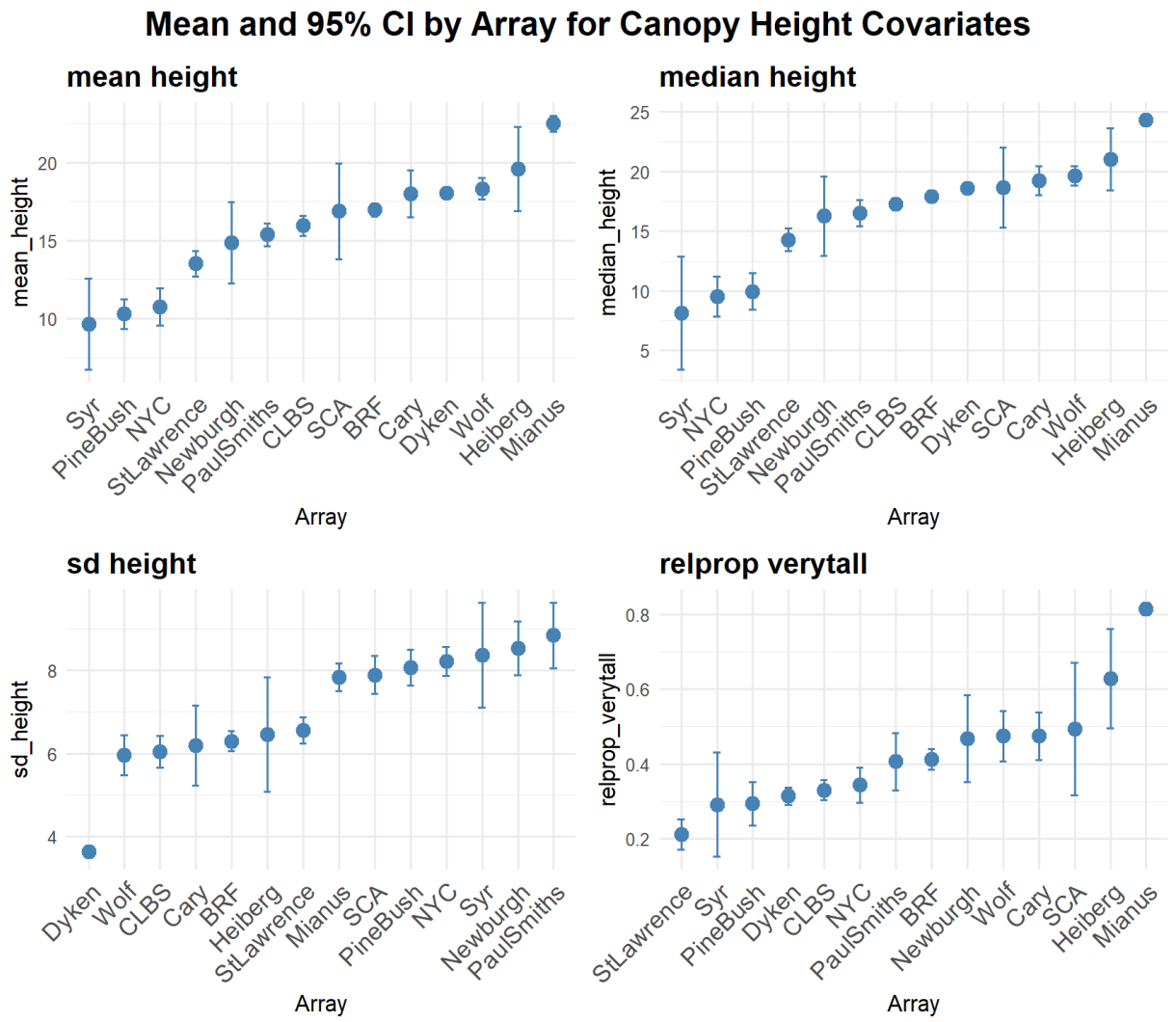


Figure 1.8. Forest characteristic covariate averages with 95% confidence intervals for camera trap arrays showing high variability of array characteristics.

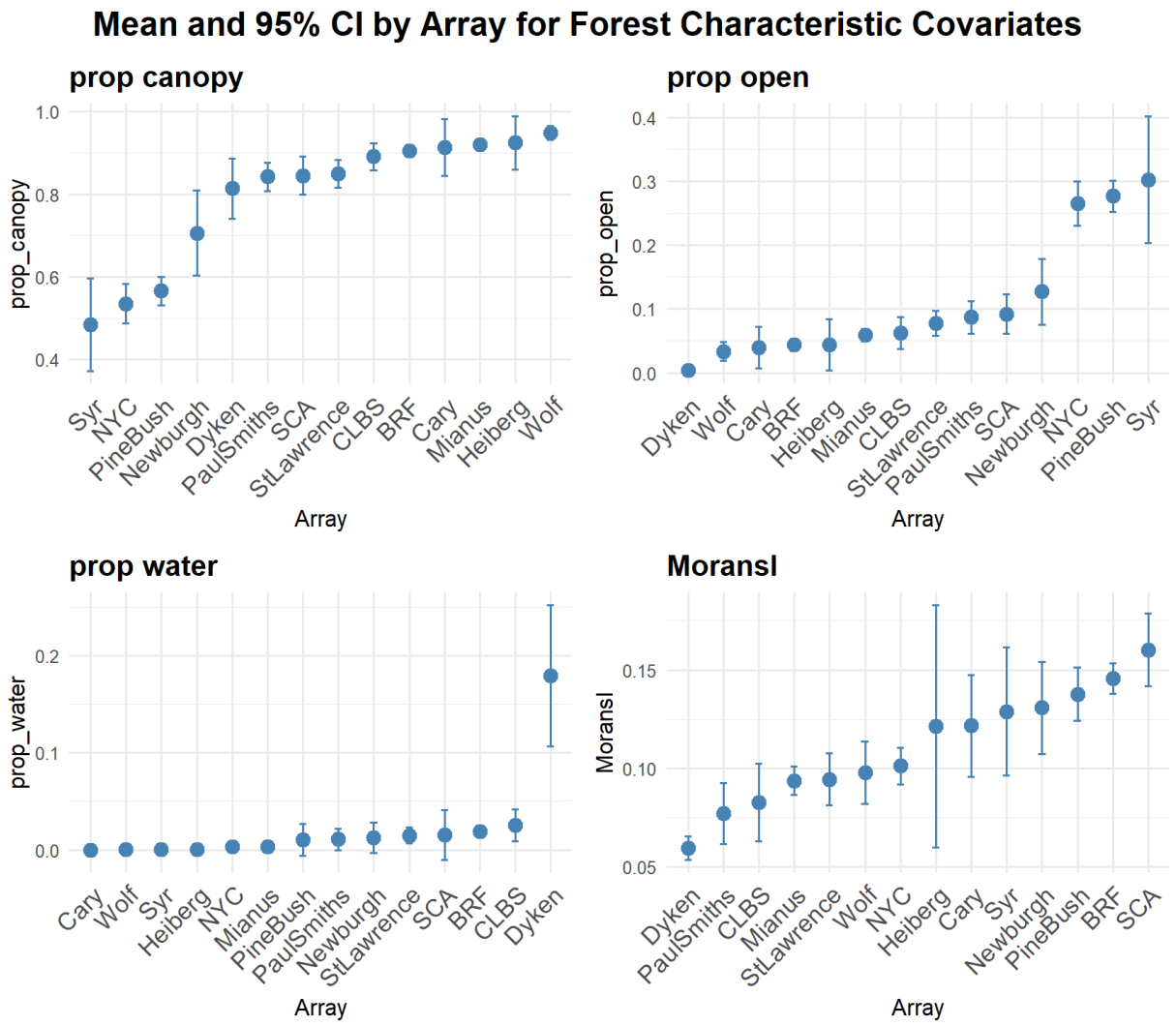


Figure 1.9. Human disturbance covariate averages with 95% confidence intervals for camera trap arrays showing high variability of array characteristics.

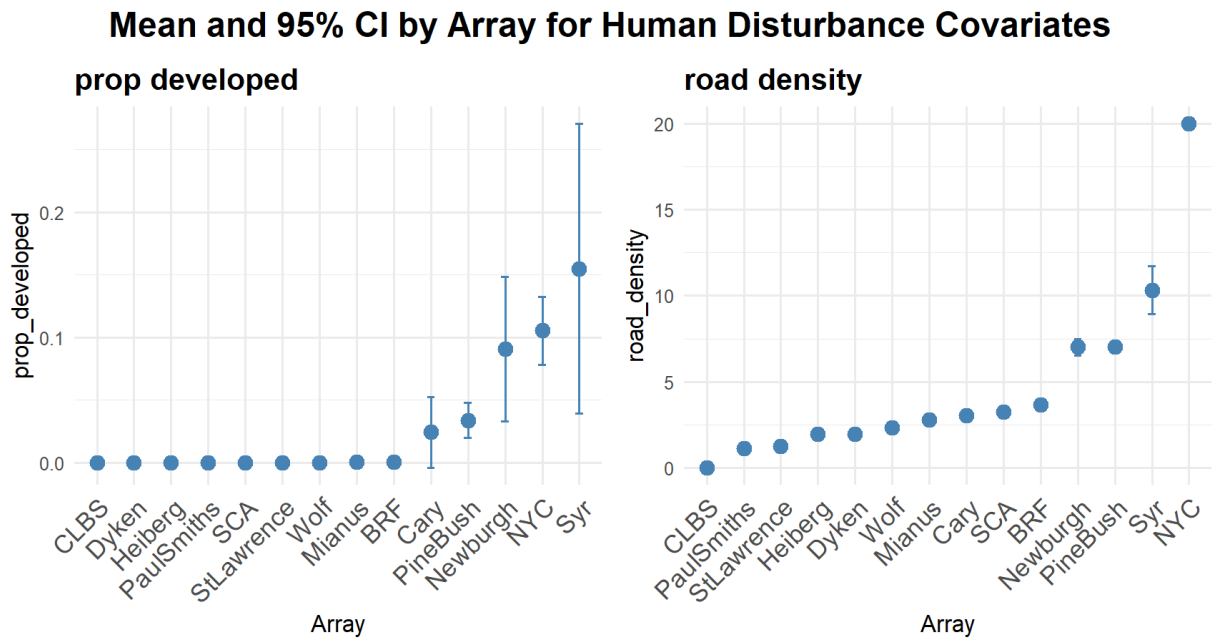
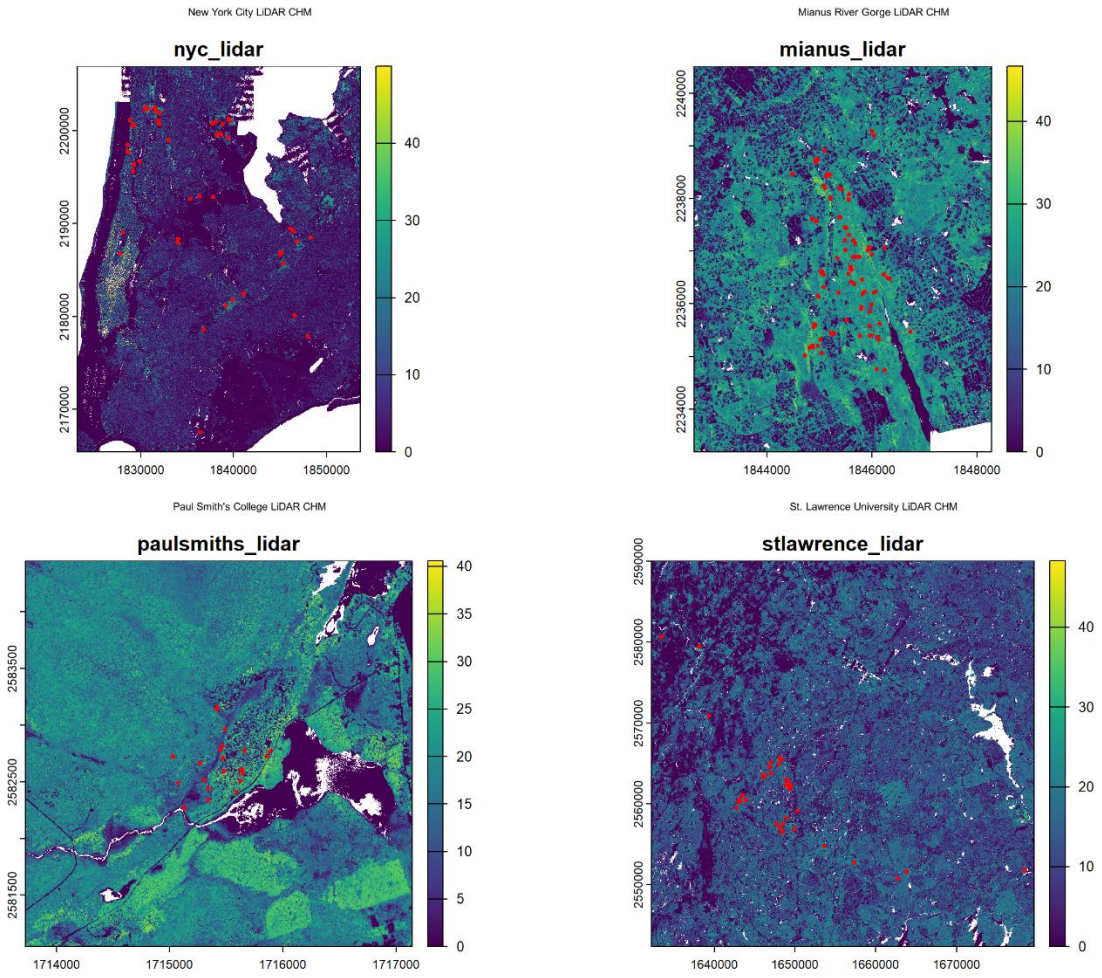
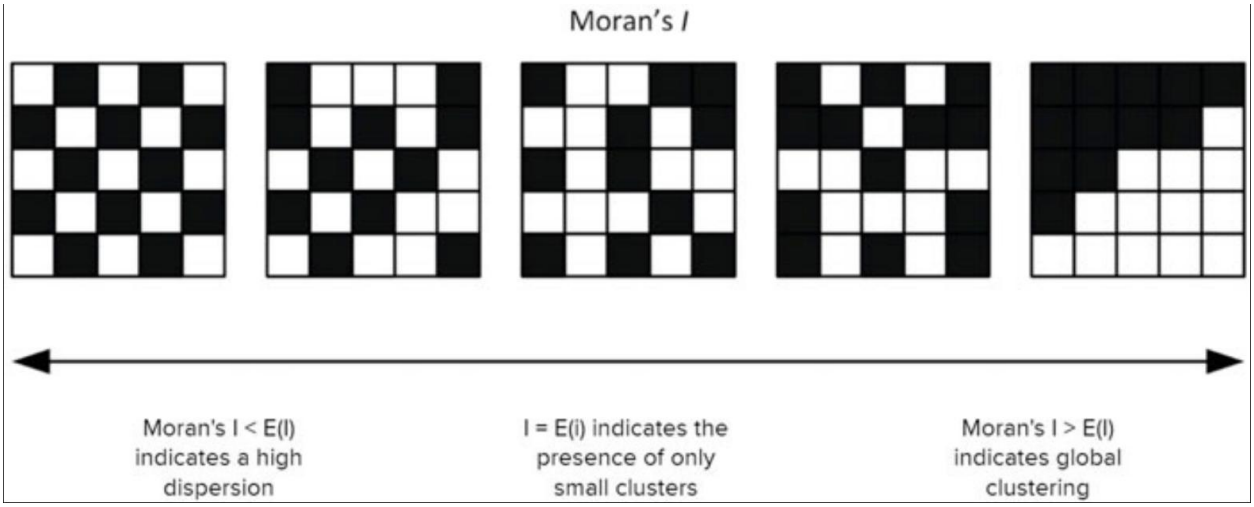


Figure 1.10. LiDAR derived canopy height model at 1m resolution with red dots showing camera deployments, of four camera trap arrays.



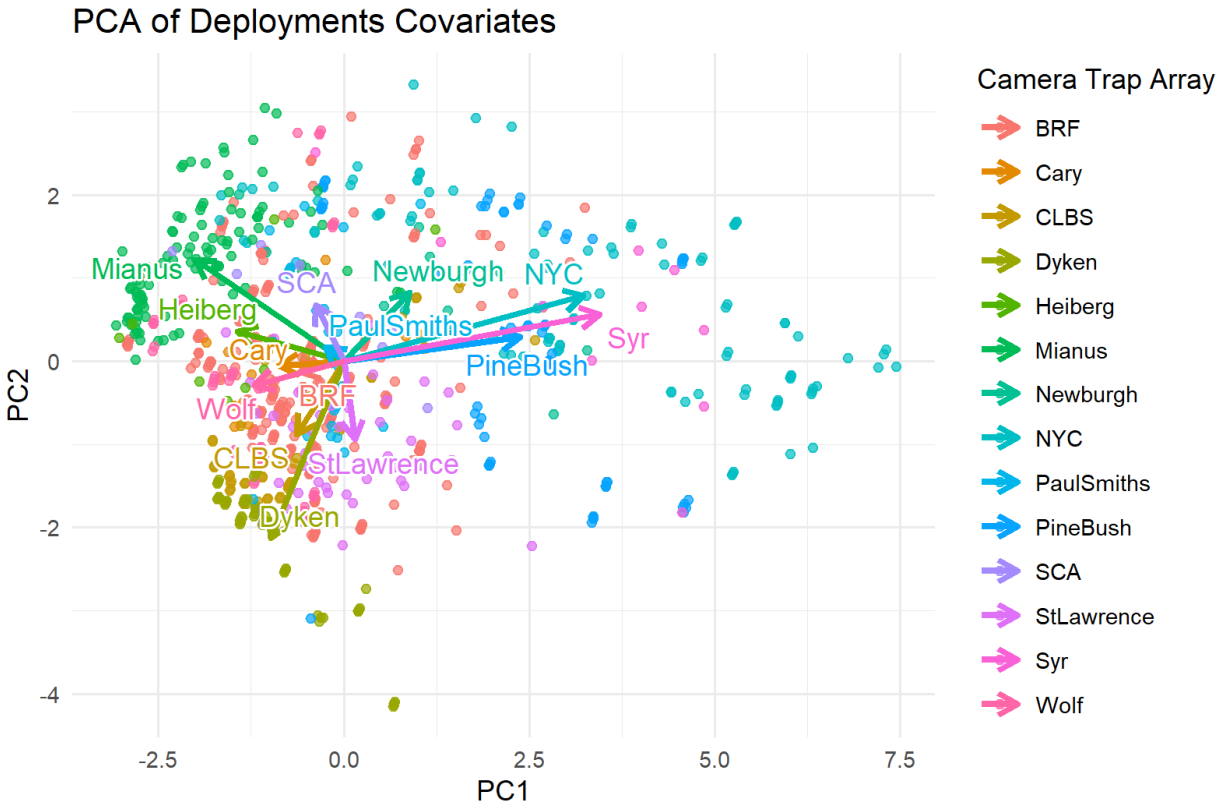
LiDAR derived canopy height model at 1m resolution with red dots showing camera deployments, of four camera trap arrays, New York City, Mianus River Gorge, Paul Smith's College, and St. Lawrence University. These arrays illustrate the dramatic urban to wild gradient my study encompasses as well as the stark differences among "similar" sites. Both the St. Lawrence and Paul Smith's arrays occur in the Adirondack's but consist of very different forest structures.

Figure 1.11. Example of interpretation of Moran's I of spatial autocorrelation.



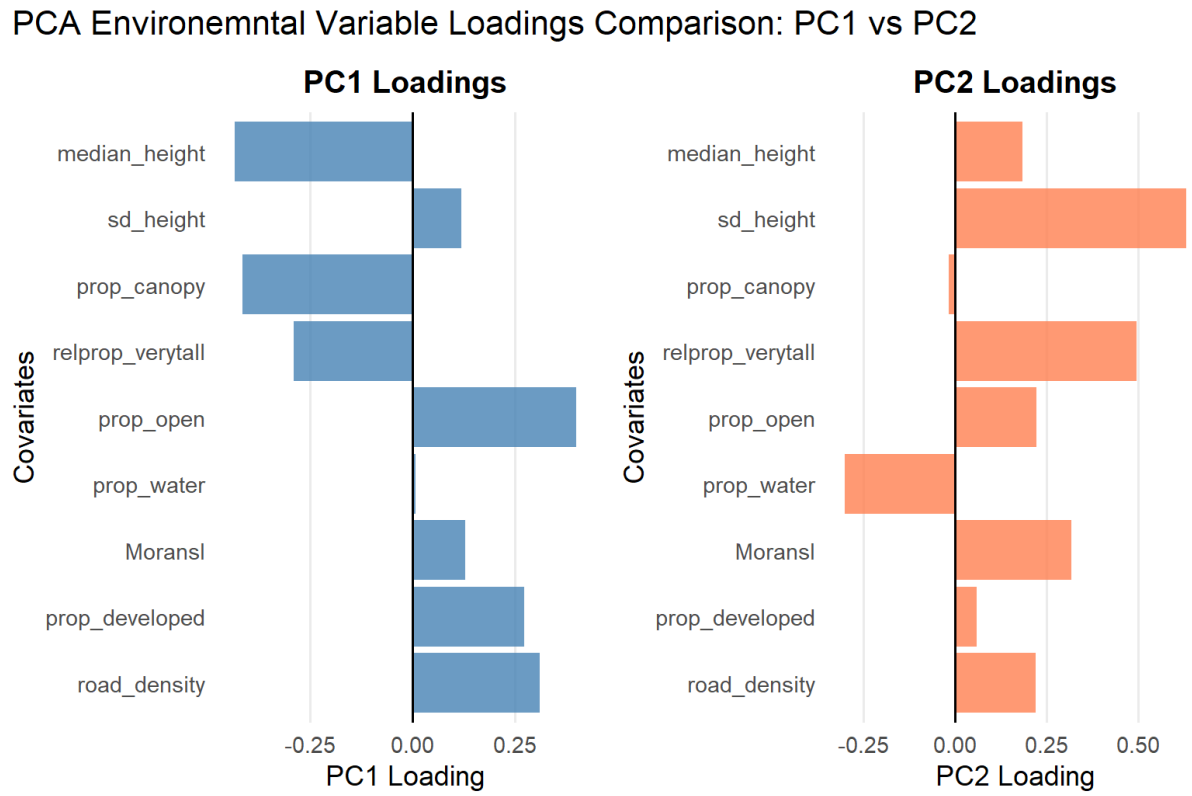
Example of interpretation of Moran's I of spatial autocorrelation where high Moran's I describes high clustering and low Moran's I describes high dispersion. Source: (Tsui et al. 2022).

Figure 1.12. Principal component analysis of environmental covariates by camera trap array.



Principal component analysis of environmental covariates by camera trap array, showing the variability in environmental characteristics of arrays with city arrays displaying high PC1 (more developed, higher road density, lower canopy height and complexity) characteristics.

Figure 1.13. Environmental loadings of principal components 1 and 2 from principal component analysis.



Environmental loadings of principal components 1 and 2 from principal component analysis performed on environmental covariates showing that PC1 describes a more urban environment with higher developed area and road density and lower canopy height and coverr. PC2 describes a more forested environment with more water present.

CHAPTER 2: Predicting carnivore occupancy response to forest characteristics and human disturbance

ABSTRACT

Worldwide human encroachment on wild habitat has resulted in habitat loss and fragmentation, the extirpation of apex predators to prevent livestock predation and human injury, and the invasion of historically non-native species. These alterations of ecosystems have huge impacts on carnivore communities. My aim was to determine the effects of human disturbance and forest structure on native mammal species' occurrence. I utilized Snapshot USA data from 786 camera trap sites collected in the fall of 2018-2024 at 14 different arrays located across New York State. These arrays encompass a dramatic urban-wild gradient from New York City to the Adirondack Park. Six focal carnivore species were selected for their body size (large and meso- carnivores) and number of observations (N>85). I applied single species, single season occupancy models using a 1-week interval to determine important environmental predictors of carnivore occurrence.

INTRODUCTION

Mesocarnivores are a diverse and abundant class of smaller and mid-sized mammalian predators that play an important function in mediating food web dynamics in temperate forest communities. Their role, however, is highly context dependent: greater in the absence of apex predators, and dependent on the overall complexity of intraguild and prey communities (Roemer et al. 2009). In the Northeastern states, the ecological context of forested landscapes is complex and dynamic. Until the turn of the 20th century, the settling of Northeastern states for agricultural purposes was accompanied by mass deforestation and the extirpation of top predators (Gompper 2016). As agriculture shifted westward and land-use has otherwise shifted, there has been dramatic reforestation of abandoned farmland (Klepeis et al. 2013), the appearance and rapid expansion of

coyotes (*Canis latrans*) (Gompper 2002, Fener et al. 2005), and an increase in Wildland-Urban Interface (WUI). Mesocarnivore communities are likely highly affected by all these changes. Most notably, the extirpation of apex predators (wolves *Canis lupus* and cougar *Puma concolor*) has led to "mesopredator release" (Ritchie and Johnson 2009, Prugh et al. 2009), which is reflected both as an increase in the populations of native mesopredator species and in the invasion of non-native mesopredators, notably coyote. Consistent with mesopredator release, the community of mesocarnivores in New York State is diverse and – at the largest scale – expanding (Prugh et al. 2009), but much is unknown about how communities are structured in the context of variable forest cover and human impacts.

My overarching goal was to characterize the occurrence of carnivore species across a large portion of New York State encompassing a dramatic urban (NYC) to wild (Adirondack Park) gradient. My objectives were to identify and quantify the existing carnivore communities across multiple camera trap arrays and to model the role of forest characteristics and human development in structuring these communities. The focal species of my study include the American black bear *(Ursus americanus)*, bobcat *(Lynx rufus)*, coyote, red fox *(Vulpes vulpes)*, fisher *(Pekania pennanti)*, and Northern raccoon *(Procyon lotor)*.

Building on the research done elsewhere and my own knowledge of mesocarnivore ecology, I explored several predictions and hypotheses. I expected raccoons and red fox to be the least sensitive to human influences by occurring ubiquitously throughout the study area and showing the least response to forest characteristic predictors (Lavin et al. 2003, Lombardi et al. 2017, Cervantes et al. 2023, Hansen et al. 2024). While I expected coyotes to be omnipresent as well, it is known that they will avoid the urban-most areas of the cities they occur in represented by their absence from Manhattan and the downtown and university areas of Syracuse and Newburgh

despite their presence in more suburban parts of these cities (Fener et al. 2005, Lombardi et al. 2017, Breck et al. 2019, Hansen et al. 2024). Due to this, I predicted there to be a minimum canopy cover requirement and a maximum proportion of developed area and road density for coyote occupancy. I similarly expected bears to be less sensitive to human presence due to their opportunistic nature and their well-documented behavior of taking advantage of human resources (Gompper et al. 2016, Kautz et al. 2021, Procko et al. 2023, Hansen et al. 2024). Despite this, their habitat requirements restrict their occurrence to the densely forested regions of New York State, the Adirondack Park and rural/wild areas of the Hudson Valley. Thus, I expected a higher minimum canopy cover, median canopy height, and proportion of tall trees (>20m, relative to canopy cover) and a maximum of road density and proportion of developed areas for bears to occur. Meanwhile, I predicted bobcats and fisher to be the most sensitive to human development and expect to see a positive effect of canopy cover, median canopy height, and relative proportion of tall trees to have a positive effect on bobcat and fisher occupancy while road density and proportion of developed area will negatively impact occupancy (Fox and Brocke 1983, Riley et al. 2003, Chamberlain and Leopold 2005, Clare et al. 2015, Lombardi et al. 2017, Dyck et al. 2022, Cerreta et al. 2023).

METHODS

Study Area

My study area consisted of 786 deployments across 14 camera trap arrays and 3 regions of New York State (Figure 1.5). The Adirondack Park (ADK) region consisted of 3 arrays, Cranberry Lake Biological Station (CLBS), St. Lawrence University, and Paul Smith's College. The Central New York (CNY) region contained 3 arrays as well in Heiberg, Skaneateles Conservation Area (SCA), and Syracuse. Most arrays occurred within the Hudson Valley (HV) region, consisting of Black Rock Forest (BRF), Cary, Dyken Pond, Mianus River Gorge Preserve, Newburgh, Albany Pine

Bush, and Scenic Hudson (Wolf). The final, southernmost region was New York City (NYC) which contained only one array of the same name. These arrays were highly variable in terms of sampling effort with some arrays, such as Syracuse, having only 9 deployments and 1 year of data collection, while other arrays had intense sampling efforts exemplified by BRF which collected data from 427 cameras across 7 years (Appendix 1.2). These arrays encompass a dramatic urban to wild gradient with NYC being the most extreme urban region and the ADK region representing extreme wilderness and observing >30 of New York State's mammal species.

Data

The camera trap data I utilized was accessed via Wildlife Insights on August 5, 2025 and consists of data provided by Black Rock Forest (LaPoint et al. 2018, Lapoint et al. 2021), a 501 (c) 3 not-for-profit organization that maintains a 3,920-acre forest and scientific field station in the Hudson Highlands of New York, and Snapshot USA ((Rooney et al. 2025), a national collaborative survey of terrestrial wildlife populations using camera traps that follow a standardized protocol (Appendix 1). The Snapshot USA data was filtered to New York state only and all data that BRF had contributed to Snapshot USA was removed to avoid pseudo-replication. Data collected from the Jone's Beach camera trap array was also removed due to the habitat consisting of shrubland rather than forest. When both datasets were combined the sequences were subset further to only mammal species and deployments in August through November, as there were not enough observations in other months for analysis, resulting in a dataset that contains camera trap data collected from 2018-2025 and consisting of 786 deployments and 53,242 observations of mammals.

In order to obtain forest and human influence covariates (Table 1.1) to use as predictors in my analysis I integrated several spatial data streams: detailed 1m resolution forest canopy height model (CHM) derived from LiDAR imaging sourced from the NYS GIS Clearinghouse (NYS GIS

Clearinghouse 2023) and processed by the SUNY ESF forestry department using the lidR package (Roussel et al. 2020, 2025, R Core Team 2025) in R (Figure 1.8), land cover data at a 30m resolution from the National Land Cover Database (NLCD) (Jin et al. 2023) and road data provided by the United States Census Bureau (USCB) (U.S. Census Bureau 2024) as part of the U.S. Department of Transportation (USDOT)/Bureau of Transportation Statistics (BTS) National Transportation Atlas Database (NTAD).

I broadly looked at three kinds of predictor covariates: those related to forest structure, those related to human impact, and aggregated predictors derived from ordination. The relevant spatial scale at which these predictors might be relevant is an open question. I therefore explored these variables at three spatial scales within 200 m, 500 m and 1 km radii.

The forest structure covariates used to describe forest structure were derived from the LiDAR CHM within a 200 m, 500m, and 1km radius of each deployment, and included mean, median, and standard deviation of canopy height, proportion of open area, proportion of water, proportion of canopy cover, proportion of trees greater than 20m tall (relative to canopy cover), and Moran's I, a measure of spatial autocorrelation that I used to describe heterogeneity – higher values of Moran's I correspond to areas with more variable structure (Figure 1.11). For covariates intended to describe human impact I estimated the proportion of developed area based on NLCS within a 200m, 500m, and 1km radius of each deployment by masking the LiDAR with the medium and high intensity developed classes from the land cover data. Road data was used to estimate total road density (km/km^2) within a 5km radius of each deployment. Due to the high concentration of roads and the large area of the NYC array it was deemed inefficient to estimate road density so a fixed value of 37 km/km^2 was assigned. These values were estimated based on NYC DOT estimates of 302 square miles of total land area and 6300 miles of road plus >12,000 miles of

sidewalk. I designated human presence to be a categorical variable of whether a deployment captured a human. All continuous covariates were scaled for analysis, and a principal component analysis (PCA) was employed for data reduction of covariates (Figure 1.10). The PCA was performed using the base R function prcomp (R Core Team 2025) which calculates the principal components using singular value decomposition. Principal components are linear combinations of the original covariates that capture the variance of the data. The first principal component accounts for the most variance and decreases with further components (Abdi and Williams 2010). Only the first two principal components were used in analysis (Figure 1.11).

Single Species Occupancy Modelling

To quantify occurrence and influence of covariates on individual species occupancy probability I employed single-species, single-season, occupancy models using the unmarked R package (Fiske and Chandler 2011, Kellner et al. 2023, R Core Team 2025). Occupancy models estimate the occupancy probability while accounting for imperfect detection (MacKenzie et al. 2002). With observations being restricted to one season, August-November, single-season models were selected due to the assumption that colonization and extinction would not occur, and occupancy would remain stable during this time period (MacKenzie et al. 2002). In this case, occupancy probability is interpreted at probability of initial use, though for the sake of simplicity it will be referred to as occupancy probability for the extent of this study. Only two of the camera trap arrays allow for trapping of furbearer species, and this season begins in late October for most species included in this study, which is the end of the camera trapping season for SnapshotUSA. For the purposes of this study probability of occupancy and use were assumed to be the same (Mackenzie and Royle 2005). I tested the individual main effects of the forest, human, and principal component covariates on individual species occupancy and used Akaike's Information Criterion (AIC) to

determine the variables that were the best predictors of occupancy and detection probabilities overall and among the forest, human, and PCA groupings. I also explored second order polynomials for some covariates selected by comparing AIC of forest covariates with and without second order effects for each species. Second order polynomials are useful for determining whether there is an intermediate optimum or "sweet spot" for occurrence. Observation data were converted to presence absence matrices of each focal species for this analysis. Principal component 1 (PC1) which combines covariates to describe a more urban environment with low canopy height and cover, and higher open area, development, and road density. While principal component 2 (PC2) describes habitat with higher canopy height and water presence and lower development and road density (Figure 1.10 and Figure 1.11) PC1 and PC2 were used additively (PC1 +PC2) for the detection covariates across all six species to minimize confounding of detection and occupancy probability predictors. I then tested the effects of forest and human covariates as well as PC1 and PC2 on each species' occupancy. All covariates were standardized to have a mean of 0 and standard deviation of 1 to facilitate comparison of results. Prediction plots of fitted models were used to visually assess and compare the effects of different covariates on the occupancy of different species (Figure 2.1, 2.2, and 2.3).

RESULTS

The data contained a total of 11,295 observations of the six focal species, raccoon (N=8186), coyote (N=1389), red fox (N=1114), bear (N=400), fisher (N=117), and bobcat (N=89). Using a $\Delta AIC < 2$ I determined that 200m was the best detection scale for bears, coyotes, fishers, and raccoons, while 500m was best for red foxes, and 1km was best for bobcats. A ΔAIC of < 2 was used to determine the best predictor for single species occupancy models with PC1 + PC2 influencing detection probabilities at the previously specified scale for each species. I found that

median canopy height at a 1km radius was the best predictor of bear occupancy (Table 2.1, Appendix 2.1a). Moran's I at 500m was the best predictor of bobcat occupancy with and without an interaction with road density (Table 2.1, Appendix 2.1b). The effect of Moran's I, road density and the interaction between both were negative (Table 2.2) implying that bobcat occupancy is reduced when both Moran's I and road density are high, and that the negative effect of Moran's I is weakened when road density is higher. The proportion of area developed at 1km was the best predictor for coyote occupancy with a negative effect and interactions with relative proportion of tall trees at 200m (positive effect) and road density (negative effect) (Table 2.2). The negative interaction (-0.274, Table 2.2) between development (1km) and relative proportion of tall trees (200m) implies that the positive effect of tall trees on coyote occupancy weakens in areas with high development. Alternatively, the negative effect of development on occupancy is more pronounced in areas with a high proportion of tall trees. Meanwhile, the interaction between development (1km) and road density was positive (0.327, Table 2.2), meaning the negative effect of development (1km) on occupancy is less severe in areas with higher road density. Canopy cover at 1km (2^{nd} order, positive effect) and road density (positive effect) interaction was the best predictor of fisher occupancy (Table 2.1 and 2.2, Appendix 2.1d). This interaction was negative (-29.38, -76.12, Table 2.2) and means that areas with both high road density and high canopy cover show particularly steep declines in fisher occupancy probability. Like coyotes, the best predictor of raccoon occupancy was proportion of area developed at 500m (positive effect) and road density (positive effect) interaction (Table 2.1, Appendix 2.1e). This interaction was also positive (0.071, Table 2.2), implying that areas with high road density and high development would result in higher raccoon occupancy. Lastly, covariates describing forest canopy height (median canopy height and relative proportion of tall trees), both of which having a positive effect, with and without an

interaction with each other or road density (negative effect), were the best predictors of red fox occupancy (Table 2.1, Appendix 2.1f). The interaction between proportion of tall trees (positive) and road density (negative) was slightly positive (0.022, Table 2.2), implying that the positive effect of tall trees increases slightly in areas with high road density. Meanwhile, the interaction between median canopy height (positive) and relative proportion of tall trees (positive) was negative (-0.096, Table 2.2), meaning that red fox occupancy is reduced in areas with higher median canopy and proportion of tall trees, though neither of these results are statistically significant.

Road density had a negative effect on bear, red fox, and fisher occupancy probability, but a positive effect on raccoon occupancy. Median canopy height positively affected coyote and red fox occupancy probability but negatively impacted bear occupancy. The relative proportion of tall trees displayed a positive relationship with coyote, red fox, and raccoon occupancy and a negative relationship with bear and fisher occupancy. The standard deviation of canopy height, proportion of open area, proportion of water and Moran's Index were not considered good predictors of carnivore occupancy probability due to most results being insignificant. (Figure 2.1, 2.2, and 2.3)

I tested second order effects of covariates most relevant to my hypotheses (road density, median canopy height, relative proportion of tall trees, and canopy cover) by adding a polynomial component to the single species occupancy models to determine if there was a minimum, max, and peak species' preference. Regarding median canopy height I found that bobcat, coyote, raccoon, and red fox occupancy was predicted to increase with median canopy height, reaching maximum predicted occupancy at a median canopy height of ~3m for coyotes and raccoons, ~6.5m for red foxes, and ~9m for bobcats (Figure 2.4, 2.5, and 2.6). Bear and fisher occupancy decreased with median canopy height, both reaching minimum occupancy at ~1.5m median canopy height (Figure

2.4, 2.5, and 2.6). Road density displayed more variation in the estimated occupancy curves (Figure 2.7). Bears and fisher again displayed a decreasing occupancy with road density that reached minimum occupancy at 2-2.5 km/km^2 road density (Figure 2.7). Red fox occupancy initially increased with road density, reaching peak occupancy at ~1 km/km^2 before plummeting and reaching minimum occupancy at ~3.5 km/km^2 (Figure 2.7). Raccoon and coyote occupancy was predicted to increase with road density reaching maximum occupancy at ~4 km/km^2 and ~6.5 respectively (Figure 2.7). Raccoon, coyote, and red fox occupancy were predicted to increase with the relative proportion of tall trees, while bear and fisher estimated occupancy decreased and bobcat remained relatively the same (Figure 2.4, 2.5, and 2.6). The relationship between predicted occupancy and relative proportion of tall trees was much more linear than with the previous two covariates. Red fox and coyote occupancies were predicted to increase with canopy cover while bear and fisher were predicted to decrease. Fisher and raccoon estimated occupancy showed slight declines with canopy cover while other species displayed slight increases (Figure 2.4, 2.5, and 2.6).

DISCUSSION

I tested and documented the responses of six carnivores native to New York State to various predictors that describe forest canopy characteristics and degree of human influence. My prediction that raccoons would be the least sensitive to human disturbance was supported by the occupancy modeling results. Proportion of developed area and road density showed a positive effect on raccoon occupancy, supporting the notion that they are the most adaptable to urban environment species of study. My expectation that forest characteristic covariates would not illicit much response from raccoon estimated occupancy was also supported, mean and median canopy height, proportion of open area and Moran's Index were not significant predictors, and canopy

cover had a negative effect. Red fox occupancy probability, however, was quite responsive to forest characteristic covariates, with 5 out of 8 showing significantly positive results, only proportion of open area showed a negative impact on red fox occupancy and standard deviation of canopy height and proportion of water area were insignificant predictors for red foxes. Red fox occupancy was also negatively influenced by proportion of developed area, which did not support my prediction that they would be less sensitive to human disturbance.

Regarding my predictions that coyotes would require minimum canopy cover and maximum road density to occur were not fully supported. While coyote occupancy did increase with canopy cover, there was no minimum canopy cover requirement and coyote occupancy increased with road density. This did meet my expectation that they would be less sensitive to human disturbance, though proportion of developed area was the best predictor of coyote occupancy.

The occupancy models for beats showed some unexpected results with tall trees having a negative effect on bear occupancy, which was the opposite of my expectation. Canopy cover, however, had a positive effect on bear occupancy supporting my prediction that bears cannot occur without forest cover. Bear occupancy response to road density, however, did reach a maximum density where bears were predicted to no longer occur.

Bobcat occupancy was positively related to Moran's I (at 500 m) and to canopy cover (at 1 km). This is inconsistent with the their assumed requirement for extensive and complex forest structure (Neale and Sacks 2001, Clare et al. 2015, Hubbard et al. 2022, Cerreta et al. 2023). Considering the interaction Fisher also had a lot of insignificant results due to low sample size with only road density having significant results, both of which were negative as expected.

All six of my focal species are considered habitat and diet generalists with fisher displaying specialist behavior when selecting their denning/resting location during which time they require

taller trees and greater canopy cover (Olson et al. 2024). Due to the generalist nature of these species, I expected their occurrence would be driven more by habitat being unsuitable (too developed/urban) than preferred forest characteristics. This expectation was supported by many models of forest characteristic covariates displaying insignificant results. I also found that there was not a lot of variation in proportion of open area and proportion of water across arrays and that proportion of developed area was skewed towards no development due to the 200m camera radius and the tendency to place cameras on trees and out of the way of human activity. Other forest characteristics of interest that may be better predictors of carnivore occupancy may include patch characteristics, other indices of heterogeneity and tree species data.

I had expected that for species with larger home ranges, such as bears and bobcats, a larger spatial scale (500m and 1km) would produce better occupancy results, while 200m would be a sufficient scale for species with much smaller home ranges such as red foxes and raccoons. This proved true to some extent depending on the covariate. Covariates at a 1km radius were generally best for at least half the species, for instance, canopy cover at 1km was a good scale for all species except red fox, for which a 200m radius was best. Meanwhile, 1km was a good scale for development for all species except bobcats which surprisingly found that 200m was the best scale and 500m for raccoons. In general, 500m was a good scale for covariates for bobcats for median canopy height, Moran's I, and relative proportion of tall trees, the three remaining covariates were best at 1km. Moran's I functioned best at 200m for all species except for bobcats and fishers where 500m worked best for both. Covariates scaled to 1km all worked best for bears who have the largest home range of the focal species. Covariates at a 200m scale were often best for coyote occupancy except for canopy cover, development, and median canopy height.

The biggest challenge in modelling these species' occupancy was the lack of statistical power in my models. For future research I would utilize more data from other sources such as iNaturalist and the New York Mammal survey. Having a larger data set with sites more evenly spread across New York would have significantly improved the power of my models and provided a better representation of the state.

Table 2.1. Top occupancy models (ΔAIC <2) compiled from models of six focal species.

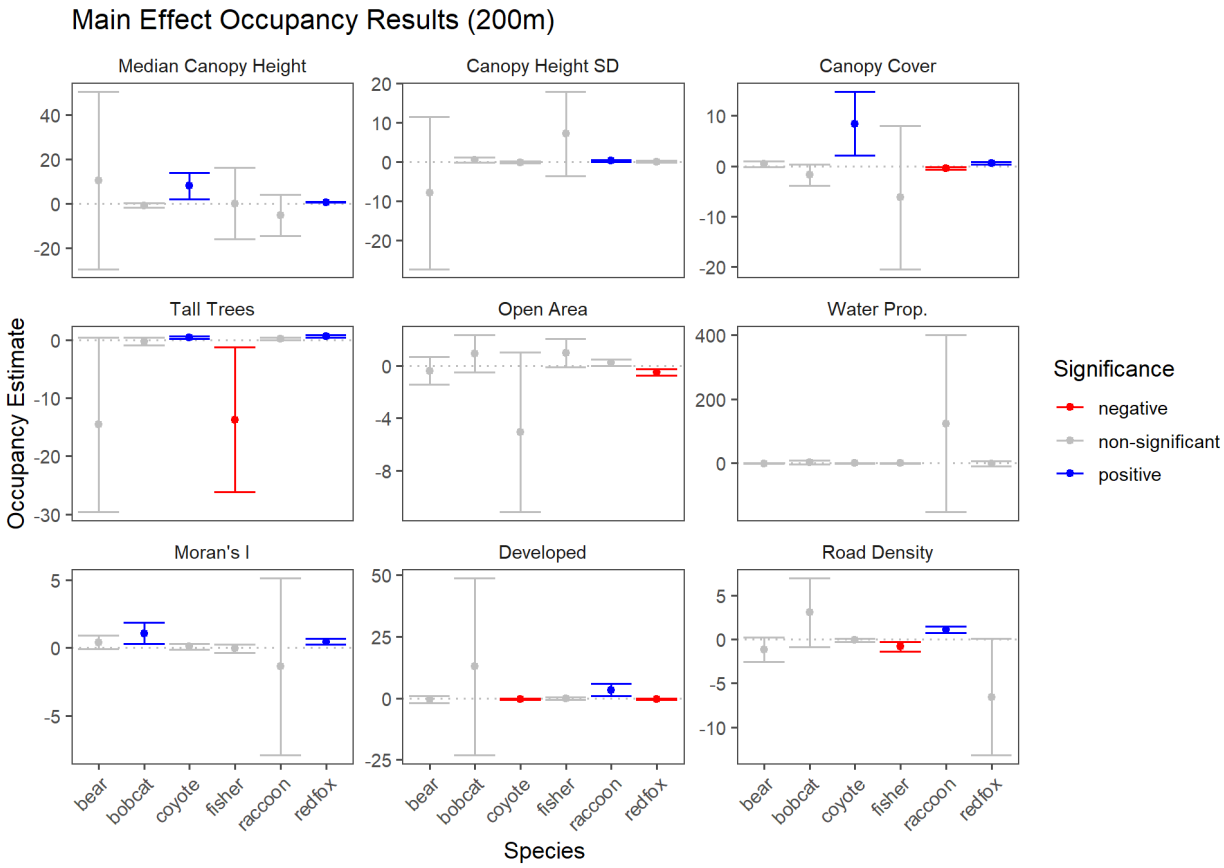
Top Occupancy Models (ΔAIC <2) For Each Species				
species	model	k	AIC	ΔAIC
bear	median canopy height (1km)	6	830.9	0
bobcat	Moran's I (500m)	5	528.2	0
	Moran's I (500m) X road density	7	530.2	2
coyote	proportion developed (1km) X road density	7	2645.8	0
	proportion developed (1km) X relative proportion of tall trees (200m)	7	2647.4	1.6
fisher	canopy cover (1km) X road density	9	622	0
raccoon	proportion developed (500m) X road density	7	3409	0
red fox	relative proportion of tall trees (200m) X road density	7	1947.3	0
	median canopy height (200m)	5	1948.15	0.845
	median canopy height (200m) X relative proportion of tall trees (200m)	7	1948.35	1.05
	relative proportion of tall trees (200m)	5	1948.48	1.17

Top occupancy models (ΔAIC <2) compiled from models of six focal species. Species, model predictor, total number of parameters, AIC, ΔAIC, and AIC cumulative weight are included. Models were compared independently for each species and then top models from each species were selected and compiled here.

Table 2.2. Top interaction occupancy models compiled from models of six focal species.

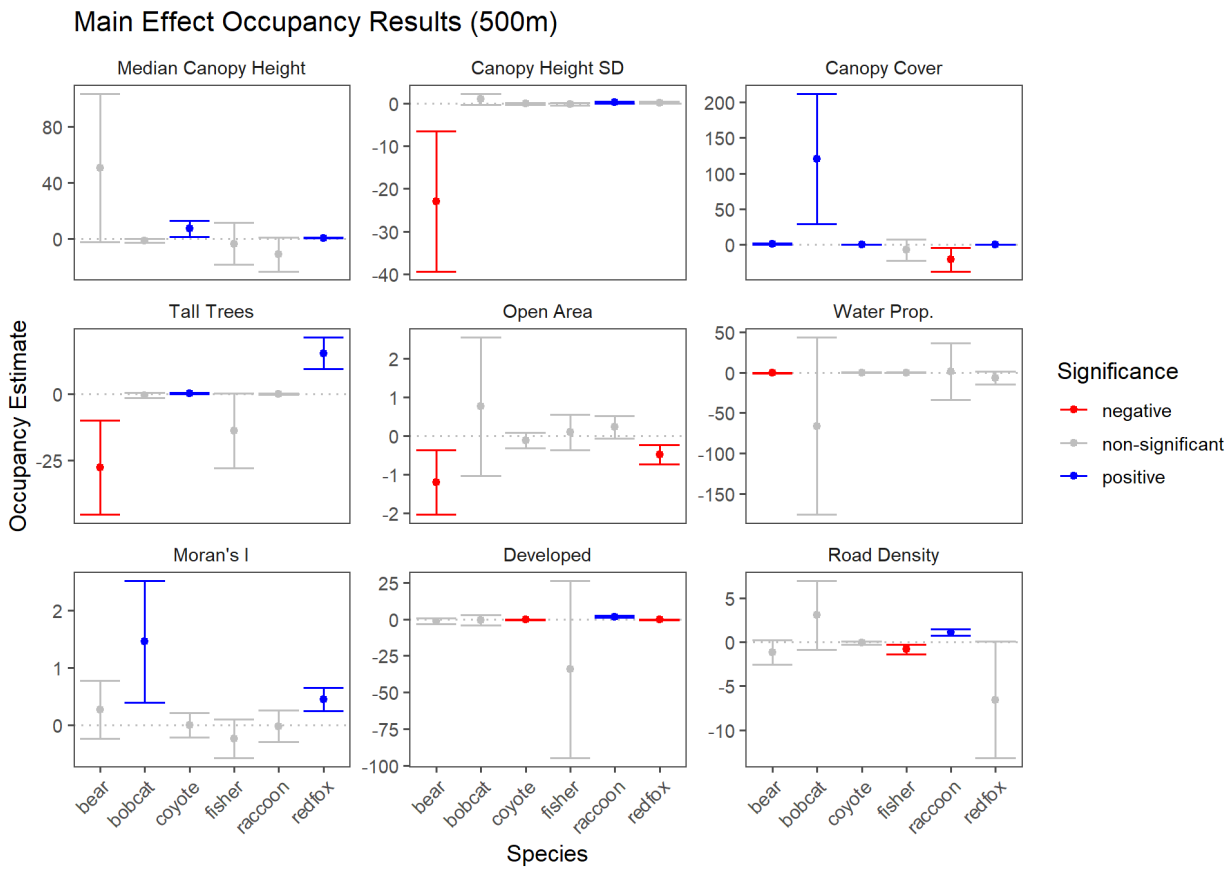
Top Interaction Model Results for Each Species				
Species	Model	Estimate	SE	p-value
bobcat	Moran's I (500m)	-0.812	1.200	0.909
	road density	-0.211	2.149	0.498
	Moran's I (500m) X road density	-4.908	3.096	0.113
coyote	prop developed (1km)	-0.382	0.120	0.424
	relative proportion of tall trees (200m)	0.351	0.140	0.001
	prop developed (1km) X relative proportion of tall trees (200m)	-0.274	0.100	0.006
	prop developed (1km)	-1.300	0.319	0.659
	road density	0.446	0.162	$4.47*10^{-5}$
	prop developed (1km) X road density	0.327	0.133	0.014
fisher	canopy cover (1km):1	58.006	17.186	$7.38*10^{-4}$
	canopy cover (1km):2	29.377	14.901	0.049
	road density	4.874	1.437	$6.92*10^{-4}$
	canopy cover (1km):1 X road density	-29.38	23.268	0.207
	canopy cover (1km):2 X road density	-76.12	30.970	0.014
raccoon	proportion developed (500m)	0.903	0.504	0.074
	road density	0.600	0.218	0.006
	proportion developed (500m) X road density	0.071	0.323	0.827
red fox	relative proportion of tall trees (200m)	0.595	0.117	0.000
	road density	-0.237	0.108	0.029
	relative proportion of tall trees (200m) X road density	0.022	0.108	0.840
	median canopy height (200m)	0.295	0.196	0.131
	relative proportion of tall trees (200m)	0.401	0.202	0.047
	median canopy height (200m) X relative proportion of tall trees (200m)	-0.096	0.121	0.427

Figure 2.1. Occupancy estimates with 95% confidence intervals of single season occupancy models with main effects for each focal species at 200m radius.



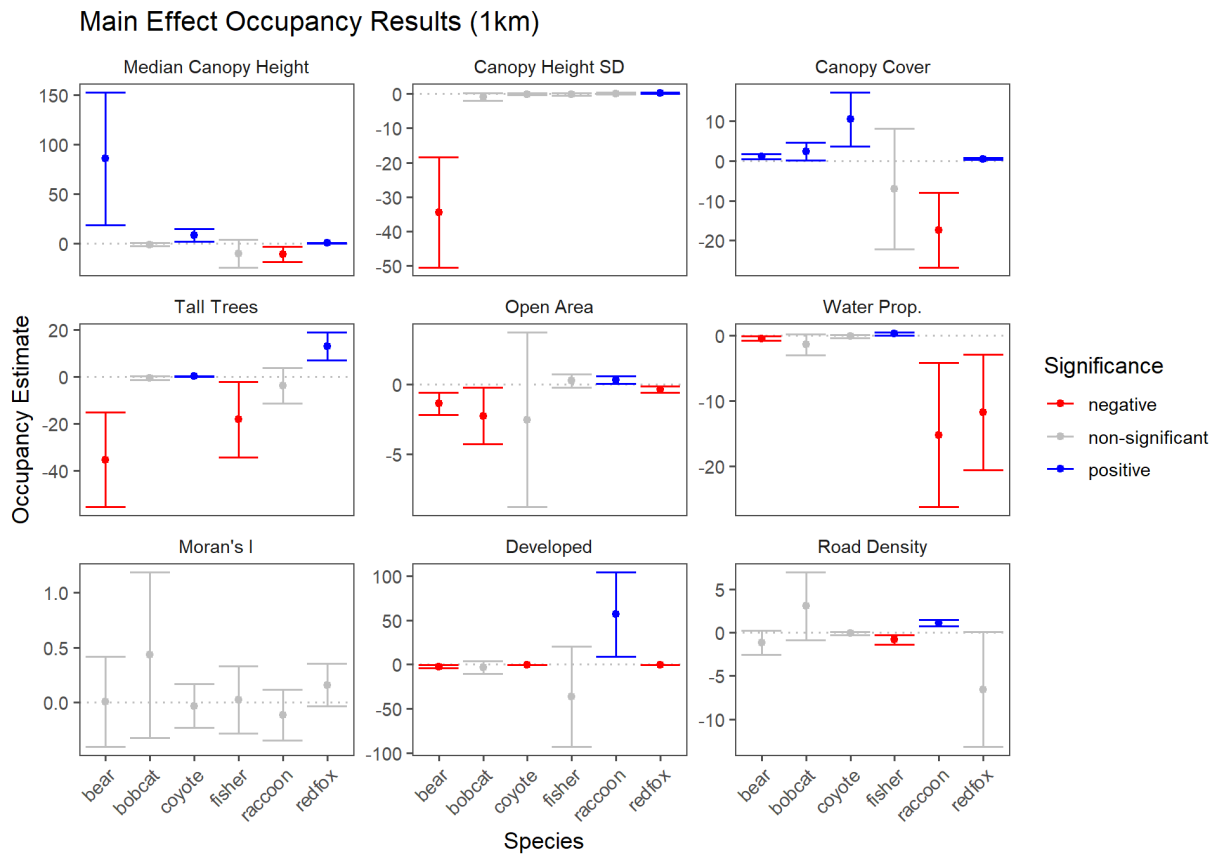
Occupancy estimates with 95% confidence intervals of single season occupancy models with main effects for each focal species at 200m radius. Blue, red and grey bars indicate positive, negative, and non-significant relationships, respectively

Figure 2.2. Occupancy estimates with 95% confidence intervals of single season occupancy models with main effects for each focal species at 500m radius.



Occupancy estimates with 95% confidence intervals of single season occupancy models with main effects for each focal species at 500m radius. Blue, red and grey bars indicate positive, negative, and non-significant relationships, respectively.

Figure 2.3. Occupancy estimates with 95% confidence intervals of single season occupancy models with main effects for each focal species at 1km radius.



Occupancy estimates with 95% confidence intervals of single season occupancy models with main effects for each focal species at 1km radius. Blue, red and grey bars indicate positive, negative, and non-significant relationships, respectively.

Figure 2.4. Occupancy probability predictions with 95% confidence intervals against median canopy height, proportion of tall trees, and canopy cover for six focal species at 200m radius.

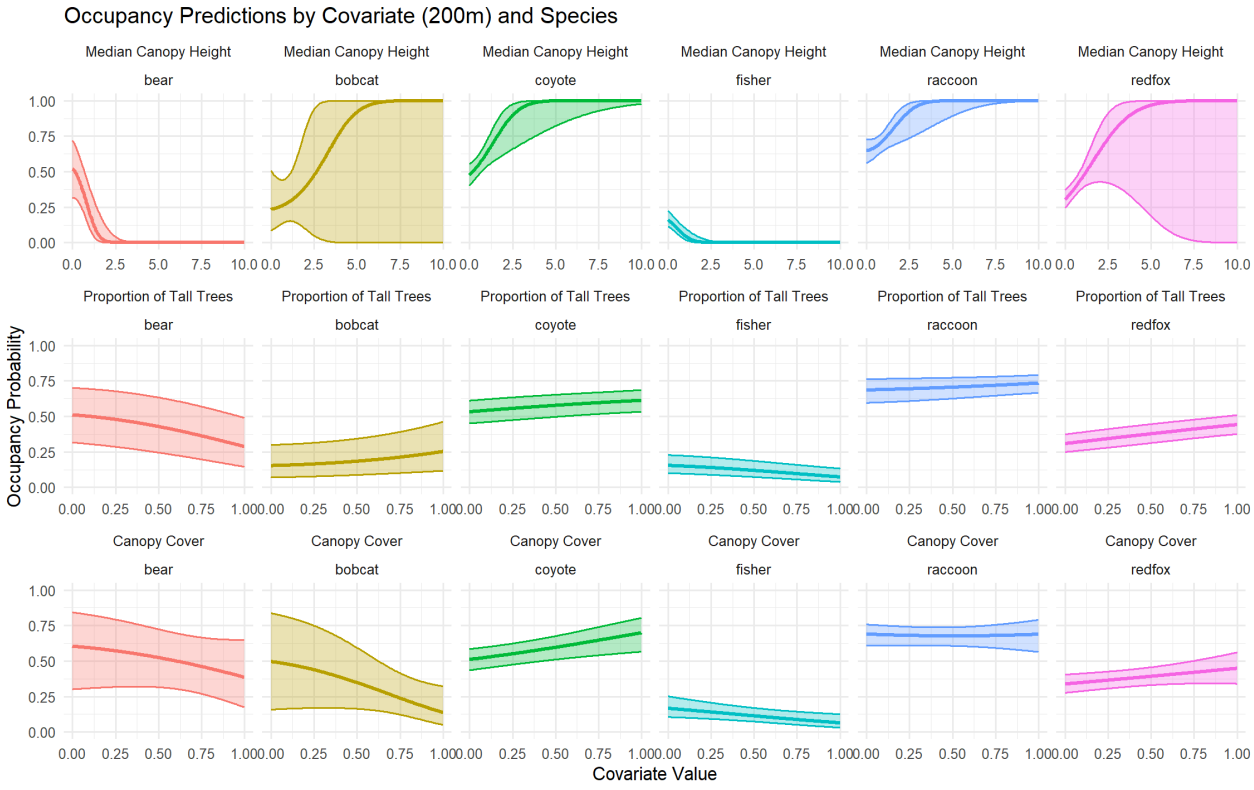


Figure 2.5. Occupancy probability predictions with 95% confidence intervals against median canopy height, proportion of tall trees, and canopy cover for six focal species at 500m radius.

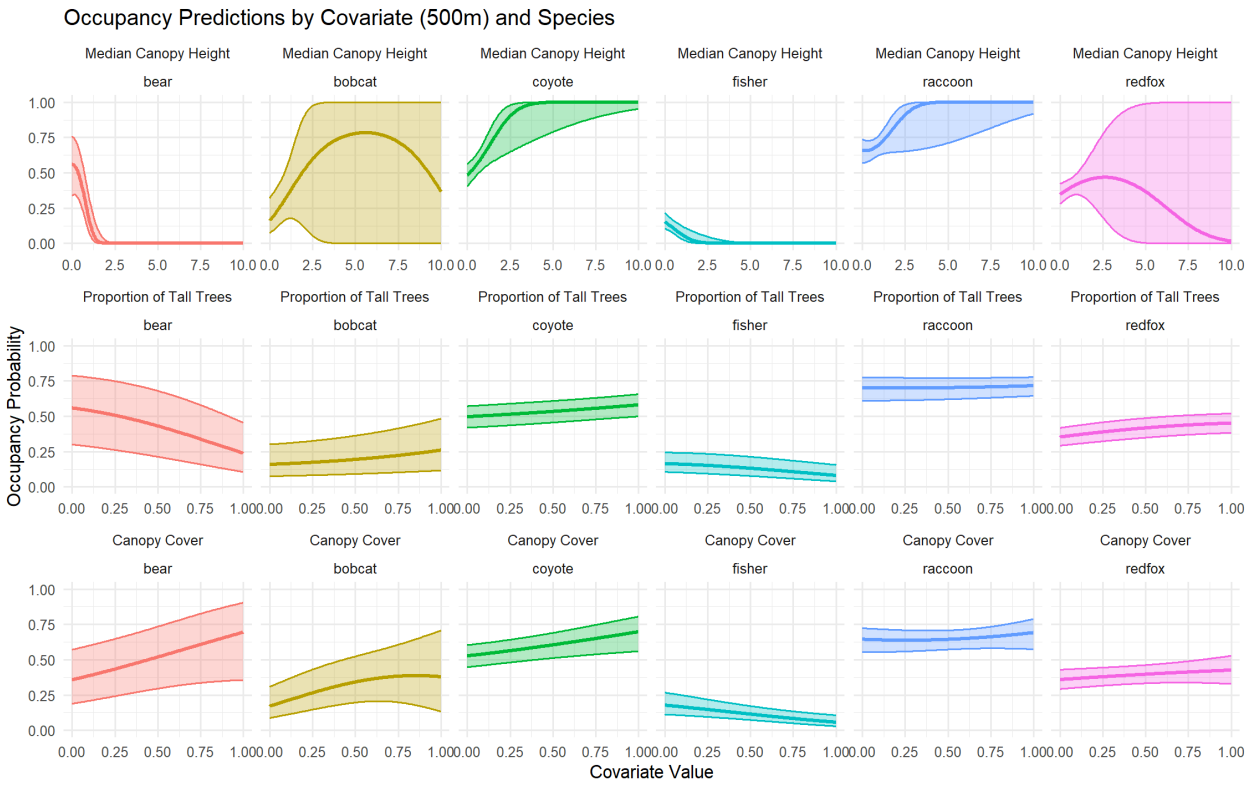


Figure 2.6. Occupancy probability predictions with 95% confidence intervals against median canopy height, proportion of tall trees, and canopy cover for six focal species at 500m radius.

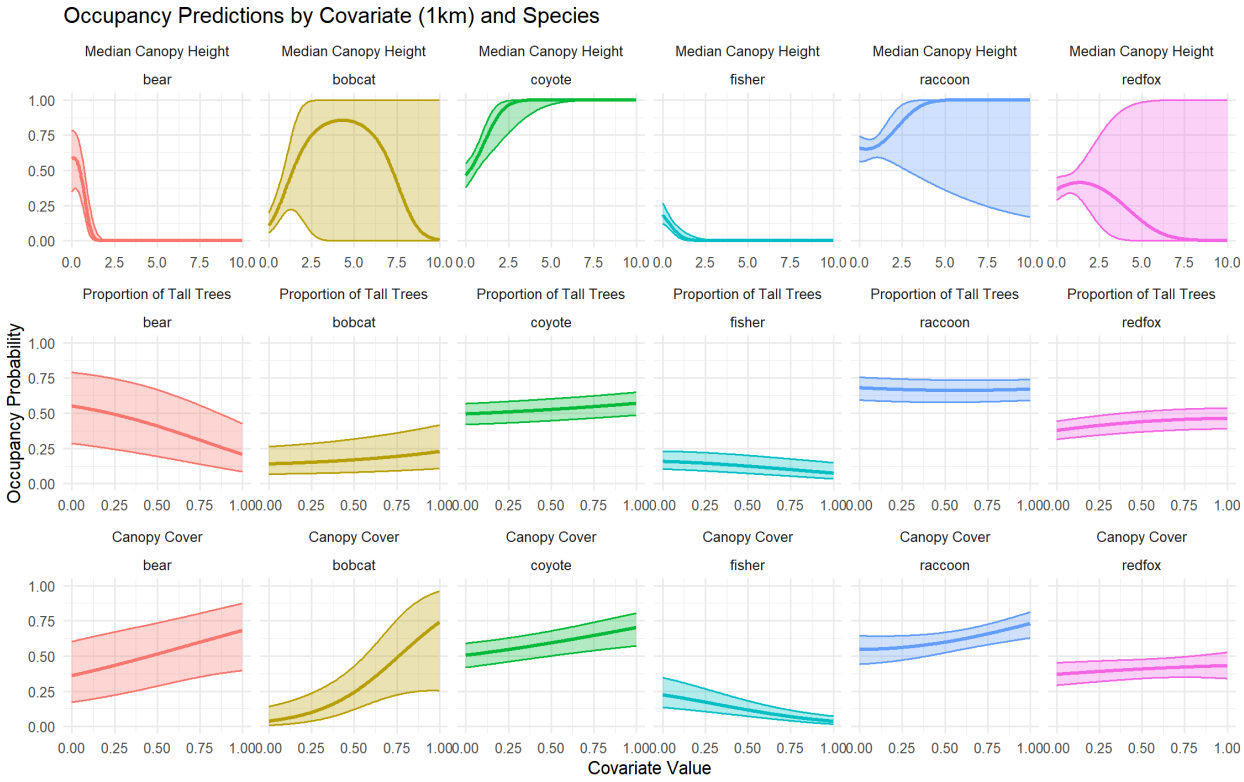
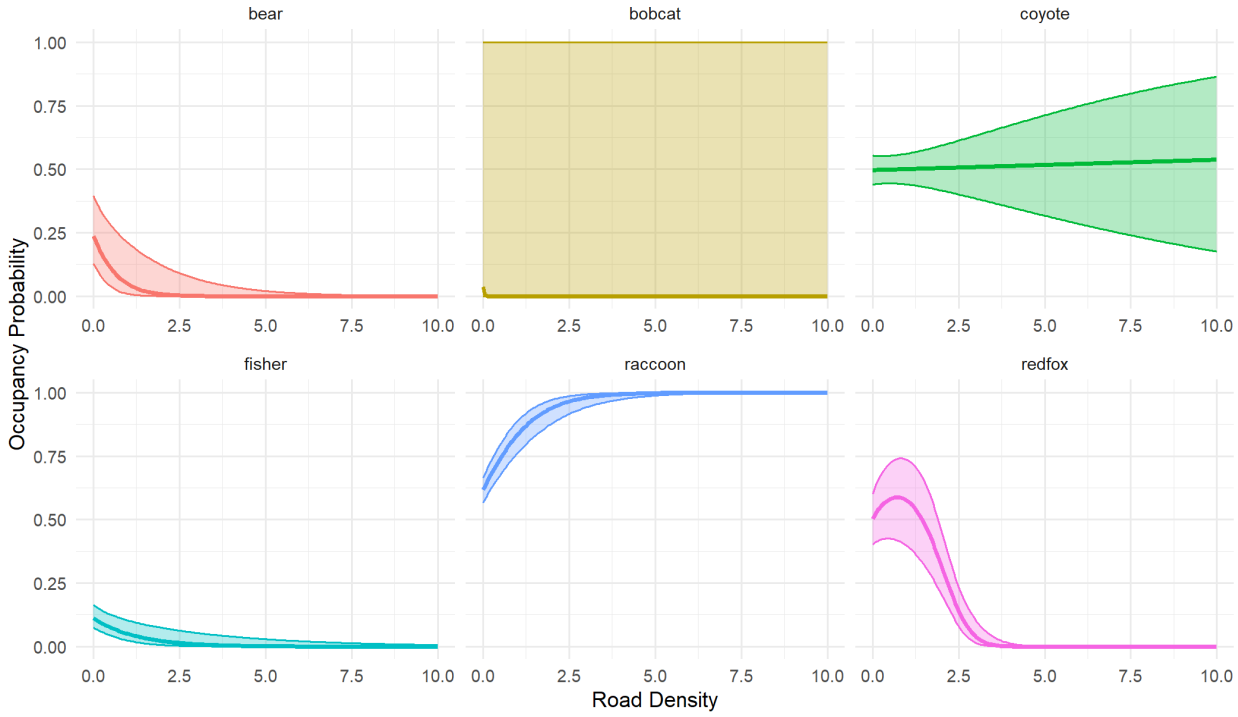


Figure 2.7. Occupancy probability predictions with 95% confidence intervals against road density for focal species at 5km radius.



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CHAPTER 3: Evaluating species interactions and temporal niche partitioning

ABSTRACT

Utilizing the combined total of 786 deployments of cameras from 14 arrays distributed across the state from 2018-2024 I compared daily activity pattern overlaps of six native New York species to better understand species' temporal partitioning in different habitat conditions. I found that carnivore species temporally partition in more human disturbed landscapes and forests and show greater temporal overlap in less disturbed sites and with both species in a pair being present. Subordinate species also showed decreased activity overlap with dominant species in areas of high disturbance and forests with shorter trees. This implies that niche partitioning is a mechanism these species utilize to facilitate the highest level of coexistence in less ideal habitat.

INTRODUCTION

The interactions between sympatric coyotes, bobcats (*Lynx rufus*), and foxes have been studied extensively across North America (Litvaitis and Harrison 1989, Lovell 1996, Neale and Sacks 2001, Levi and Wilmers 2012, García et al. 2014, Witczuk et al. 2015, Flores-Morales et al. 2019, LeFlore et al. 2019, Dyck et al. 2022, Rodríguez-Luna et al. 2023, Cervantes et al. 2023). The explosive expansion of coyotes in the US has recently become a hot topic of study in an effort to better understand their ecology in areas where they had been historically absent (Brundige 1993, Crête et al. 2001, Gompper 2002, Fener et al. 2005, Warsen 2012, Breck et al. 2019). The interactions of bobcats between pumas (*Puma concolor*) and Canadian lynx (*Lynx canadensis*) have also been studied in relation to the latter two's potential reintroduction to the Adirondacks (Brocke 1981, 1983, Fox and Brocke 1983). With the interactions of fisher (*Pekania pennanti*), with coyote and foxes being more minimal, the relationship between fishers and bobcats have been examined (Wengert et al. 2013, 2014). There has also been research into understanding how these

species interactions and community structures can change in response to human presence and development (Riley et al. 2003, Dowling Danks 2008, Flores-Morales et al. 2019, Heim et al. 2019, Frey et al. 2020, Hubbard et al. 2022, Poisson et al. 2023, Procko et al. 2023).

My overall objective was to characterize the competition and coexistence structure of mesocarnivore communities in New York State to better understand how human development and disturbance affect these communities. I used three investigative routes to accomplish this objective: identifying and quantifying the existing communities and co-occurrence structure across sites, modeling the role of forest characteristics and human disturbance in structuring carnivore communities, and exploring the mechanisms that facilitate coexistence.

Building on my previous research with single species occupancy models, I explored several predictions and hypotheses related to the co-occurrence of six focal carnivore species, American black bear *(Ursus americanus)*, bobcat *(Lynx rufus)*, coyote, red fox *(Vulpes vulpes)*, fisher *(Pekania pennanti)*, and Northern raccoon *(Procyon lotor),* to achieve my objective. I tested the effects of the environmental covariates that were most relevant in predicting single species occupancy, median canopy height, proportion of trees >20m (relative to canopy cover), and road density. Overall, I expect to see higher levels of co-existence at less developed sites due to the exclusion of species (bears, bobcats, and fisher) from urban-most sites. In line with this I would expect to see forest characteristics (median canopy height, canopy cover, and proportion of tall trees) have a positive effect on co-occurrence and a negative effect of road density on co-occurrence. I predict that carnivore species will either avoid sites or display temporal shifts in regard to humans in high disturbance areas (Ridout and Linkie 2009, Frey et al. 2020, Procko et al. 2023).

METHODS

Study Area

My study area consisted of 786 deployments across 14 camera trap arrays and 3 regions of New York State (Figure 1.5). The Adirondack Park (ADK) region consisted of 3 arrays, Cranberry Lake Biological Station (CLBS), St. Lawrence University, and Paul Smith's College. The Central New York (CNY) region contained 3 arrays as well in Heiberg, Skaneateles Conservation Area (SCA), and Syracuse. Most arrays occurred within the Hudson Valley (HV) region, consisting of Black Rock Forest (BRF), Cary, Dyken Pond, Mianus River Gorge Preserve, Newburgh, Albany Pine Bush, and Scenic Hudson (Wolf). The final, southernmost region was New York City (NYC) which contained only one array of the same name. These arrays were highly variable in terms of sampling effort with some arrays, such as Syracuse, having only 9 deployments and 1 year of data collection, while other arrays had intense sampling efforts exemplified by BRF which collected data from 427 cameras across 7 years (Appendix 1.2). These arrays encompass an extreme urban to wild gradient with NYC being the most extreme urban region and the ADK region representing extreme wilderness and observing >30 of New York State's mammal species.

Data

The camera trap data I utilized was accessed via Wildlife Insights on August 5, 2025 and consists of data provided by Black Rock Forest (LaPoint et al. 2018, Lapoint et al. 2021), a 501 (c) 3 not-for-profit organization that maintains a 3,920-acre forest and scientific field station in the Hudson Highlands of New York, and Snapshot USA (Rooney et al. 2025), a national collaborative survey of terrestrial wildlife populations using camera traps that follow a standardized protocol (Appendix 1). The Snapshot USA data was filtered to New York state only and all data that BRF had contributed to Snapshot USA was removed to avoid pseudo-replication. Data collected from the Jone's Beach camera trap array was also removed due to the habitat consisting of shrubland rather

than forest. When both datasets were combined the sequences were subset further to only mammal species and deployments in August through November, as there were not enough observations in other months for analysis, resulting in a dataset that contains camera trap data collected from 2018-2025 and consisting of 786 deployments and 53,242 observations of mammals.

In order to obtain forest and human influence covariates to use as predictors in my analysis I integrated several spatial data streams: detailed 1m resolution forest canopy height model (CHM) derived from LiDAR imaging sourced from the NYS GIS Clearinghouse and processed by the SUNY ESF forestry department using the lidR package in R (Figure 1.8), land cover data at a 30m resolution from the National Land Cover Database (NLCD), and road data provided by the United States Census Bureau (USCB) as part of the U.S. Department of Transportation (USDOT)/Bureau of Transportation Statistics (BTS) National Transportation Atlas Database (NTAD). The covariates used to describe forest structure were obtained using the LiDAR CHM to estimate the mean, median, and standard deviation of canopy height, proportion of open area, proportion of water, proportion of canopy cover, proportion of trees greater than 20m tall, and Moran's within a 200m radius of each deployment. For covariates intended to describe human impact I estimated the proportion of developed area within a 200m radius of each deployment by masking the LiDAR with the medium and high intensity developed classes from the land cover data. Road data was used to estimate the total road length (m) and density (km/km^2) within a 5km radius of each deployment. Due to the extremely high concentration of roads and the large area of the NYC array it was deemed inefficient to estimate road length and density so fixed values of 29,450,995 m and 37 km/km^2 were assigned respectively. These values were estimated based on NYC DOT estimates of 302 square miles of total land area and 6300 miles of road plus >12,000 miles of sidewalk. I designated human presence to be a categorical variable of whether a deployment captured a human.

All continuous covariates were scaled for analysis, and a principal component analysis (PCA) was employed for data reduction. The PCA was performed using the R function prcomp which calculates the principal components using singular value decomposition. The principal components are linear combinations of the original covariates that capture the variance of the data (Figure 1.10). The first principal component accounts for the most variance and decreases with further components (Abdi and Williams 2010). Only the first two principal components were used in analysis (Figure 1.11).

Daily Activity Pattern Similarity

In order to evaluate co-existence, avoidance, and niche partitioning I used estimated similarity of daily activity patterns by computing the overlap in the kernel density of recorded times of camera observations using the overlap R package (Ridout and Linkie 2009, Meredith et al. 2024). The overlap analysis calculates wrapped kernel density functions of times of observation and computes an overlap index (Δ) from 0 to 1 with 0 representing no overlap and 1 representing 100% overlap (Ridout and Linkie 2009). For estimates that include species with greater than 50 observations, Δ_4, vectors of densities estimated at the times of the observations of the species, x and y, was estimated with a smoothing parameter of 1, and for species with fewer than 50 observations, Δ_1, calculated from vectors of densities estimated at T equally-spaced times, t, between 0 and 2π, was estimated with a smoothing parameter of 0.8 (Ridout and Linkie 2009, Meredith et al. 2024). Confidence intervals (95%) were calculated using 1000 smoothed bootstrap samples.

I was interested in contrasting overlap patterns against several dimensions: Where animals did and did not co-occur, and against a range of environmental covariate values. For co-occurrence, we split the data against locations (i.e. camera deployments) where both species were present and where only one of the two species was present. Differences in temporal overlap between these

different subsets suggest that the presence of the other species directly influences a given species' activity. To see how environmental factors influence activity patterns, we further split the data by intensity (low and high) where low is up to and including the median and high is all values greater than the median. While activity overlaps could be compared across all environmental subsets, many of the co-occurrence subsets did not have enough observations overlap analysis with only five pairs having enough data for this analysis against covariates (Tables 3.2 and 3.3).

RESULTS

The daily activity pattern overlap analysis showed that overlap between all focal species is definitively lower in high road density vs low road density (Figure 3.1). Red foxes displayed a clear shift towards nocturnality in more developed areas with peak activity occurring in late evening (~23:00 EST). Road density influenced activity overlaps less consistently than median canopy height with bobcats and fisher displaying no difference in overlap with bears between high and low road density (Figure 3.1). The remaining three species, coyote, red fox and raccoon, showed significant decreases (20%, 20%, and 35% respectively) in overlap with bears in high road density versus low (Figure 3.1). Again, fisher displayed no difference in activity overlap with coyotes in regard to road density, while bobcats, foxes, and raccoons showed significantly lower overlap with coyotes in high road density with decreases of 31%, 9%, and 9% respectively (Figure 3.1). Overlap between bobcats and fishers reduced from 71% ±4.8 at low road density to 60% ±7.6 at high road density (Figure 3.1).

Higher median canopy height consistently predicted higher activity overlap between dominant and subordinate species. Bobcats showed no change (2%) in overlap with bears between high (73 ±5.2) and low (71 ±7.4) canopy heights while fisher showed the most change (25%) (Figure 3.2).

Raccoon activity overlapped with bears the least ranging from 42% ±2.3 - 58% ±3.1 overlap, bobcat activity overlapped with bears most consistently (71% ±7.4 - 73% ±5.2), and red fox activity overlap was the highest overall with 77% ±2.9 overlap in high median canopy height (Figure 3.2). Activity overlap of bobcats, red fox, fisher, and raccoons with coyotes was also consistently higher with high median canopy height (Figure 3.2). Fisher displayed the least change in overlap with coyotes at low and high median canopy height 76% ±4.4 - 78% ±5.3 overlap (Figure 3.2). Bobcat and red fox displayed highest overlap with coyotes at high median canopy height, with 82% ±4.2 and 84% ±2.5 overlap respectively (Figure 3.2). However, bobcats displayed the lowest overall overlap with coyotes at 42% ±6.2 in low median canopy height as well as the largest change (40%) in overlap between low and high median canopy height (Figure 3.2). Bobcat and fisher activity overlap was 32% higher at high median canopy height with overall overlap ranging from 40% ±7 - 72% ± 5.5 (Figure 3.2). Similar results were seen with activity overlap against relative proportion of tall trees with overlap being significantly higher at high proportion of tall trees than low (Figure 3.3).

Overall, species pairs were higher when both species were present rather than only one being present (Table 3.1 and Figure 3.4). The bear and coyote pair overlap saw no difference between both species occurring (65% ±4.5) and either occurring (63% ±2.8), as well as the bear and fox pair with an overlap with both species present being 72% ±6.8 and either present being 69% ±2.6 (Table 3.1 and Figure 3.4). All other pairs saw significantly higher overlap estimates with both species present (Table 3.1 and Figure 3.4). The bobcat raccoon pair had the highest difference in overlap between both present (80% ±4.7) and either present (48% ±5.8, Table 3.1 and Figure 3.4). Against road density, overlap remained higher with both species present and at low road density (Table 3.2 and Figure 3.5.). The bear and coyote pair was once again an exception with higher

overlap occurring with either species present at low road density (72% ±3.5) rather than both occurring at low road density (62% ±7.8), though these confidence intervals overlap so the difference is not significant (Table 3.2 and Figure 3.5). Overlap was lower with high road density and only one species present, with the biggest difference in overlap occurring in the coyote and raccoon pair with 83% ±2.7 overlap with both present at low road density and 41% ±3 overlap with only one present at high road density (Table 3.2 and Figure 3.5). There was no change in overlap for the fox and raccoon pair between high (74% ±3.4) and low road density (73% ±1.8) with both present (Table 3.2 and Figure 3.5).

Overall, overlap was higher with both species in a pair present and high median canopy height, though the bear and raccoon pair saw higher overlap when only one was present at high canopy height and when both were present at low canopy height. with these estimates averaging 60% overlap (Table 3.3.). The fox raccoon also displayed higher overlap with both present at low median canopy height (Table 3.3.). All pairs displayed lowest overlap with only one occurring at low median canopy height with the exception of the bear and coyote pair which had lowest overlap with both present at low canopy height (Table 3.3.). Coyotes, red foxes, and raccoons had the highest activity overlaps with estimates between 86% and 89% (Table 3.3.).

DISCUSSION

Understanding the mechanisms that facilitate coexistence among carnivore species in a world where habitat is lost and fragmented is essential to their conservation. I documented differential responses among six carnivores native to New York State to human disturbance and forest characteristics to better understand these interactions and mechanisms of coexistence. I found that temporal partitioning is a mechanism these communities employ to facilitate coexistence in less ideal habitat.

Findings from daily activity pattern overlaps supported my predictions that forest canopy characteristics would have a positive effect on species coexistence and development would have a negative effect. High median canopy height proved to be an excellent driver of coexistence between carnivore species. Bobcat sample size was not large enough to evaluate the relative proportion of trees >20m though this forest characteristic showed similar results to median canopy height for other species (Figure 3.3). Road density also displayed expected results, though with less consistency, showing that low road density drives coexistence. At high road density and low median canopy height, pairs of species had lower overlap, showing that species temporally partition more in less ideal habitat. Conversely, when road density is low and median canopy height is high, species partition less. Species pairs also had consistently higher similarity with both species present, implying that when habitat is sufficient for both species to occur, less temporal partitioning is needed. Alternatively, when species are allopatric, their behavior is driven less by other carnivore species presence and driven more by either their own "natural" activity inclinations or by human or prey activity.

As humanity continues to increase its encroachment on and development of the natural environment, native wildlife is under increasing pressure to survive in smaller and smaller habitats. With nowhere to go to avoid human disturbance, wild animals may adapt by shifting temporal patterns in avoidance (Gaynor et al. 2018, Frey et al. 2020, Rodríguez-Luna et al. 2023, Procko et al. 2023). With all species in my study sharing the same peak activity patterns with humans, all have reduced activity during human peak activity in highly disturbed areas in avoidance. This will impact the dietary resources available to them and will require shifts in learned behavior to adapt (Lombardi et al. 2017, Heim et al. 2019, Hill et al. 2022, Hubbard et al. 2022). Given that development is unlikely to stop or decrease in the foreseeable future conservation efforts should

be focused on maintaining remaining natural habitat in ways that allow carnivore species to coexist peacefully. Median canopy height and proportion of trees >20m are two forest characteristics that have proved to positively affect coexistence and management that allows for a greater proportion of mature forests would be beneficial to conservation of carnivore communities.

Table 3.1. Estimated daily activity pattern overlaps (no covariate) of paired presence results table with standard deviation (sd).

Pair	Both-est	Both-SD	Sep-est	Sep-SD
bear-coyote	0.65	0.045	0.63	0.028
bear-fox	0.72	0.068	0.69	0.026
bear-raccoon	0.55	0.039	0.45	0.026
bobcat-coyote	0.75	0.07	0.61	0.067
bobcat-raccoon	0.8	0.047	0.48	0.058
coyote-fisher	0.96	0.054	0.82	0.043
coyote-fox	0.89	0.018	0.62	0.022
coyote-raccoon	0.77	0.014	0.52	0.023
fox-fisher	0.81	0.068	0.59	0.042
fox-raccoon	0.74	0.016	0.48	0.032
raccoon-fisher	0.86	0.033	0.75	0.044

Daily activity pattern overlaps of paired presence results table with estimates (est) and standard deviation (sd). Showing that when both species are present (both), overlap is higher and when only one species is present (Sep) overlap is generally lower. Yellow indicates highest overlap of a pair and blue indicates lowest overlap of a pair.

Table 3.2. Estimated daily activity pattern overlaps against road density of paired presence results table with standard deviation (sd).

Pair	Both-low-Est	Both-high-Est	Sep-low-Est	Sep-high-Est
bear-coyote-road	0.62	0.54	0.72	0.45
bear-raccoon-road	0.73	0.58	0.63	0.34
coyote-fox-road	0.82	0.9	0.69	0.55
coyote-raccoon-road	0.83	0.76	0.71	0.41
fox-raccoon-road	0.74	0.73	0.62	0.4

Daily activity pattern overlaps of paired presence results table with estimates (est) and standard deviation (sd). Showing that when both species are present (both), overlap is higher and when only one species is present (Sep) overlap is generally lower. Yellow indicates highest overlap of a pair and blue indicates lowest overlap of a pair.

Table 3.3. Estimated daily activity pattern overlaps against median canopy height (500m) of paired presence results table with standard deviation (sd).

Pair	Both-low-est	Both-high-est	Sep-low-est	Sep-high-est
bear-coyote-median500m	0.53	0.72	0.57	0.64
bear-raccoon-median500m	0.6	0.52	0.37	0.6
coyote-fox-median500m	0.85	0.86	0.54	0.75
coyote-raccoon-median500m	0.73	0.88	0.54	0.58
fox-raccoon-median500m	0.77	0.62	0.48	0.61

Daily activity pattern overlaps of paired presence results table with estimates (est) and standard deviation (sd). Showing that when both species are present (both), overlap is higher and when only one species is present (Sep) overlap is generally lower. Yellow indicates highest overlap of a pair and blue indicates lowest overlap of a pair.

Figure 3.1. Daily activity pattern overlap networks of six focal species at low and high road density, showing significantly reduced overlap with high road density.

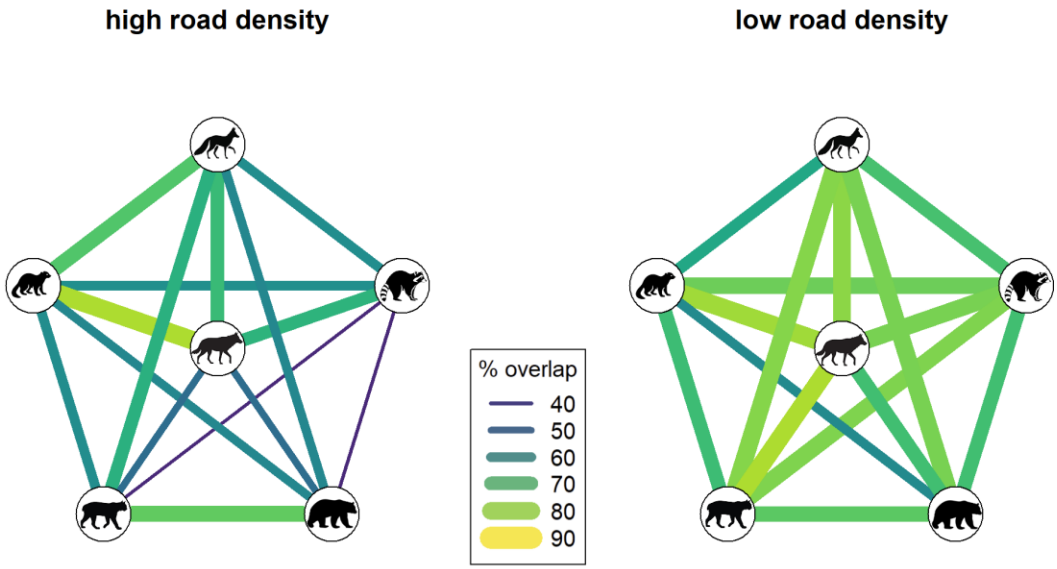


Figure 3.2. Daily activity pattern overlap networks comparing overlap of focal species at low and high median canopy height, showing consistently higher overlap with high median canopy height.

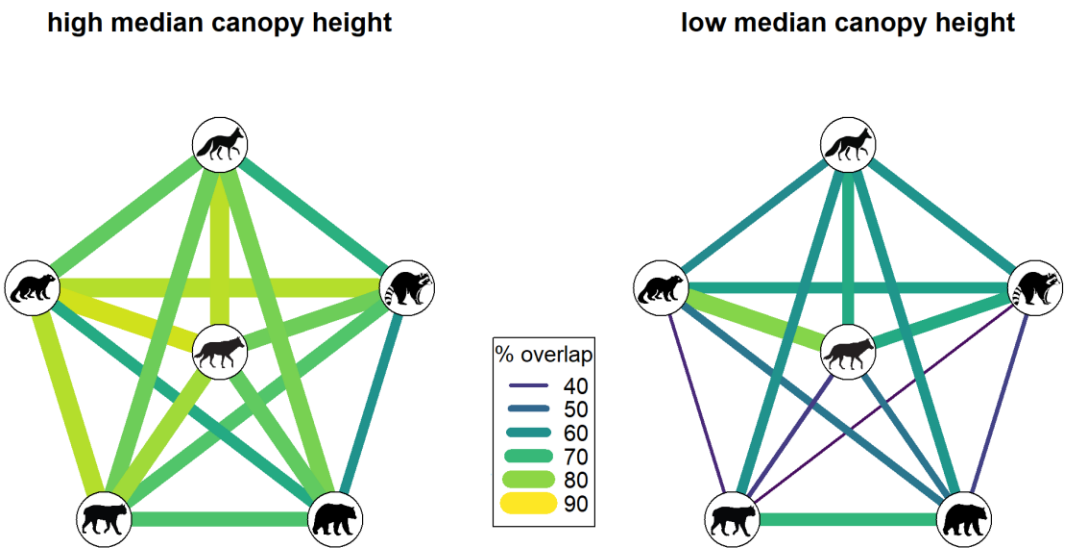


Figure 3.3. Daily activity pattern overlap networks comparing overlap of focal species at low and high proportion of trees >20m (relative to canopy cover), showing consistently higher overlap with high proportion of tall trees.

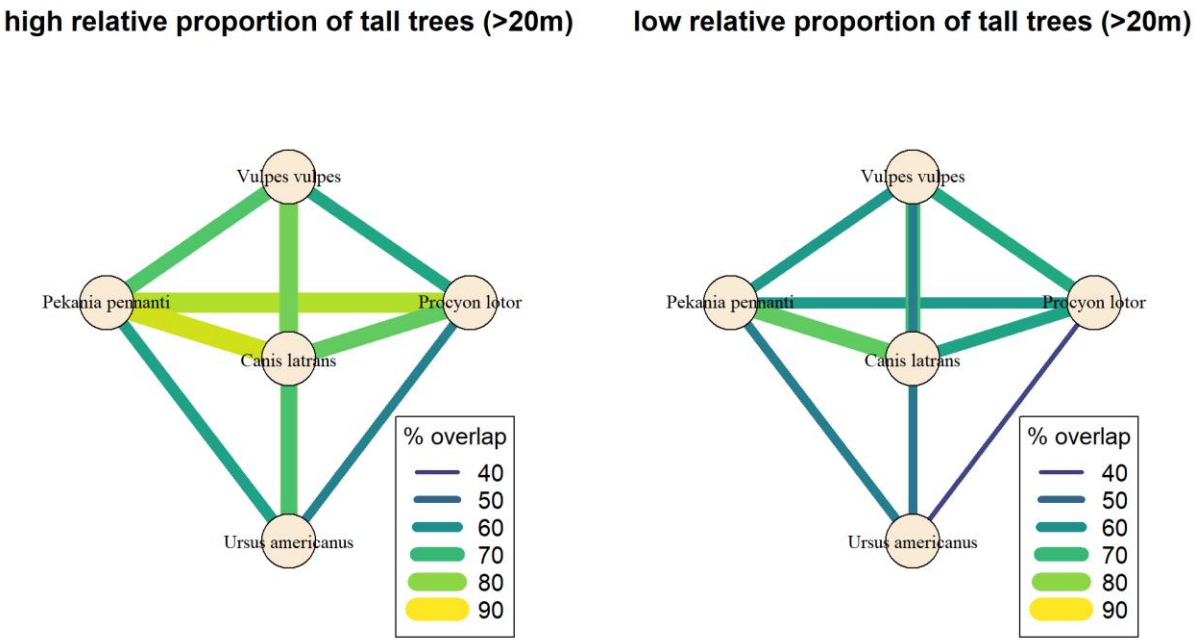
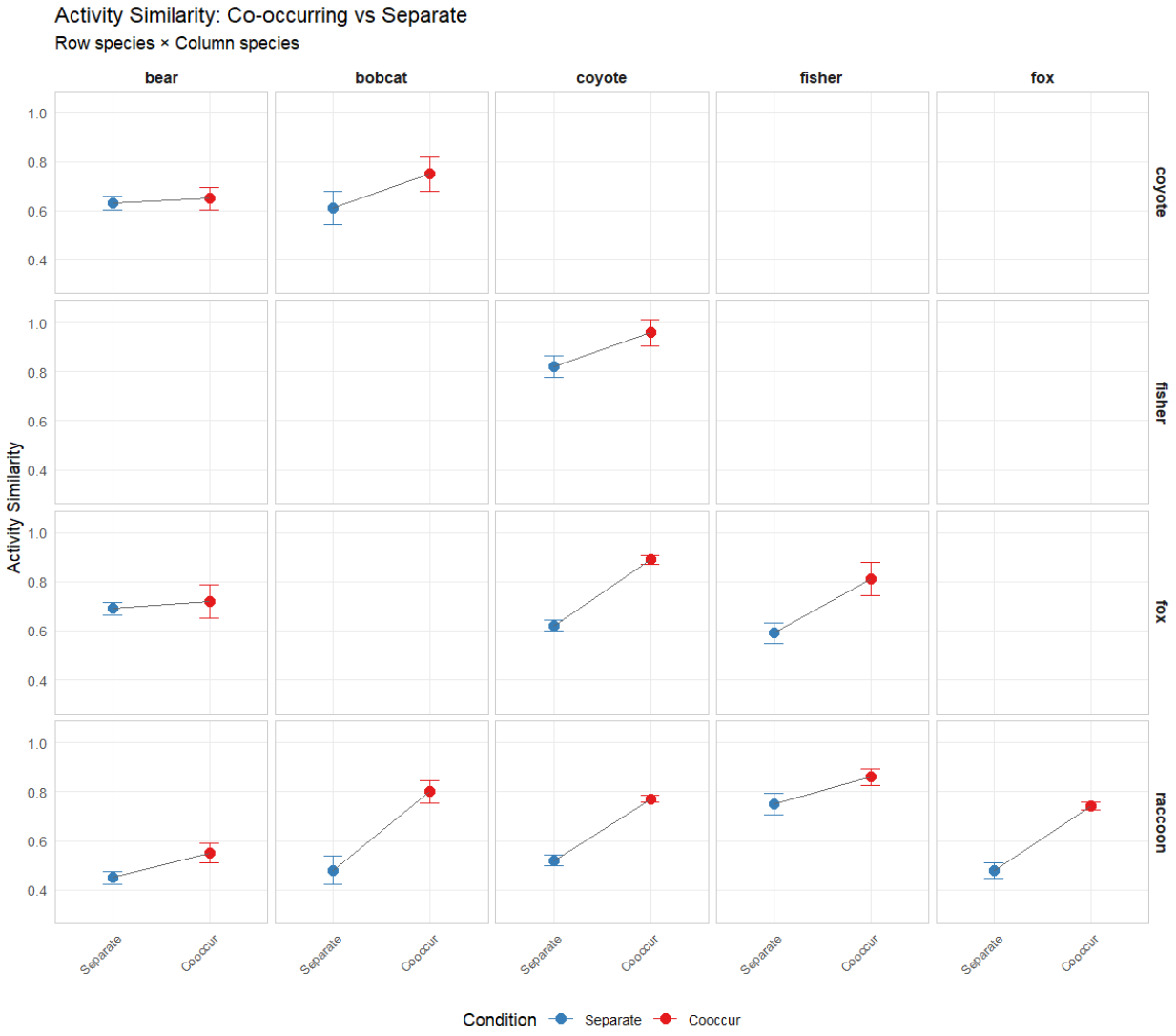
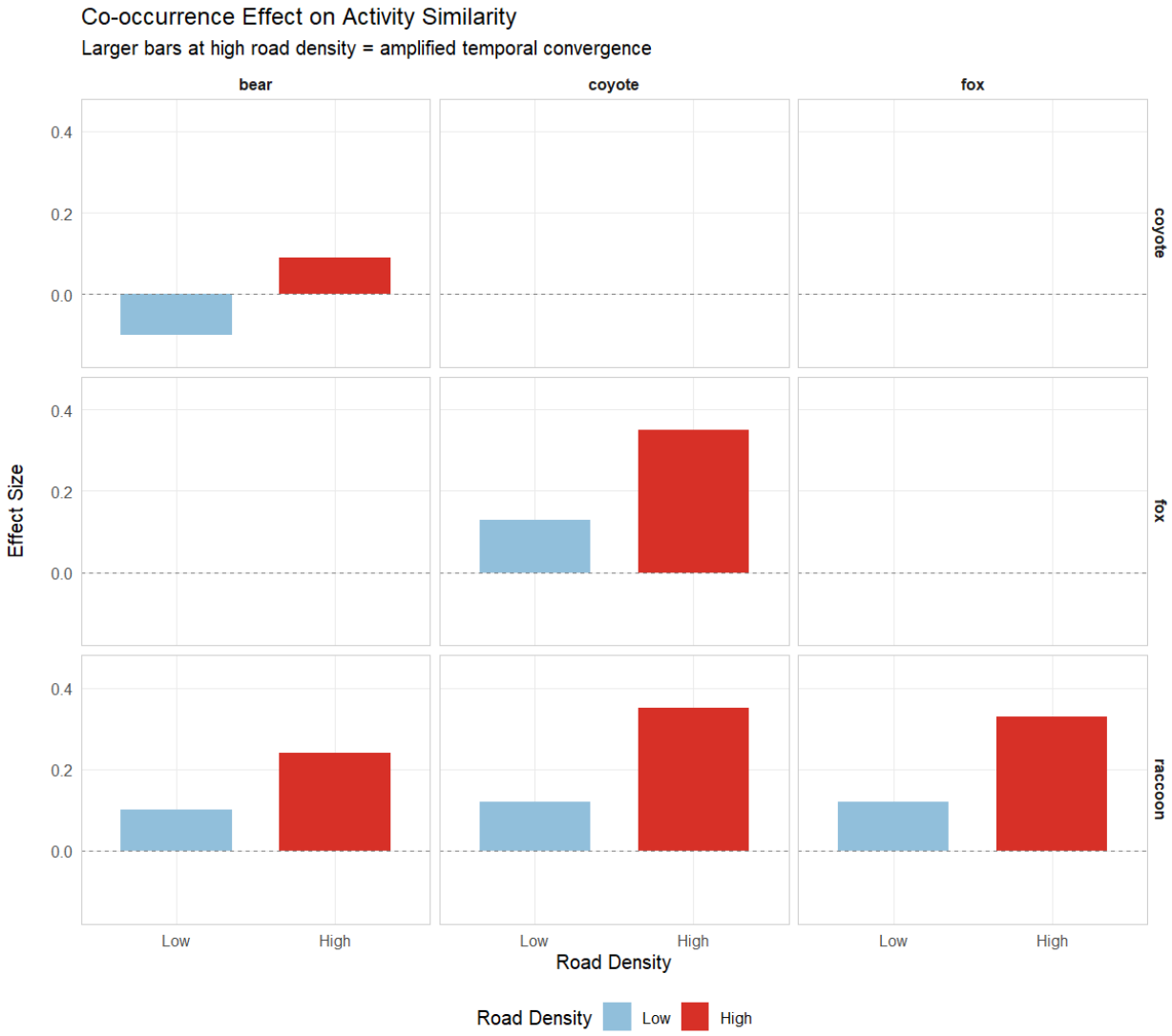


Figure 3.4. Activity pattern similarity of species when co-occurring or occurring separately.



Activity pattern similarity of species when co-occurring or occurring separately, showing that similarity is higher when species co-occur.

Figure 3.5. Activity pattern similarity of species when co-occurring or occurring separately against road density.



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CONCLUSIONS

The overarching objective of this study was to evaluate how human disturbance, primarily the magnitude of roads and development, and forest characteristics, primarily describing forest canopy, shape carnivore communities and drive interactions. This study found that even the most adaptable carnivore species, like raccoons, are sensitive to human disturbance and alter their behavior in human presence. The forest characteristics that impacted individual occupancy and interactions the most described the height of the forest canopy, rather than the amount of canopy, providing insight into management strategies for the conservation of these communities. While not a perfect proxy, old growth forests tend to have higher overall canopy height, aka taller trees. The positive influence of high median canopy height and high proportion of trees >20m tall on species occupancy and coexistence implies management for old growth forests would be critical to maintaining healthy carnivore communities.

Utilizing LiDAR image derived 1m resolution forest canopy height models (CHM) was a novel approach to analyzing wildlife habitat and communities. Landcover is much more commonly used but I found that it described my study area as either deciduous forest or developed, providing no variation in description of forested sites. The CHM provided highly detailed imaging of the forest to the point where individual trees were recognizable, providing much more detailed descriptions of site-level forest characteristics. While these carnivore species and their interactions have been studied extensively across North America, especially sympatric coyotes, red foxes, and bobcats, my study expanded on this research by examining a much larger study area allowing for the comparison of many different locations throughout the state. As well as encompassing such a dramatic gradient of development with the inclusion of New York City as the most densely

populated city in the US and Adirondack Park, the largest area protected by the public in the lower 48 US states, consisting of 6 million acres of wilderness.

There are still several ways this study could be improved upon in future investigations. Primarily, including more observational data of species, due to the large area of my study and the highly variable sampling effort of the camera trap arrays I often lacked the statistical power for occupancy modelling with less observed species such as bobcats and fishers. Several species of interest were excluded from my study due to low observations like the American pine marten *(Martes americana)* and grey fox *(Urocyon cinereoargenteus)*. I had also initially planned to employ multi-species occupancy models (MSOM's) to evaluate species' co-occurrence and interactions but lacked the required sample size to achieve statistically significant results. I found that the daily activity pattern overlaps provided better insight into behavioral shifts of the species in response to forest characteristics and human disturbance than the MSOM's which were unable to detect differences in co-occurrence and conditional occupancy. With the increasing availability of open access wildlife monitoring data, like Snapshot USA and iNaturalist, non-invasive wildlife monitoring data can more easily be compiled from multiple sources and should be utilized in the future to provide a more robust data set for analyses.

Another way this study could be improved is to explore more environmental predictors as well as interactive effects of predictors. My use of the 1m resolution LiDAR imaging canopy height model (CHM) was a unique approach to characterizing forest habitat for wildlife studies and as such I feel I barely scratched the surface of the information that can be extracted from the CHM. Other measures of landscape heterogeneity and patch characteristics would be very useful to explore as predictors. A detailed understanding of the mechanisms that facilitate co-existence of carnivore

species and allow them to persist in an ever-changing and human-dominated landscape is essential to the conservation of native mammal communities.

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APPENDICES

Appendix 1.1. Snapshot USA Protocol:
1. Each collaborator selects one habitat type (Forest, Grassland, Anthropogenic, Other) and one development zone (Urban, Suburban, Rural, Wild) in which to deploy camera traps. Although you can survey multiple arrays, we ask that you avoid mixing habitats and zones across a single array.
2. The sampling window is September 1st until October 31st with a 2-week leeway on both sides of the period.
3. Within the sampling window, survey at least 15 locations for at least 3 weeks each. With 8 cameras, you can move them once halfway through the season to achieve 16 locations. We require a minimum of 400 camera nights (# cameras X # nights), but the more effort the better. If you have a minimum of 7 cameras functioning for the entire study period (60 days), you can still reach the minimum (60 nights x 7 cams = 420 cam nights).
4. The deployment locations must be at least 200 meters away from other cameras but no further than 5 kilometers.
5. For each camera deployment, record the location (latitude and longitude in degrees minutes), start date, end date, and camera make and model.
6. Make sure to capture at least one image of a camera trapper when each camera is deployed and retrieved, as these determine the start and end dates (if no final image of a camera trapper, we will have to use the date on the last image the camera took).
7. Cameras used must meet these baseline capabilities and be set to these settings:
a. Trigger speed <0.5 seconds
b. Infrared flash (no white-flash allowed)
c. 3-5 image bursts per trigger
d. No delay between triggers (if necessary a few seconds delay is ok)
e. No videos
8. These are just some examples of permitted camera makes and models:
a. Browning (Strike Force Elite HD, 2017 Strike Force HD Pro, or camera of = or > quality)
b. Bushnell (Trophy Cam HD, Essential, Aggressor, or camera of = or > quality)
c. Moultrie (M-999I, M-1100i, or camera of = or > quality)
d. Primos (Proof Cam 02, Proof Cam 03, or camera of = or > quality)
e. Spypoint (Solar, Force 10, Force 11D, Force GM, or camera of = or > quality)
f. Stealth Cam (G45NP Pro, G42NG, or camera of = or > quality)
g. Reconyx (all models)
9. Cameras should be placed ~ 50cm off the ground (about knee-height) and with orientation parallel to the slope.
10. No food bait or scent lure will be used.
11. While cameras can be placed on trails or logging roads, this must be indicated by the collaborator.
12. Once field work is complete, the collaborator will upload images and metadata to Wildlife Insights. Our intent is to have all data uploaded by December 15th.
13. Collaborators are responsible for identifying all the images within their array(s).
All registered participants will receive a link to webinars in early August, where the protocol will be reviewed and questions answered.
Please reach out to Survey Coordinator Brigit Rooney (rooneybr@si.edu) with any questions.

Data accessibility and co-authorship: At the Wildlife Insights website, there will be a 48-month embargo on the data for public display. At the end of the embargo period, all data (except the location of endangered species) will be accessible to the public. All contributors can access uploaded data at all times. Any scientific paper produced by CO-PIs, or any other co-participants during the embargo phase, would offer authorship to all contributors during the manuscript preparation phase. Once the data are public, each author will make decisions on co-authorship for data contributors.

Appendix 1.2. Number of deployments, active period, total number of years active, average days per deployment, total trap nights, and average trap nights per deployment for camera trap arrays.

Camera Trap Array	Deployments	Active Period	# Years Active	Total Trap-Nights	Avg Trap-Nights/Deploy
BRF	225	2018 - 2024	7	12904	57.4
Mianus	112	2019 - 2023	5	4799	42.8
NYC	101	2020 - 2023	4	4497	44.5
PineBush	72	2019 - 2023	5	2231	31.0
Wolf	54	2021 - 2023	3	1835	34.0
StLawrence	43	2019 - 2021	3	1823	42.4
Dyken	62	2019 - 2023	5	1781	28.7
CLBS	50	2022 - 2023	2	1483	29.7
PaulSmiths	22	2019 - 2021	3	824	37.5
Newburgh	10	2023 - 2023	1	508	50.8
Cary	10	2023 - 2023	1	317	31.7
Heiberg	8	2021 - 2021	1	252	31.5
SCA	8	2022 - 2022	1	233	29.1
Syr	9	2021 - 2021	1	224	24.9

Appendix 1.3a. Area (km^2) and average distance between cameras (m) of each array for the year 2023 ordered from largest to smallest area.

Camera Array Spatial Characteristics - 2023

Array	Cameras	Area (km^2)	Mean Distance (m)
NYC	26	427.12	13666
BRF	31	33.53	3141
PineBush	12	19.23	6265
Newburgh	10	15.99	4031
CLBS	25	5.47	1452
Mianus	20	4.39	1527
Wolf	15	3.31	1410
Cary	10	0.40	531
Dyken	8	0.20	372

Appendix 1.3b. Area (km^2) and average distance between cameras (m) of each array for the year 2022 ordered from largest to smallest area.

Camera Array Spatial Characteristics - 2022

Array	Cameras	Area (km^2)	Mean Distance (m)
NYC	30	301.90	12044
BRF	36	33.53	3029
Mianus	32	7.30	1686
CLBS	25	5.47	1494
Wolf	15	3.30	1409
PineBush	16	0.68	599
SCA	8	0.68	734
Dyken	12	0.30	418

Appendix 1.3c. Area (km^2) and average distance between cameras (m) of each array for the year 2021 ordered from largest to smallest area.

Camera Array Spatial Characteristics - 2021

Array	Cameras	Area (km^2)	Mean Distance (m)
NYC	25	239.29	12057
BRF	50	168.56	5272
StLawrence	16	34.74	4799
Syr	9	27.52	4021
Heiberg	8	12.24	2723
Mianus	20	3.38	1484
Wolf	24	3.05	1364
PineBush	15	0.69	588
Dyken	18	0.30	380
PaulSmiths	9	0.23	399

Appendix 2.1a. Occupancy modeling AIC results for black bear.

species	model	k	AIC	ΔAIC
bear	**median canopy height (1km)**	**6**	**830.9113**	**0**
bear	mean canopy height (1km)	6	833.9288	3.017542
bear	relative proportion of tall trees (1km) (2^{nd} order) and road density interaction	9	834.8974	3.986146
bear	standard error of canopy height (1km)	6	835.1145	4.203217
bear	relative proportion of tall trees (1km)	6	841.2068	10.29553
bear	median canopy height (500m)	6	843.0574	12.14613
bear	mean canopy height (500m)	6	843.419	12.50772
bear	relative proportion of tall trees (500m)	6	846.4338	15.52254
bear	canopy cover (1km)	5	849.8185	18.90723
bear	standard error of canopy height (500m)	6	853.8954	22.98406
bear	proportion of open area (1km)	5	855.1786	24.26726
bear	canopy cover (500m)	5	855.4176	24.50631
bear	median canopy height (200m)	6	857.3922	26.48089
bear	relative proportion of tall trees (200m)	6	857.9362	27.02493
bear	mean canopy height (200m)	5	859.7395	28.82821
bear	proportion of open area (500m)	5	860.4303	29.51898
bear	proportion of water (1km)	5	861.367	30.45574
bear	proportion developed (1km)	5	861.8661	30.95482
bear	proportion of water (500m)	5	863.6683	32.75704
bear	standard error of canopy height (200m)	6	863.8893	32.978
bear	Moran's I (200m)	5	865.4709	34.55959
bear	road density	5	866.2623	35.35098
bear	canopy cover (200m)	5	866.6876	35.77635
bear	proportion developed (500m)	5	867.0027	36.09141
bear	Moran's I (500m)	5	867.6003	36.689
bear	proportion of water (200m)	5	867.6447	36.73343
bear	proportion of open area (200m)	5	868.6418	37.73055
bear	proportion developed (200m)	5	868.829	37.91773
bear	Moran's I (1km)	5	869.0672	38.15586

Appendix 2.1b. Occupancy modeling AIC results for bobcat.

species	model	k	AIC	ΔAIC
bobcat	**Moran's I (500m)**	**5**	**528.2137**	**0**
bobcat	**Moran's I (500m) and road density interaction**	**7**	**530.2116**	**1.997866**
bobcat	Moran's I (200m)	5	530.2395	2.025744
bobcat	canopy cover (1km)	5	532.8478	4.634076
bobcat	proportion of water (1km)	5	535.3044	7.090726
bobcat	proportion of open area (1km)	5	536.2235	8.009748
bobcat	mean canopy height (500m)	5	536.8997	8.686038
bobcat	canopy cover (200m)	5	537.8882	9.67453
bobcat	median canopy height (500m)	5	538.0355	9.821783
bobcat	standard error of canopy height (500m)	5	538.1024	9.888704
bobcat	median canopy height (200m)	5	538.5448	10.33105
bobcat	mean canopy height (200m)	5	538.7742	10.56053
bobcat	proportion of open area (200m)	5	539.8242	11.61047
bobcat	road density (200m)	5	539.8438	11.63012
bobcat	standard error of canopy height (200m)	5	540.1173	11.90356
bobcat	standard error of canopy height (1km)	5	540.1199	11.9062
bobcat	relative proportion of tall trees (500m)	5	540.2018	11.9881
bobcat	proportion of water (200m)	5	540.2386	12.0249
bobcat	proportion developed (200m)	5	540.3645	12.15077
bobcat	Moran's I (1km)	5	540.4662	12.25251
bobcat	median canopy height (1km)	5	540.4756	12.26189
bobcat	proportion developed (1km)	5	540.6251	12.41137
bobcat	relative proportion of tall trees (1km)	5	540.7356	12.52189
bobcat	proportion of open area (500m)	5	541.3288	13.11511
bobcat	relative proportion of tall trees (200m)	5	541.3466	13.13288
bobcat	mean canopy height (1km)	5	541.5026	13.2889
bobcat	proportion developed (500m)	5	542.075	13.86131
bobcat	canopy cover (500m)	6	549.7005	21.48678
bobcat	proportion of water (500m)	6	573.1308	44.91711

Appendix 2.1c. Occupancy modeling AIC results for coyote.

species	model	k	AIC	ΔAIC
coyote	**proportion developed (1km) and road density interaction**	**7**	**2645.754**	**0**
coyote	**proportion developed (1km) and relative proportion of tall trees (200m) interaction**	**7**	**2647.369**	**1.6149**
coyote	relative proportion of tall trees (200m) and road density interaction	7	2648.542	2.788391
coyote	proportion developed (1km)	5	2655.458	9.703961
coyote	median canopy height (1km)	6	2655.805	10.05103
coyote	relative proportion of tall trees (200m)	5	2656.125	10.37061
coyote	canopy cover (1km)	6	2656.996	11.24228
coyote	mean canopy height (1km)	6	2657.773	12.01947
coyote	proportion developed (200m)	5	2658.538	12.78434
coyote	median canopy height (200m)	6	2659.148	13.39429
coyote	mean canopy height (200m)	5	2659.59	13.83645
coyote	mean canopy height (500m)	6	2659.706	13.95158
coyote	canopy cover (200m)	6	2659.773	14.01937
coyote	median canopy height (500m)	6	2659.902	14.14802
coyote	proportion developed (500m)	5	2660.545	14.79129
coyote	canopy cover (500m)	5	2661.164	15.41048
coyote	relative proportion of tall trees (500m)	5	2661.223	15.46871
coyote	proportion of open area (200m)	6	2662.073	16.3192
coyote	relative proportion of tall trees (1km)	5	2662.378	16.62367
coyote	proportion of open area (1km)	6	2663.614	17.86019
coyote	standard error of canopy height (200m)	5	2666.586	20.83186
coyote	proportion of open area (500m)	5	2666.641	20.88735
coyote	Moran's I (200m)	5	2667.023	21.26899
coyote	road density (200m)	5	2667.025	21.27123
coyote	proportion of water (200m)	5	2667.511	21.75753
coyote	proportion of water (1km)	5	2667.603	21.84893
coyote	Moran's I (1km)	5	2667.988	22.23403
coyote	standard error of canopy height (500m)	5	2668.002	22.24823
coyote	standard error of canopy height (1km)	5	2668.046	22.29158
coyote	proportion of water (500m)	5	2668.08	22.3256
coyote	Moran's I (500m)	5	2668.087	22.33302

Appendix 2.1d. Occupancy modeling AIC results for fisher.

species	model	k	AIC	ΔAIC
fisher	**canopy cover (1km) and road density interaction**	**9**	**621.9758**	**0**
fisher	canopy cover (1km)	6	648.255	26.27921
fisher	median canopy height (200m)	6	656.1357	34.1599
fisher	mean canopy height (200m)	6	656.5997	34.62393
fisher	relative proportion of tall trees (1km)	6	657.1129	35.13713
fisher	median canopy height (1km)	6	657.3149	35.33916
fisher	mean canopy height (1km)	6	658.7438	36.768
fisher	relative proportion of tall trees (500m)	6	659.0986	37.12286
fisher	proportion developed (1km)	6	659.3216	37.34577
fisher	road density (200m)	5	660.4875	38.5117
fisher	canopy cover (500m)	6	661.7234	39.74757
fisher	relative proportion of tall trees (200m)	6	661.8113	39.83547
fisher	proportion developed (500m)	6	664.3037	42.3279
fisher	median canopy height (500m)	6	664.438	42.46226
fisher	proportion of water (1km)	5	664.51	42.53422
fisher	standard error of canopy height (200m)	6	665.9579	43.98213
fisher	proportion of open area (200m)	5	666.1238	44.14801
fisher	canopy cover (200m)	6	666.7117	44.73588
fisher	proportion of water (500m)	5	667.3344	45.35863
fisher	mean canopy height (500m)	5	667.961	45.98518
fisher	Moran's I (500m)	5	668.5477	46.57196
fisher	proportion of open area (1km)	5	669.3792	47.40346
fisher	standard error of canopy height (500m)	5	670.0368	48.06104
fisher	proportion developed (200m)	5	670.595	48.61917
fisher	proportion of open area (500m)	5	670.6053	48.62955
fisher	standard error of canopy height (1km)	5	670.6849	48.70909
fisher	proportion of water (200m)	5	670.7021	48.7263
fisher	Moran's I (200m)	5	670.7405	48.7647
fisher	Moran's I (1km)	5	670.757	48.7812

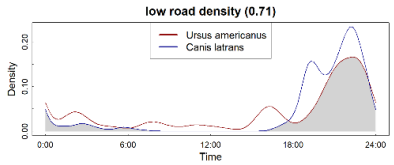
Appendix 2.1e. Occupancy modeling AIC results for raccoon.

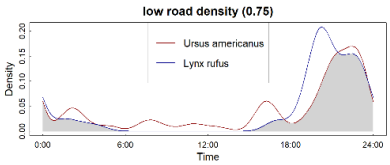
species	model	k	AIC	ΔAIC
raccoon	**proportion developed (500m) and road density interaction**	**7**	**3409.398**	**0**
raccoon	road density (200m)	5	3414.237	4.838961
raccoon	proportion developed (500m)	5	3414.675	5.276622
raccoon	proportion developed (1km)	6	3433.33	23.93148
raccoon	proportion developed (200m)	5	3434.761	25.36224
raccoon	proportion of water (1km)	6	3437.661	28.26217
raccoon	canopy cover (1km)	6	3445.14	35.74181
raccoon	proportion of water (500m)	6	3451.723	42.32419
raccoon	mean canopy height (1km)	6	3457.508	48.10913
raccoon	canopy cover (500m)	6	3458.149	48.75025
raccoon	median canopy height (1km)	6	3468.884	59.48574
raccoon	canopy cover (200m)	5	3469.468	60.06996
raccoon	mean canopy height (500m)	6	3471.087	61.68863
raccoon	median canopy height (500m)	6	3471.591	62.19243
raccoon	mean canopy height (200m)	6	3472.451	63.05285
raccoon	proportion of water (200m)	6	3472.581	63.18276
raccoon	proportion of open area (1km)	5	3473.093	63.69445
raccoon	median canopy height (200m)	6	3473.617	64.2189
raccoon	relative proportion of tall trees (1km)	6	3474.399	65.0009
raccoon	Moran's I (200m)	6	3475.434	66.03531
raccoon	standard error of canopy height (500m)	5	3475.763	66.36466
raccoon	standard error of canopy height (200m)	5	3476.248	66.84908
raccoon	proportion of open area (200m)	5	3476.701	67.3029
raccoon	proportion of open area (500m)	5	3477.299	67.90063
raccoon	relative proportion of tall trees (200m)	5	3478.57	69.17197
raccoon	Moran's I (1km)	5	3479.228	69.82936
raccoon	standard error of canopy height (1km)	5	3479.364	69.96537
raccoon	Moran's I (500m)	5	3480.158	70.75924
raccoon	relative proportion of tall trees (500m)	5	3480.167	70.76858

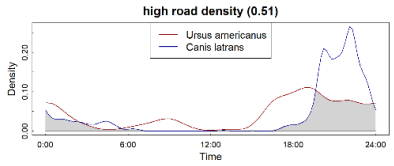
Appendix 2.1f. Occupancy modeling AIC results for red fox.

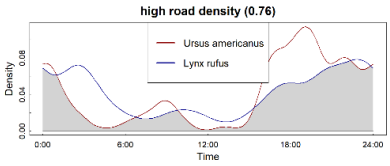
species	model	k	AIC	ΔAIC
red fox	**relative proportion of tall trees (200m) and road density interaction**	**7**	**1947.304**	**0**
red fox	**median canopy height (200m)**	**5**	**1948.154**	**0.849666**
red fox	**median canopy height (200m) and relative proportion of tall trees (200m) interaction**	**7**	**1948.35**	**1.046382**
red fox	**mean canopy height (200m) and relative proportion of tall trees (200m) interaction**	**7**	**1948.372**	**1.068357**
red fox	**mean canopy height (200m)**	**5**	**1948.379**	**1.074631**
red fox	**relative proportion of tall trees (200m)**	**5**	**1948.479**	**1.174628**
red fox	mean canopy height (200m) and road density interaction	7	1950.725	3.421255
red fox	median canopy height (200m) and road density interaction	7	1951.112	3.808153
red fox	mean canopy height (500m)	5	1958.305	11.00042
red fox	median canopy height (500m)	5	1959.97	12.66584
red fox	canopy cover (200m)	5	1960.129	12.82531
red fox	canopy cover (1km)	5	1960.25	12.94575
red fox	road density (200m)	6	1961.065	13.76098
red fox	canopy cover (500m)	5	1961.336	14.03178
red fox	proportion of open area (200m)	5	1963.219	15.91532
red fox	Moran's I (200m)	5	1963.601	16.29694
red fox	median canopy height (1km)	5	1964.714	17.40967
red fox	mean canopy height (1km)	5	1965.212	17.90817
red fox	Moran's I (500m)	5	1965.685	18.38052
red fox	relative proportion of tall trees (500m)	6	1967.593	20.28854
red fox	proportion of open area (500m)	5	1967.746	20.44203
red fox	proportion developed (1km)	5	1967.815	20.51101
red fox	relative proportion of tall trees (1km)	6	1969.939	22.63504
red fox	proportion of open area (1km)	5	1975.675	28.37137
red fox	proportion developed (500m)	5	1976.039	28.73501
red fox	proportion developed (200m)	5	1978.209	30.90514
red fox	standard error of canopy height (1km)	5	1980.676	33.37208
red fox	proportion of water (1km)	6	1982.077	34.77259
red fox	standard error of canopy height (500m)	5	1982.385	35.08091
red fox	Moran's I (1km)	5	1982.602	35.29824
red fox	standard error of canopy height (200m)	5	1985.273	37.96854
red fox	proportion of water (500m)	6	1990.898	43.59367
red fox	proportion of water (200m)	6	1995.797	48.49256

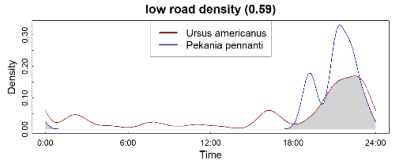
Appendix 3.1a. Daily activity pattern overlap networks comparing overlap of bears and five other focal species at low and high road density, showing consistently higher overlap with low road density.

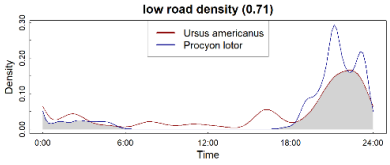


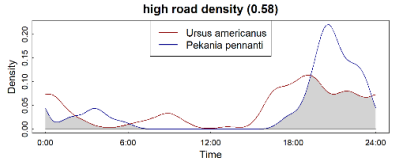


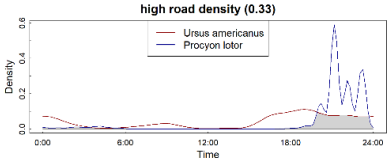


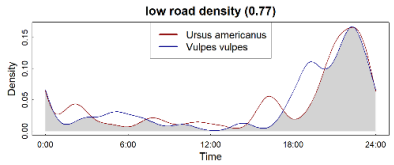


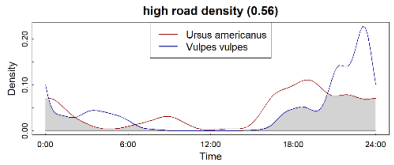




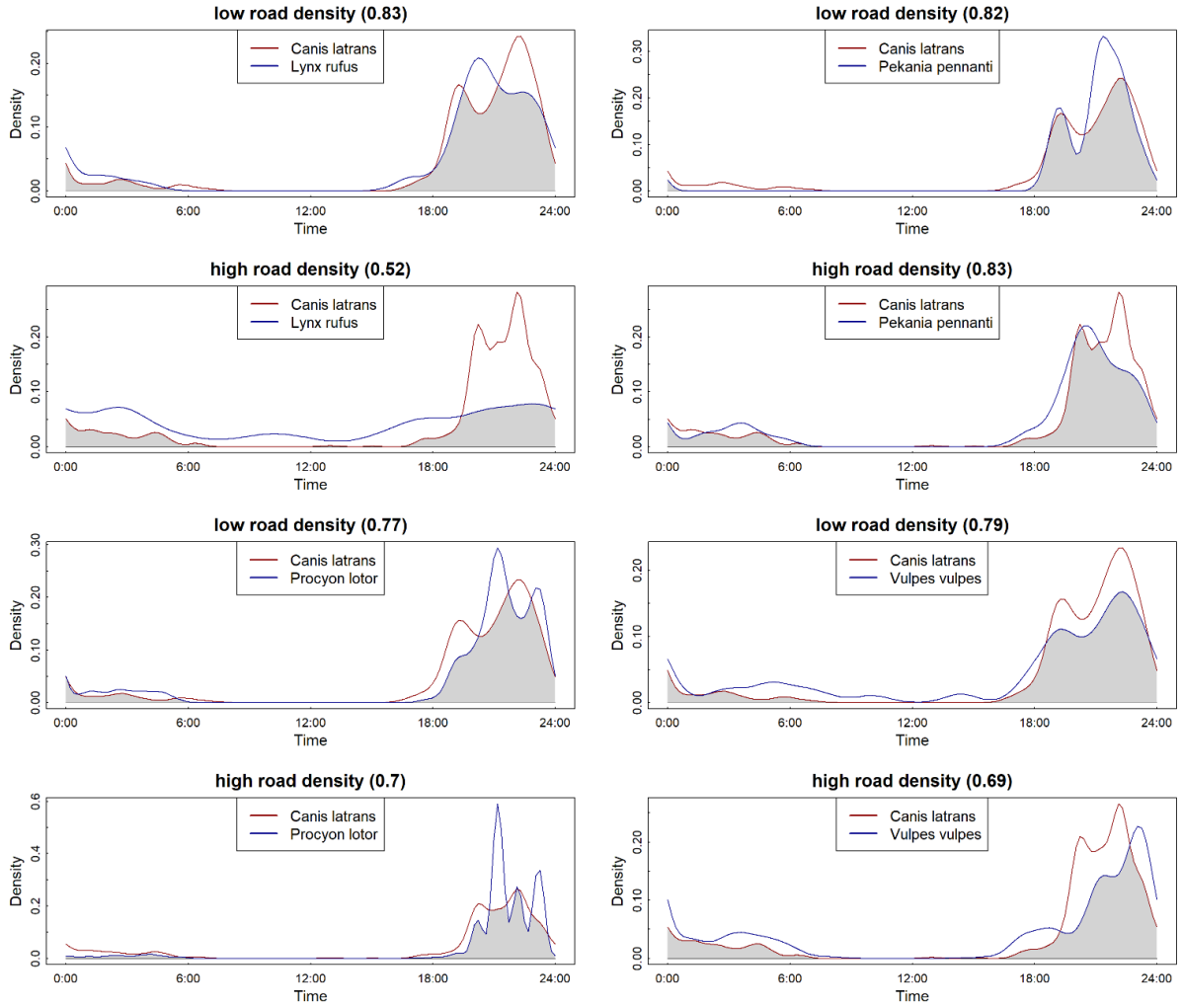




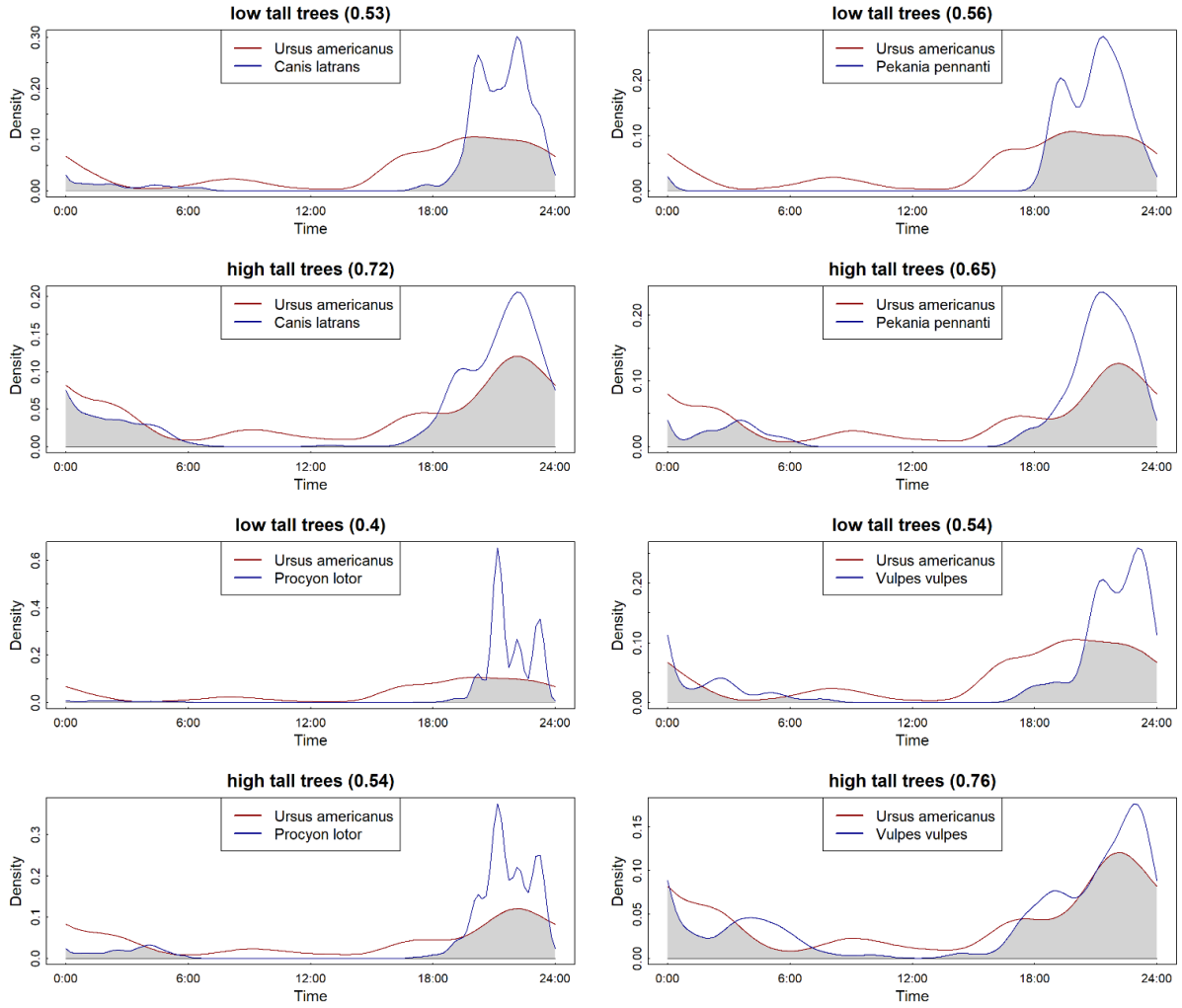




Appendix 3.1b. Daily activity pattern overlap networks comparing overlap of coyotes and four other focal species at low and high road density, showing consistently higher overlap with low road density.



Appendix 3.1c. Daily activity pattern overlap networks comparing overlap of bears and five other focal species at low and high proportion of trees >20m (relative to canopy cover), showing consistently higher overlap with high proportion of tall trees.



SYDNEY OPEL

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EDUCATION

B.S. SUNY College of Environmental School and Forestry (SUNY-ESF)
Environmental & Forest Biology Department, Wildlife Science Major, Graduated 2021 Summa Cum Laude

M.S. SUNY College of Environmental School and Forestry (SUNY-ESF)
Environmental Biology, Wildlife Ecology and Management, MP Dr. Elie Gurarie, Current

RESEARCH AND FIELD EXPERIENCE

Mesocarnivore Community Ecology- Thesis Research (Elie Gurarie, MP), *New York* January 2023-present
M.S. student

- Committee Members: Jacqueline Frair and Scott LaPoint
- Designed and developed research to study mesocarnivore (coyote, bobcat, fisher, fox, raccoon, marten) community structure along an urban-wild gradient across multiple sites in New York State using non-invasive methods including camera traps and scat sampling
- Conduct and lead field work to maintain camera trap arrays and collect fecal samples
- Employ and mentor undergraduate students in field work and data collection and processing
- Composed and submitted grant proposals to fund thesis research

Muskrat Housing Density Study- Research Foundation for SUNY (John Farrell), *New York* January 2025-August 2025
Senior Research Aide

- Identified, counted, and documented site measurements of muskrat houses along St. Lawrence River channels in Clayton, New York as data collection for muskrat housing density modeling
- Modeled muskrat housing density against digital elevation models (DEM) and water depth
- Guided design of water depth measurement sampling to obtain accurate and precise water depth measurements in combination with DEM's obtained from the NYS GIS Clearinghouse

Deer Density Study- Mississippi State University (Dana Morin), *MS Delta & Benton County, Mississippi* June-July 2022
Field Technician

- Performed trail camera set up and transects to collect fecal samples for analysis
- Gained proficiency in navigation methods using GPS units and compass
- Exercised flexibility and adaptability when transect and camera locations were flooded
- Learned field techniques for collecting fecal samples

The Jaguar Project- Virginia Tech (Marcella Kelly), *Mountain Pine Ridge & Chiquibul, Belize* February-March 2022
Volunteer Field Assistant

- Performed camera checks for 66 stations with 2 cameras
- Gained proficiency in operating different models of trail cameras
- Hiked and navigated through difficult terrain and weather conditions

NY Mammal Survey, *Adirondack Mountains and Central NY* July-August 2021
Intern

- Conducted small mammal trapping with Sherman, pitfalls, and cameras as part of first statewide mapping of NY mammals
- Mastered timely and efficient sample site setup, take down and daily trap check of multiple sites
- Learned field techniques for selecting sample sites using GPS coordinates and units
- Gained proficiency in tissue sample collection for genetic analysis including ear punching and toe clipping
- Conducted a vegetation survey of the sample sites
- Recorded field data using the NY Mammal Survey application

TEACHING EXPERIENCE

***Graduate Teaching Assistant (M.S.), SUNY-ESF**, Syracuse, NY*

Applied Wildlife Science Spring 2024

- Assist faculty by developing R-based labs, leading lab sessions, grading assignments, and teaching students
- Further students' practical experience with quantitative and field tools used to monitor and manage wildlife populations in a course designed for students with intentions of pursuing careers in wildlife biology

Wildlife Ecology and Management Fall 2023/2024

- Assist faculty by leading recitation sessions, developing content, grading assignments, and teaching students
- Further student understanding of the ecological principles governing wild animal populations and their habitats, and the relationship of these principles to management programs and decisions

General Biology II: Cell Biology and Genetics Spring 2023

- Assist faculty by leading recitation sessions, developing content, grading assignments, and teaching students
- Further student understanding of the organization and function of living cells including biological molecules, organelle structure and function, gene expression, cell division, metabolism, photosynthesis, cell signaling, genomics, and population genetics

***Undergraduate Teaching Assistant, SUNY-ESF**, Syracuse, NY*

General Biology I: Organismal Biology an Ecology Fall 2021

- Assist faculty by implementing lab sessions, grading assignments, and teaching students
- Further student understanding of form, function, diversity, ecology, and evolution of living organisms

Animal Tracks & Sign Fall 2021

- Assist students to effectively identify, record, and interpret animal sign to gain insight into animal species and behavior
- Develop student field journaling skills

Applied Wildlife Science Spring 2021

- Assist faculty by implementing lab sessions, grading assignments, and teaching students
- Further students' practical experience with tools used to monitor and manage wildlife populations in a course designed for students with intentions of pursuing careers in wildlife biology

ACADEMIC ACHIEVEMENT

Undergraduate

- Completed all necessary coursework for The Wildlife Society Associate Wildlife Biologist Certification
- Alpha Xi Sigma (AXS) Honor Society member due to excellence in academic achievement and community involvement
- Achieved either Dean's List or President's List for all semesters at ESF; graduated Summa Cum Laude

AWARDS

- Edna Bailey Sussman Fund: Graduate Environmental Internship recipient in 2023 in support of mesocarnivore community ecology research ($11,375)

PRESENTATIONS

- Prepared and presented poster on mesocarnivore community ecology research at 2023 Black Rock Forest Research Symposium

OTHER

- Experience in tagging photos for graduate student's research study on fisher demography
- Software skills: Program R, Mark, Distance, Presence, digiKam, Mesquite, Timelapse, and ArcGIS
- Computer skills: Word, Excel, and PowerPoint
- The Wildlife Society member, NY chapter