ABSTRACT

Title of Thesis: BITES AND BEARDS: EXAMINING TICK-TURKEY DYNAMICS ACROSS AN URBAN-RURAL GRADIENT

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Eastern wild turkey *(M. gallopavo silvestris*) sightings are becoming increasingly common in urban landscapes, potentially indicating a shift in turkey home ranges. Additionally, there are recent concerns that turkey and tick presence may be related, however the relationship remains poorly understood. In this study, I evaluated the occupancy and abundance of turkey populations across in eight parks in Montgomery County, MD. Additionally, I collected ticks in five out of the eight parks to assess local tick populations. I developed single-season occupancy models and hierarchical N-mixture abundance models for two seasons ecologically relevant to turkeys. This information enhances our understanding of turkey habitat preferences in county parks in Maryland, which is valuable for wildlife management in areas with significant human development. By better understanding turkey and tick distributions, we can mitigate human wildlife conflicts and contextualize the turkey-tick relationship.

BITES AND BEARDS: EXAMINING TICK-TURKEY DYNAMICS ACROSS AN URBAN-RURAL GRADIENT

by

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Dedication

This thesis is dedicated to my two wonderful nieces, Mayah Sophia and Ava Jaydn. May this serve as a reminder to both of you to never let anyone tell you that you cannot achieve your dreams, and to never give up, no matter the circumstances. Watching you two grow has been the greatest joy of my life, and I love you both more than words can express.

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CHAPTER I: TURKEYS IN MONTGOMERY COUNTY

INTRODUCTION

Throughout the 21st century, increasing human populations and urbanization have dramatically altered the composition and quality of wildlife habitats (Fischer et al. 2015). Most landscapes in North America now exhibit a gradient of fragmentation due to the expansion of urban and suburban sprawl (Moll et al. 2019; Liu et al. 2016; Fischer et al. 2015). Fragmentation leads to smaller intact habitat patches, more edge effects, longer perimeters, and fewer core interior habitats (Fahrig 2003). It can also lead to the degradation of the remaining habitat, allowing for easier propagation by invasives and more disturbance, including noise, use by humans, light, etc. (Fahrig 2003). Therefore, we need a better understanding of how human development impacts the dispersal, abundance, and density of wildlife to better manage the populations in these areas (Rodewald and Gehrt 2014).

Urbanization-facilitated habitat loss can degrade wildlife habitats, thus impacting the movement and dispersal of species that have historically inhabited these regions (Rodewald and Gehrt 2014). Game birds are a notable species that are particularly vulnerable to these effects, especially given their specialized habitat requirements and the need to move between different habitats for foraging, roosting, and nesting (Gullion 1996; Brennan and Kuvlesky, 2005). Large patches of agricultural lands and open areas are thought to provide ample movement corridors for birds, particularly turkey flocks and adult males traveling between mating locations (Pollentier et al. 2017; Isaksson 2018). Therefore, as urbanization increases and expands upon agricultural regions to accommodate human development, the dispersal of these birds is impacted, resulting in game bird populations that are either confined to specific areas or forced to

be highly mobile in search of better-quality habitats (Isaksson 2018).

As agricultural areas shrink or experience increased usage due to urbanization, human and wildlife communities are brought into closer proximity, which in turn increases the risk of human-wildlife conflicts (Nyhus 2016; Miller 2018). Notable human-wildlife conflicts include collisions, property damage, and zoonotic disease spread (Sonenshine 2018; Miller 2018). As the global human population grows, understanding urbanization's impact on wildlife and formulating strategies to mitigate potential human-wildlife conflicts is important. In particular, the spread of tick-borne diseases remains a significant human-wildlife conflict and continues to pose both public health and economic challenges in the United States (Madison-Antenucci et al. 2020). The prevalence of tick-borne diseases, specifically Lyme disease, has increased in recent years (Nawrocki and Hinckley 2021; Hook et al. 2021). It is estimated that Lyme disease impacts approximately 329,000 individuals annually (Nawrocki and Hinckley 2021). Existing literature focused on how tick populations and tick-borne diseases were increasing due to changes in landscape composition (Mathisson et al. 2021). For example, Mathisson et al. (2021) analyzed how blacklegged tick abundance was impacted by vegetation such as forest cover and grasslands. However, there remains a general lack of understanding regarding urban-suburban landscapes' impact on the distribution and density of tick populations. Studying ticks across varying levels of human development provides valuable insight into tick ecology in human-dominated landscapes, as urbanization impacts tick hosts and vegetation— factors that influence the abundance and distribution of ticks. By better understanding tick ecology in urban areas scientists can reach a better understanding of the transmission of tick-borne diseases in these environments.

Ticks have a complex life cycle consisting of three stages: larvae, nymph, and adult (Rodino et al. 2020). Ticks will feed on different hosts depending on their life stage (Rodino et

al. 2020). For example, larval and nymphal ticks are known to feed on smaller wildlife species, whereas adult ticks are documented feeding on larger mammals (Eisen and Stafford 2021). Known reservoirs of tick-borne diseases include white-footed mice (*Peromyscus leucopus*) and deer mice (*Peromyscus maniculatus*) (Sonenshine 2018*;* Fiset et al. 2015). Larger wildlife species (e.g. white-tailed deer, etc.) influence tick abundance and dispersal in an ecosystem through their role as host and blood meal (Sonenshine 2018; Ostfeld and Lewis 1999; Eisen and Stafford 2021). Therefore, the abundance and distribution of ticks on a landscape are influenced by the presence and density of various wildlife species (Eisen and Stafford, 2021). Previous research suggested that Eastern wild turkeys (*Melagris gallopavo silvestri*s: hereafter turkey) may play a role in the life cycle of ticks (Mock et al. 2001; Lane et al. 2006; Ostfeld and Lewis 1999). Many ticks prefer specific wildlife species for their blood meal, depending on their present life stage. Nymphal ticks (second life stage) and adult ticks (third/final life stage) have been documented feeding on turkeys throughout the spring and fall seasons (Mock et al. 2001). Mock et al. (2001) also documented turkeys consuming ticks through their grooming and foraging behaviors. However, the intricacies of how the two species may influence each other remains poorly understood and understudied. One posited hypothesis was that turkeys, being opportunistic feeders, actively consumed ticks in their feeding areas, reducing tick abundance on a landscape (Ostfeld and Lewis 1999). Conversely, it has been suggested that turkeys may be consistent hosts for tick species (Mock et al. 2001; Lane et al. 2006), potentially increasing ticks in landscapes with established turkey populations to sustain and move them around the landscape. These hypotheses described opposing effects that the presence of turkeys may have had on the overall tick populations of an area. If turkeys influence tick populations, they may mitigate or increase the potential spread of tick-borne diseases in densely populated areas

(Ostfeld and Lewis 1999; Lane et al. 2006), which could lead to different surveillance and response requirements. As such, a better understanding of the spatial relationship between turkeys and ticks would be helpful.

In the Mid-Atlantic region, wild turkeys are a game species with a unique history. In the early 1900s, turkeys were almost harvested to extinction, but successful wildlife reintroduction programs replenished the population (Dickson 1992; Ostfeld and Lewis 1999). Historically, turkeys have occupied rural landscapes that provide ample foraging and roosting habitats but are now experiencing potential range shifts to include non-traditional, urban areas (MDDNR 2022a). In Maryland over the past ten years, turkey populations have increased in some regions while remaining stable in others (MDDNR 2019). More specifically, the Maryland Department of Natural Resources reported a significant increase in the number of turkeys in the Baltimore-Washington region (MDDNR 2022a). Landscapes with high rates of turkey occupancy may also face negative economic and ecological impacts due to turkeys' interactions with the surrounding environment (Groepper et al. 2013; Miller 2018). For example, In more rural areas, turkeys cause damage to agricultural fields through their direct consumption of crops and behaviors (Miller et al. 2000; Gabrey et al. 1993). In more urban environments, turkeys pose health and economic risks when they become habituated to people. For example, turkeys have been documented chasing and harassing humans (Miller 2018). Aggressive birds are primarily males, and most harassment occurs during breeding season (Miller 2018). Turkey may also cause private damages and monetary loss through their mating and territorial behaviors, as they perceive their reflection as another bird (Miller 2018) and have been recorded scratching windows and other reflective surfaces such as parked cars (Miller 2018). Given the economic, ecological, and safety implications, understanding the distributions of turkeys across urban-rural settings can help

wildlife managers mitigate region-specific human-wildlife conflicts.

From 1993 to current, turkey populations in Maryland have been monitored through statewide, opportunistic community surveys conducted in July-August led by the Maryland Department of Natural Resources (MDDNR 2022b). The Maryland Department of Natural Resources survey primarily focused on assessing the reproductive success of the population. Combined with other information, the survey aimed to help wildlife managers monitor and predict changes in the regional turkey population. Surveyors were asked to identify the number of turkeys, by age and sex, for a given sighting, but the datasets were not collected systematically. Generally, these surveys were useful as a coarse index of population change and productivity but were not useful for estimating population numbers or tracking populations at a finer scale. Furthermore, local factors such as weather patterns and habitat quality can impact turkey populations, but the surveys rarely incorporate habitat at a scale or level that accounts for environmental variation.

Maryland also monitors its turkey population through annual hunter-harvest data. The consumptive use of turkeys in Maryland has significant economic benefits (Dickson 1992). With approximately 10,000 participants, turkey breeding has an estimated economic benefit of approximately 4.8 million dollars annually in Maryland (MDDNR 2019). During the 2023 spring harvest, Maryland reported a record-high harvest of turkeys, with 5,356 birds collected. (MDDNR 2023). However, in 2024, the number of turkeys harvested was 7% less than in 2023 but was still a record high compared to previous years (MDDNR 2024). To better understand the dynamics of turkeys in the state, Maryland needs a continuous and comprehensive wildlife monitoring method. That information would allow wildlife managers to make better informed decisions for sustaining a stable turkey population throughout the state.

OBJECTIVES AND HYPOTHESIS

My study aimed to explore turkey occupancy and relative abundance in human dominated environments. This study also explored the potential relationship between turkey and tick populations, specifically to examine how turkey abundances may relate to the abundance of ticks in urban and suburban areas. To do this, I used occupancy and N-mixture models to estimate the likelihood and abundance of turkeys in Montgomery County, Maryland. For both analyses, I modeled sources of variation in turkey occupancy and abundance in relation to land cover covariates relevant to turkey ecology. Then, I used general linear mixed models to estimate how tick abundances on the landscape might vary with turkey habitat, counts and abundance in urban and suburban areas. I addressed these goals and aims via two research hypotheses:

Hypothesis 1: I hypothesized that turkey occupancy and abundance would be higher in suburban parks bordering single-family residential areas due to the increased availability of open, foraging habitats such as turf grass, manicured lawns, and bird feeders, as well as the potential for fewer predators and more confined spaces typical of suburban environments. This objective addresses the anecdotal increase of turkey sightings across the Mid-Atlantic, specifically in the District of Columbia and Maryland. Additionally, this objective increases our understanding of turkey populations in urban and suburban areas. I tested this hypothesis by comparing estimates of turkey occupancy and abundance in relation to landscape and urbanization covariates.

Hypothesis 2: I hypothesized that areas with higher turkey abundances would have a greater overall abundance of ticks, suggesting that turkeys contribute to the expansion of tick populations by serving as hosts. Such information would enable a better understanding of the relationship between turkey relative abundances and tick abundance and what this potential

correlative relationship may mean for the risk of tick-borne diseases in human-dominated ecosystems.

STUDY AREA

With just over one million residents, Montgomery County was Maryland's most populous county in 2023 (World Population Review 2023). Located just outside of the D.C. Metropolitan area, this region has undergone rapid development in recent years to accommodate its growing population. In particular, the southernmost region of Montgomery County has experienced relatively high rates of urbanization. This region borders the Washington, D.C. border and is currently dominated by urban and suburban landscapes that contain patches of spatially fragmented greenspaces. In contrast, the northern region of Montgomery County has experienced low rates of development and is characterized by continuous agricultural landscapes with pockets of developed land dispersed throughout. To examine variations in turkey occupancy and relative abundance across Montgomery County, Maryland, I used camera trap data collected from 92 Boly BG962-X36W cameras (Boly, Santa Clara, CA, USA) deployed in eight parks throughout the county. I sampled parks that varied in their levels of human development, spatial configuration, and surrounding land cover composition. All parks in this study were managed and operated by the Montgomery County Parks and Planning Commission (MCPPC).

The urban study area encompassed three park units: Cabin John Regional Park, Rock Creek Stream Valley Park and Sligo Creek Stream Valley Park. These three urban parks surround a unique city center according to 2020 census information. These parks were in the southernmost portion of Montgomery County, Maryland. All three of these parks experienced high levels of recreational use and are located near intense urban centers including city centers,

single-family and multiple-family residential housing. The suburban areas in this study included three parks: Muddy Branch, Great Seneca, and Upper Paint Branch, all of which were in the central part of the county. The suburban areas were characterized by residential households, mostly single-family homes, with park locations dispersed throughout. The rural area in this analysis consisted of two parks: Little Bennett Regional Park and Woodstock Equestrian Park. These two parks are in the northernmost region of Montgomery County, Maryland and are characterized by larger tracts of agricultural land with low-density human development.

CHAPTER II: OCCUPANCY AND RELATIVE ABUNDANCE OF WILD TURKEYS IN MONTGOMERY COUNTY, MARYLAND

INTRODUCTION

Once hunted near extirpation in the state of Maryland, the Eastern wild turkey (*Meleagris gallopavo silvestris* hereafter; turkey) population has been restored due to successful reintroduction programs (MDDNR 2003; Dickson 1992). Turkeys are a game bird with great economic and cultural importance throughout the state. Across the Mid-Atlantic region, abundant turkey populations are associated with the presence of forested areas mixed with agricultural and open landscapes (Niedzielski and Bowman 2016; Pollentier et al. 2021). However, turkey populations in Maryland have begun to establish in unlikely areas (MDDNR 2022a). Populations of urban and suburban turkeys were thought to be impacted by the presence of human development, which inherently decreases their foraging and roosting sites (Chamberlain et al. 2022). Additionally, urban and suburban birds are at greater risk of human-wildlife collisions, impacting the distribution and survival of the species (Miller 2018). Despite the inherent risks to turkeys in urban and suburban areas, the Maryland Department of Natural Resources has reported an increase in turkey sightings across the Baltimore-Washington Metropolitan region in recent years (MDDNR 2022a). However, there is a knowledge gap on how turkeys utilize urban landscapes and their abundances in these areas. An accurate assessment of urban and suburban turkey populations can guide wildlife management strategies in unique human-dominated landscapes.

Multiple survey methods have been used to monitor turkey populations. Currently, the state of Maryland utilizes data from opportunistic, in-person surveys to provide an index of their

population (MDDNR 2022b). However, this survey method is often subject to surveyor bias because the data is not collected systematically and is subject to the effort and activity level of observers (Reid et al. 2013). Camera surveys are an alternative to in-person surveys that can be used to assess the occupancy and abundance of a species (Stein et al. 2008; O'Brien and Kinnaird 2008). Turkeys are ideal subjects for camera trapping because they are large-bodied birds that primarily move by walking (Healy 2000). Urban and suburban parks are ideal candidates for camera study designs as cameras passively collect data, avoiding direct impact on the human population nearby or the wildlife populations being observed. Camera surveys are well suited for documenting turkeys in these areas as they provide precise location information to describe when and where turkeys were observed. These photos provide data across age-class and sex, which informs how these demographics change seasonally and annually.

As camera surveys can be systematically designed to sample available habitat, they may provide more accurate information about urban and suburban turkey populations compared to opportunistic survey estimates. Furthermore, detection/non-detection data collected from a camera array have been used within an occupancy analysis to describe turkey presence on the landscape while accounting for detection bias (MacKenzie et al. 2006). Additionally, models describing abundance have utilized camera survey data by recording the total number of individuals present during a sampling period (Pearce and Ferrier 2001). Effects of covariates on turkey occupancy and relative abundance can then be quantified to provide insights into turkey ecology in unique human-dominated landscapes (MacKenzie et al. 2006). Understanding the relationships between land cover, urbanization, and turkey presence and relative abundance provides insight into turkey populations and their habitat preferences in urbanized areas. This, in

turn, enhances estimates by accounting for the variations introduced by urbanization and land cover, thereby reducing uncertainty in management decisions.

Here I assessed turkey occupancy and relative abundance across eight parks in Montgomery County, Maryland. My objectives were to (1) estimate turkey occupancy for all males, females, poults and unidentifiable turkeys during the brood-rearing and breeding seasons; and (2) estimate relative abundance of hens, toms, poults and unidentifiable turkeys during the brood-rearing and breeding seasons using N-mixture models. For both analyses, I modeled variations in turkey occupancy and relative abundance, examining their relationship to land cover covariates that are ecologically relevant to turkeys.

Based on current MDDNR reports, I hypothesized that suburban parks would show the highest probability of turkey occupancy and the greatest relative abundance. This is due to the presence of features such as manicured lawns, bird feeders, turf grasses, and gardens—locations that are ample for foraging. I hypothesized that turkey occupancy and relative abundance would positively correlate with natural factors, such as open and forested habitats. Turkeys use forested areas for roosting and nesting, while open and agricultural spaces are used for foraging and mating displays (Pollentier et al. 2021). Therefore, open and forested land cover types were expected to be the strongest predictors of turkey occupancy and abundance.

METHODS

Study Area

For information about the study area please see *Chapter 1*.

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Camera Array

To examine how turkey occupancy and relative abundance varied across the study parks, I used camera trap data collected from 98 Boly BG962-X36W cameras (Boly, Santa Clara, CA, USA). I deployed cameras in eight different parks in Montgomery County, Maryland. Exact camera locations within each park were generated via the "Create Random Points" toolbox in ArcGIS©. The cameras were positioned on the nearest canopy tree to the randomly generated location and set to capture three consecutive photo bursts with zero-second intervals between each burst. Prior to camera deployment, we surveyed locations to determine landscape suitability. I did not deploy cameras in areas where game or anthropogenic trails were detected within the camera's viewshed to prevent bias. To ensure optimal detection, I placed the cameras approximately one meter above ground level.

The distance between cameras within each park was approximately 800 meters, based on the average diameter of a white-tailed deer (*Odocoileus virginianus*) home range (Roden-Reynolds 2020). This camera setup was part of a larger-scale research project that examined wildlife communities in relation to tick populations and tick-borne illnesses across varying levels of urbanization. For this analysis, we used the same camera array to address the study objectives. The two highly urban parks in this study, Cabin John Regional and Rock Creek Stream Valley, contained an array of 25 cameras based on the results of a previous power analysis for random encounter staying time and random encounter models. The remaining six parks had between 6 and 9 cameras, with the number determined by park size and shape, and were set up to conduct species richness and diversity analyses. To determine if there were any seasonal changes in occupancy and relative abundance, cameras were active approximately three years (Spring 2021-Winter 2024). Cameras and camera cards were checked and replaced once a month to avoid large gaps of missing data due to stolen cameras or camera malfunctions. Camera survey imagery was

examined, sorted, and labeled with turkey identification by a reviewer using the program TIMELAPSE (Saul Greenberg, University of Calgary, Version 2.3.2.3). Double authentication was conducted for each image to confirm the total number of poults, hens, toms, and unknown turkeys. The sexing of an individual was based on turkey biology and morphology (Dickson 1992). For example, male turkeys were typically larger than females and had a more defined snood (Dickson 1992). Additionally, males had darker feathers and heads that were red/white/blue in coloration (Dickson 1992). In contrast, the most notable characteristics of female turkeys were dull coloration and feathers on the head leading down to the base of the neck (Dickson 1992). Turkeys were classified as "unknown" if it was difficult to accurately sex a bird in an image.

As of 2024, there was little literature to describe turkey home ranges in urban and suburban settings, however turkey home ranges in rural settings average 1.5-3km^2 (Niedzielski and Bowman 2016). Thus, the initial 800m spacing between cameras was likely insufficient to prevent violations of the site independence assumption for both occupancy and N-mixture modeling (MacKenzie et al. 2006). If violations occurred, in which a bird was detected at two cameras in the same sampling occasion, then estimates of turkey occurrence and relative abundance may have been inflated. To avoid such violations of the assumption of site independence, I superimposed a grid to partition the cameras into sampling cells (i.e., as demonstrated in Herrera et al. 2022) (See Figure 1). Given the 1.5-3km^2 home range estimate for turkeys in rural areas, I distributed a grid of 2-km^2 diameter, hexagonal cells across the study area. Hexagonal cells reduced sampling bias through edge effects (via a low perimeter to area ratio) and allowed for a continuous and evenly spaced grid overlay (Birch et al. 2007). The grid

was randomly positioned across the extent of Montgomery County, MD to include all camera locations.

Each grid cell contained at least one camera unit whereas some grid cells contained multiple camera units. For the occupancy analysis, I generated detection matrices at the grid-cell level. If a turkey was present in a grid cell during the sampling period, the cell was assigned a value of 1 to indicate turkey presence. Similarly, for the abundance (N-mixture) analysis, to reduce the risk of double-counting the same bird across different camera locations within the same sampling period, I used the maximum number of turkeys observed in each grid cell when constructing the count matrices. I obtained estimates of probability of occupancy and relative abundance for each grid cell that contained at least one camera. Additionally, the number of cameras within a given grid cell was included as a detection covariate in both occupancy and relative abundance analyses to account for variation in sampling.

Statistical Analysis

I used two modeling approaches to describe turkey distributions and examine potential relationships with covariates that might have influenced turkey occupancy (occupancy model) and abundance (N-mixture model). For my analysis, I focused on two biologically relevant seasons for turkeys: the breeding and brood-rearing seasons. The brood-rearing season in Maryland, which spanned from March to early August, was ecologically significant because hens were confined to the ground, foraging alongside their poults (Dickson 1992). For this analysis, I focused on a 27-day period within the brood-rearing season, from July 13 to August 17. The second season, the breeding season, spanned from April 18 to May 23 (MDDNR 2003). For the abundance analysis, I created daily maximum count matrices for each grid cell over the two 27-

day sampling periods (brood-rearing and breeding). This approach resulted in two single-season abundance models. Similarly, for the occupancy analysis, I developed encounter histories based on daily observations of turkeys during each 27-day season, resulting in two single-season models (brood-rearing and breeding).

Occupancy

I used single-season occupancy models to estimate the probability of turkey presence at a grid cell, while accounting for variability in detection (MacKenzie et al. 2006). I analyzed each season separately and included the year (2022 or 2023) as a covariate in both models. The occupancy model for grid cell (*i*) is the following:

$$y_{i,t} = bernoulli(p_i * z_i)$$
$$z_i = bernoulli(\Psi_i)$$
$$logit(p_i) = \alpha_0 + \alpha_1(Cov_i)$$
$$logit(\Psi_i) = B_0 + B_1(Cov_i)$$

Where $y_{i,t}$ indicates at least one turkey detected within grid cell (*i*) and p is the detection probability at each grid cell. The occupancy probability is Ψ, and *z* is the true occupancy state of the site (i.e., outcome of a Bernoulli trial with probability Ψ). If unoccupied, *z* = 0, and *y* is 0 regardless of the detection probability. If *z* = 1, then a second Bernoulli random variable determines if a turkey was detected in the grid cell. The expectation of Ψ and p were modeled using the logit link function and varied as a function of covariates when included. Whereas α_0 and β_0 are the intercept coefficients for detection and occupancy, respectively, reflecting variation associated with landscape characteristics, while α_1 and β_1 are covariates used to account for additional variation in both occupancy and detection. Because a greater number of cameras in a grid cell inherently increased the chances of observing a turkey, I incorporated the number of

cameras in each grid cell as a detection covariate (α). We ran this model separately for both the brood-rearing and breeding season.

Occupancy models have five standard assumptions that must be met to avoid potential bias in estimates. The first assumption is the system is a closed population, meaning that births, deaths, immigration, and emigration were negligible. To address this assumption, I set the analysis periods to 27 days, assuming turkey populations remained stable throughout both seasons during this period. The second assumption is observations at grid cells were independent of each other, such that occupancy at one site did not influence occupancy at adjacent sites. I accounted for assumptions of independence by generating estimates at the grid cell level. Because cameras in some study parks were highly aggregated, generating detection histories at the grid level ensured that individual turkeys were not double-counted during the 27-day sampling period. The third assumption was that there are no false detections. I addressed this by double checking all images labeled as "bird" or "turkey" to ensure that turkeys were not misidentified as birds, and vice versa, to prevent any false identification. The fourth assumption is the probability of detection was constant across all study sites or can be modeled as a function of covariates. The fifth assumption was the probability of occupancy is constant across all study sites or can be modeled as a function of covariates (β). I accounted for differences in occupancy across grid cells by incorporating land cover covariates that could influence turkey occupancy. For example, variation in forest cover across the study sites might influence turkey presence because turkeys select larger trees with a dense canopy when roosting (Dickison 1992).

An initial model fit to specific age and sex classes did not converge. Consequently, I combined observations by sex and age class to generate a "Total" detection metric for each

season. I continued all analyses based on whether a turkey was present, regardless of sex or age class, to simplify the model. To estimate the probability of occupancy for each study park by year and season, I calculated the weighted average using estimates from grid cells within each park. This metric averaged the estimates for each grid cell within the park's boundary, with each grid-cell estimate having an associated standard error that determined its weight in the overall calculation. By incorporating standard error into the weighted average calculation, estimates with smaller standard errors (i.e., lower variability) were given more weight than those with larger standard errors (i.e., higher variability). The standard error for the weighted estimates was calculated by summing the standard errors for each individual grid cell within a park. Weighted occupancy was categorized into relative tertiles by season and year. For example, in the 2022 brood-rearing season, parks with occupancy in the top third of the results ($\Psi > 0.043$) were classified as relatively high, those in the middle third ($0.025 < \Psi < 0.043$) were classified as average, and those in the bottom third were classified as relatively low occupancy ($\Psi < 0.025$). These thresholds were calculated for each season and year to account for variations in occupancy (For all occupancy thresholds see Tables 6.1 and 8.1).

N-mixture

To estimate site-specific turkey abundance in Montgomery County, I developed two N-mixture models, one for each season (brood-rearing and breeding) and included year (2022 and 20230 as a covariate. The N-mixture models estimated the relative abundance (N_i) of turkeys given that the detection of individuals was imperfect (Royle 2004). For grid cell (*i*) and season (*t*), turkey abundance was modeled as:

$$Y_{i,t} \sim Binomial\ (N_i p_i)$$
$$N_i \sim Poisson\ (\lambda_i)$$
$$logit(p_i) = \alpha_0 + \alpha_1 (Cov_i)$$
$$log\ (\lambda_i) = B_0 + B_1 (Cov_i)$$

Where $Y_{i,t}$ is the greatest number of turkeys observed in any one photo in each grid cell (i) and λ_i is the expected maximum count of turkeys in grid cell i. We used a log-link function for $\lambda_i$because count data was a positive whole number. Whereas p_t is the probability of observing an individual turkey. Detection probability, p_i, was modeled using the logit link function. Whereas N_i is the latent, unobserved abundance of turkeys at grid cell (i) and follows a Poisson distribution. While α_0 and β_0 are the intercept coefficients for detection and relative abundance, respectively, reflecting variation associated with landscape characteristics. Additionally, α_1 and β_1 are covariates used to account for additional variation in both relative abundance and detection. We ran this model separately for both the brood-rearing and breeding season.

Similar to occupancy models, N-mixture models have five main assumptions that must be addressed to minimize potential bias in the estimates. The first assumption is that turkey count data followed a Poisson distribution, and detections of turkeys was the outcome of a binomial random variable. The second assumption is abundance at each site was random and independent of abundance at other sites. I addressed this assumption of site independence by generating estimates at the grid cell level. Because cameras in some study parks were highly clumped, creating count histories at the grid level ensured that individual turkeys were not double-counted across grid-cells during the 27-day sampling period. The third assumption is the population was closed, therefore immigration, emigration and births, deaths are negligible throughout the study

period. To address this assumption, I set the analysis periods to 27 days, assuming turkey populations remained stable throughout both seasons during this period. The fourth assumption is there was no double counting of the same individual. I addressed this by carefully reviewing all photo images labeled "turkey" to determine whether each observation was a different individual or the same bird passing back and forth in front of the camera. The final assumption was that all individuals had the same detection probability, or variation could be modeled as a function of covariates (α). As the number of cameras in a grid cell increased, so did the chances of observing a turkey. Therefore, I incorporated the number of cameras in each grid cell as a detection covariate in the analysis.

I fit a preliminary N-mixture model, but models did not converge when fit to single age and sex classes. Consequently, I combined counts by sex and age class to create a "total" count metric for each season, representing the maximum number of turkeys observed in a grid cell, regardless of sex or age class. I continued my analysis based on the maximum count of turkeys observed. Similar to the occupancy analysis, to estimate relative abundance across seasons and years for each park, I calculated the weighted average of the abundance estimates. This metric averaged the estimates for each grid cell within a park's boundary, with each grid cell estimate having an associated standard error that determined its weight in the overall calculation. By incorporating standard error into the weighted average calculation, estimates with smaller standard errors (i.e., lower variability) were given more weight than those with larger standard errors (i.e., higher variability). The standard error for the weighted estimates was calculated by summing the standard errors for each individual grid cell within a park. In this study, weighted relative abundance was categorized into tertiles by season and year. Thresholds were calculated for each season and year to account for variations in relative abundance (For all relative

abundance thresholds, see Tables 13.1 and 16). All turkey occupancy and relative abundance estimates were calculated in Program R using the “unmarked” package (Fiske and Chandler 2011).

Landscape Metrics

I hypothesized that both open habitats (Pollentier et al. 2021) and forested areas (Pollentier et al. 2021) influence turkey presence and abundance. To account for this, I generated two covariates representing the proportion of these land cover types. The “Turkey Food/Open” covariate reflected turkeys as opportunistic feeders and included a variety of foraging locations, such as cropland, pasture/hay, turf grass, tree canopy over turf, and other previous areas. An additional covariate, ‘Turkey Forest,’ was created to incorporate “Forest, Tree Canopy/Other” land cover information. This covariate could capture the mature hardwood and mixed-hardwood forests used for roosting locations (Dickson 1992). The distribution and location of land cover types included in the “Turkey Open/Food” and “Turkey Forest” covariates were extracted from the 2018 Chesapeake Landcover Dataset ($1m^2$; Chesapeake Bay Program Office, 2022). An additional covariate, "mean elevation," was generated using LiDAR data (Maryland.gov, 2019) to capture how turkey presence and abundance might vary with different elevations. Previous studies suggest that turkeys tend to occupy areas of higher elevation; however, the biological or ecological reasoning behind this behavior remains unclear.

To assess how turkey occupancy and relative abundance varied with urbanization, I created two covariates—building density and road density. I calculated density from the TIGER/Line dataset (United States Census Bureau, 2024) using the line density tool in ArcPro, and calculated building density utilizing the "Buildings" dataset from the Maryland National

Capital Parks and Planning Commission Data Catalog through the “Zonal Statistics” tool in ArcPro. This tool enabled us to summarize the polygon (buildings), and line (roads) datasets generate a single metric for each grid cell. These covariates could help capture how turkey occupancy and abundance vary with different densities of human development factors.

Each of the five land cover covariates (Proportion of "Turkey Food/Open," Proportion of "Turkey Forest," Mean Elevation, Density of Roads, and Density of Buildings) was calculated for every grid cell containing at least one camera in RStudio, using the 'unmarked' (Fiske and Chandler 2011) and 'MuMin' (Bartoń 2024) packages. All land cover covariates were z-scaled. Ten models were generated for both the occupancy and relative abundance analyses, with five models for each season (breeding and brood-rearing). Each model included a single land cover covariate and year (2022 or 2023) as a categorical covariate, with the number of cameras in the grid cell included as a detection covariate. For the relative abundance and occupancy analysis, model selection was based on season, resulting in one best model for each season. The models with the lowest AIC scores were considered the most predictive and were used to generate occupancy and relative abundance estimates for each season.

RESULTS

Approximately 250,000 pictures were analyzed for turkey presence across the course of the project. During the brood-rearing season, turkey detections occurred in 8 of 76 unique grid cells across 2022 and 2023, whereas during the breeding season, detections were recorded in 23 of the 76 unique grid cells across the same years (See Figure 3).

Occupancy

Occupancy probabilities were generally higher during the breeding season than in the brood-rearing season. (See Table 4). During the brood-rearing season, the 'Building Density' model was the most predictive of turkey occupancy (AIC: 764.84, AICwt: 0.781), and it was also the best-fitting model during the breeding season (AIC: 289.85, AICwt: 0.614; See Tables 2 and 3). Building density exhibited a negative relationship with turkey occupancy in both seasons (See Figures 4 and 5). During the brood-rearing season, the "Turkey Forest" model (AIC: 778.18, AICwt: 0.000) and the Null model (AIC: 778.04, AICwt: 0.001) were the worst performing (Tabele 2). Similarly, in the breeding season, the worst performing models were also the Null model (AIC: 296.53, AICwt: 0.022) and the "Mean Elevation" model (AIC: 296.56, AICwt: 0.021) (Table 3).

When examining weighted occupancy probabilities across park, during the 2022 brood-rearing season, Woodstock Equestrian, a rural location, had the highest probability of occupancy of 14% (Ψ=0.144, SE=0.438). Similarly, Little Bennett, another rural park, had an occupancy probability of 14% (Ψ= 0.148, SE=0.677). Again, the same pattern was documented across 2023 brood-rearing season with both rural locations exhibiting the highest occupancy probability of 21% (Table 5).

Whereas in the 2022 breeding season, Little Bennett had the highest weighted occupancy probability of 57% (Ψ = 0.571, SE = 0.905), closely followed by Woodstock Equestrian with a weighted probability of 56% (Ψ = 0.565, SE = 0.598). Notably Great Seneca, a suburban location, had a weighted probability of occupancy of 33% (Ψ = 0.337, SE=0.581). In contrast, the lowest probability of occupancy was observed at Sligo Creek, an urban location (Ψ = 0.091, SE = 0.285) (Table 8). In 2023 breeding season, the probability of occupancy declined but

overall patterns remained the same. Woodstock Equestrian (Ψ = 0.393, SE = 0.589) and Little Bennett (Ψ = 0.399, SE = 0.897) both had an occupancy probability of 39%. Great Seneca had a probability of 19% (Ψ = 0.196, SE = 0.499). Sligo Creek again had the lowest probability of occupancy of 4% (Ψ = 0.046, SE = 0.184) (Table 6).

N-Mixture

During the brood-rearing season, the "Turkey Forest" model was the most predictive of turkey relative abundance. Therefore, estimates for that season were derived from this model (See Figure 8). During the brood-rearing season, the worst performing model was the Null model (AIC: 486.35, AICwt: <0.001 (Table 7). Across all grid cells, the weighted relative abundance in 2022 was 0.037 ($\boldsymbol{\lambda}$ = 0.037, SE = 4.701). In 2023, there was a general increase in weighted abundance, rising to 0.058 ($\boldsymbol{\lambda}$ = 0.058, SE = 5.473). In the breeding season, the "Turkey Food/Open" model was the most predictive of turkey abundance (See Figure 9). Therefore, estimates for this season were derived from that model. Like the brood-rearing season, the worst performing model during the breeding season was the Null model (AIC: 1031.28, AICwt: <0.001) (Table 8). The 2022 breeding season had a weighted relative abundance of 0.323 ($\boldsymbol{\lambda}$ = 0.323, SE = 15.862), and in 2023, it declined slightly to 0.249 ($\boldsymbol{\lambda}$ = 0.249, SE = 13.609) (Table 9).

In the 2022 brood-rearing season, Great Seneca, a suburban location, had the greatest weighted abundance of turkeys at 0.087 ($\boldsymbol{\lambda}$ = 0.087, SE = 0.679), closely followed by Muddy Branch, another suburban location, at 0.081 ($\boldsymbol{\lambda}$ = 0.081, SE = 0.224) (Table 10). The lowest weighted abundance was observed at Sligo Creek, an urban location, of 0.022 ($\boldsymbol{\lambda}$=0.022, SE= 0.112) (Table 10). The 2023 brood-rearing season followed a similar pattern, with Great Seneca

having the highest weighted relative abundance (λ = 0.131, SE = 0.771), closely followed by Little Bennett, a rural location (λ = 0.108, SE = 1.110). However, a slightly different pattern was observed during the breeding season. In 2022, Woodstock Equestrian, a rural location, had the highest weighted relative abundance of 0.464 (λ = 0.464, SE = 3.167), and in 2023 also had the highest relative abundance of 0.356 (λ = 0.356, SE = 2.736) (Table 11)

DISCUSSION

I originally hypothesized that turkey occupancy and abundance would be greater in urban and suburban areas due to the increased presence of open and feeding areas such as turf grass, manicured lawns, bird feeders, and the potential for less predators and more confined habitat in urban spaces. I also hypothesized that natural land cover types, such as foraging and forest habitats, would be the most predictive of turkey occupancy and relative abundance. My findings provided mixed support for these two hypotheses. Overall, from 2022 to 2023, the probability of occupancy and relative abundance increased during the brood-rearing season; however, these metrics decreased during the breeding season.

The decline in occupancy and relative abundance during the breeding season may be attributed to changes in ecological factors across Maryland's landscape. The cicada emergence in 2021 could have provided increased foraging opportunities for birds, potentially improving hen body condition. Hens in better condition tend to hatch larger broods, while stressed or poorly nourished hens typically hatch smaller broods (Porter et al., 1983). Additionally, when cicadas are present, mesocarnivores like raccoons and foxes, which usually feed on turkey nests, may shift to feeding on cicadas, potentially reducing predation pressure on turkeys (Purdue University 2021). Ultimately, the changes in probability of occupancy and relative abundance estimates

during the breeding season from 2022 to 2023 could be attributed to a variety of biological and ecological factors.

My occupancy models provided insight into turkey space use during the brood-rearing season. The two rural parks in this study, Little Bennett and Woodstock Equestrian, showed the highest probabilities of occupancy during both the 2022 and 2023 brood-rearing seasons. Little Bennett is characterized by floodplain forests and old fields, providing ample habitat for birds and other wildlife species (Montgomery County Department of Parks 2007). In contrast, Woodstock Equestrian Park is in an agricultural preserve and features both forested areas and farmland (MNCPPC 2001). The land cover composition in these two rural parks provides suitable turkey habitat during the brood-rearing season, as turkeys require both foraging and roosting locations daily (Pollentier et al. 2021). These findings are consistent with established knowledge of turkey ecology, especially within their rural and traditional home ranges.

In the brood-rearing season, during daylight hours, hens forage alongside poults (Dickson 1992). Because turkeys are opportunistic foragers, they are known to consume waste grains and other agricultural byproducts (Groepper et al. 2013). As a result, it is expected that areas with higher proportions of cropland will also experience an increased presence of turkeys during this season. Furthermore, hens and poults also forage among herbaceous vegetation typical of forested areas, where the ground cover provides ample concealment for poults from predators (Dickson 1992). Turkeys also utilize forested habitats for roosting, typically preferring mixed-hardwood forests with mature trees (Pollentier et al. 2021). Despite being a heavily urbanized area, Montgomery County contains sufficient continuous forested and cropland areas to support turkey presence in its more rural regions during the brood-rearing season.

Occupancy estimates in suburban parks were lower compared to rural parks during the brood-rearing season. However, turkeys exhibited a greater relative abundance in suburban parks when compared to other locations. Suburban parks in this analysis included Muddy Branch, Great Seneca, and Upper Paint Branch parks. Most notably, Great Seneca Park had a relatively high probability of turkey occupancy and relative abundance. These suburban parks likely provided favorable foraging opportunities for turkeys, given the prevalence of manicured lawns from single-family residences (Groepper et al. 2013). In these areas, turkeys may be feeding on grains from bird feeders, fruits from residential gardens and planters, as well as acorns from masting street trees (Groepper et al. 2013). Despite turkeys requiring continuous forest for roosting (Pollentier et al. 2021), the proximity of manicured lawns, bird feeders, and other foraging resources to these suburban forest patches may be advantageous for turkey flocks. The reduced distance between foraging and roosting sites not only conserves energy for turkeys, as they spend less time traveling between sites, but also minimizes their exposure to potential risks, such as traffic and predators. This is especially crucial during the brood-rearing season, when hens are traveling and foraging with poults, as juvenile mortality is high during the brood-rearing season (Dickson 1992). Furthermore, suburban areas may act as a "human shield," thereby encouraging turkey occupancy and presence. This is due to predators like coyotes and other mesocarnivores avoiding regions with high human activity, which inherently reduces the predation risk to turkey flocks (Elliot et al. 2016). To better understand how turkeys are utilizing suburban landscapes, a follow-up analysis that tracks turkey movements in these suburban areas would be beneficial. Given the finding that turkeys are utilizing these suburban spaces, monitoring and management efforts may be beneficial to prevent turkeys from becoming a nuisance in suburban landscapes and to mitigate potential human-wildlife conflicts.

Despite the anecdotal increase in urban turkey sightings, urban areas showed a lower probability of occupancy during the brood-rearing season and had a "low" relative abundance. The urban parks in this analysis included Rock Creek Stream Valley, Cabin John Regional, and Sligo Creek parks. Rock Creek Stream Valley Park consisted primarily of open spaces and forested areas, located in an area of high human development (Montgomery County Planning 2004). Cabin John Regional Park was primarily composed of forested areas, which were bisected by roadways and trails (Montgomery County Parks 2000). Lastly, Sligo Creek Park was characterized by wetlands, grasslands, and upland wooded areas (Friends of Sligo Creek 2003). However, due to its urbanized setting, this park lacks large, continuous fragments of forest or extensive vegetation cover (Friends of Sligo Creek 2003).

When compared to the 2018 Chesapeake Bay Land Cover dataset, grid cells in urban areas with lower estimates of occupancy and abundance were characterized by forest cover but had greater proportions of roadways and impervious surfaces compared to grid cells with greater occupancy estimates. This indicates that, despite the presence of forested habitat, urban parks may not provide the quality or quantity of forests that turkeys require for roosting. Turkeys depend on continuous forest patches, which are crucial for nesting and roosting (Pollentier et al. 2021). Additionally, turkeys may also not occupy urban areas because, like many game birds, they are sensitive to noise (Miller 2018). The elevated anthropogenic noise in urban areas from traffic and human activity may deter turkeys from occupying these spaces. Additionally, the increased traffic could pose too great a risk for hens with poults, further deterring turkey presence and abundance in these areas. Therefore, despite increased anecdotal reports, turkeys do not seem to be occupying urban areas in large numbers; rather, turkey sightings may be the result of a single nuisance flock or individual. Large, charismatic animals like turkeys often attract

significant media attention and are frequently featured in news stories. Instead, it could be the same turkey flock or individual being documented multiple times or any true population increases could be happening at a very slow rate.

Unsurprisingly, Woodstock Equestrian, a rural location, had the highest probability of occupancy during the breeding season in both years. When compared to the 2018 Chesapeake Bay Land Cover dataset, grid cells within this park with high rates of turkey occupancy were characterized by a high proportion of cropland and forest land cover types. Turkeys using open cropland areas align with known turkey behavior (Pollentier et al. 2017). Male turkeys occupied croplands and small clearing during the breeding season because these spaces increased their chances of mating, as hens forage in these areas (Dickson 1992; Pollentier et al. 2021). These findings are consistent with Pollentier et al. (2021), who reported that turkey occupancy was positively influenced by the proportion of open land cover from April-May. Their study reported that occupancy peaked when ~25% of the survey route consisted of agricultural fields, herbaceous opening, and pasture/hay (Pollentier et al. 2021). However, it is important to note that Sligo Creek, an urban park, had the second highest weighted abundance during this season across both years. When assessing the abundance in individual grid cells at Sligo Creek, overall abundance was lower compared to grid cells in other park locations. Therefore, the weighted abundance for Sligo Creek during the 2022 and 2023 breeding seasons may be due to individual grid cells having lower variability, which increases their weight in calculating the overall abundance metric at the park level.

Similar to the brood-rearing season, suburban locations again showed "average" to "high" probabilities of occupancy and relative abundance, with variation across parks. Most notably, Great Seneca had the highest probability of occupancy, while Upper Paint Branch exhibited the

highest relative abundance among suburban locations. When comparing estimates to the 2018 Chesapeake Bay Land Cover Dataset, grid cells in suburban parks with higher rates of occupancy and greater relative abundance contained larger proportions of turf grass and tree canopy over turf grass. Typical suburban areas are characterized by single-family residential homes, each with yard space. Perhaps turkeys were using cleared, manicured lawns to supplement their traditional strutting and display locations during the breeding season. Additionally, greater abundances in suburban areas could be due to low predation rates in suburban regions when compared to rural regions, where hunting is a significant factor for regulating turkey populations (Dickson 1992). The annual Maryland Spring Harvest overlaps with the turkey breeding season, and because hunting is not allowed in these areas, it has the potential to increase turkey abundance and occurrence. The increased presence of turkeys in suburban areas during the breeding season has significant implications for human-wildlife conflicts. For example, male turkeys during the breeding season can become aggressive and territorial. They often perceive their reflection in reflective surfaces as a competing male, which can lead to increased aggressive behavior (Miller 2018). This behavior is highlighted in suburban areas where there is an increased presence of reflective surfaces such as car doors and windows (Miller 2018). As a result, turkeys often engage with their reflection by scratching it with their spurs and beak, leading to cosmetic and financial damage (Miller 2018).

Not surprisingly, turkeys had a low probability of occupancy in urban areas during the 2022 and 2023 breeding seasons. The lack of continuous cover, typical of urban areas, may have limited both roosting and mating opportunities for turkeys, which are essential behaviors during the breeding season (Pollentier et al. 2021). In contrast, when comparing estimates to the 2018 Chesapeake Bay Land Cover Dataset, urban locations with a high probability of occupancy also

had a greater presence of roadways. Urban areas are often spatially fragmented, so it may be difficult for male birds to find mates. Therefore, turkeys, particularly males, may be using roadways to travel between suitable mating locations, increasing their chances of locating a mate (Dickson 1992). The low probability of occupancy observed in urban parks aligns with findings from previous turkey occupancy studies. For example, in Pollentier et al. (2021), habitat patches bordering heavily urbanized areas exhibited occupancy probability of less than 10%, indicating that urban areas are less likely to be occupied compared to more traditional turkey habitat. Ultimately, there is limited research on turkey presence in heavily urbanized areas, highlighting the importance of considering urbanization in future studies when estimating turkey use and abundance during the breeding season.

When interpreting my results, it is important to consider a few methodological issues. The spatial overlay of the grid over Montgomery County may have influenced my occupancy and relative abundance estimates. To improve the precision of these estimates, a sensitivity analysis incorporating various grid overlay orientations is recommended. By testing multiple grid overlays, the most reliable configuration could be determined, leading to more accurate estimates. Another issue of study design that could use further exploration is my choice of seasons. My 27-day analysis period during the brood-rearing season did not encompass the entire nesting and brood-rearing period for turkeys, which in Maryland typically runs from April to August. As a result, the time frame I selected for this analysis could skew the estimates of occupancy and relative abundance. To assess this, I did examine turkey counts in June to determine if a significant number of turkeys were excluded from the analysis. In June 2022, I recorded 93 observations of turkeys. To improve accuracy of metrics for the brood-rearing season, a secondary analysis that included all turkey observations and counts from the late

nesting to early brood-rearing season could enhance the precision of these estimates.

CHAPTER III: TICKS AND TURKEYS

INTRODUCTION

Blacklegged ticks *(I. scapularis*) are the primary vector for Lyme disease, the most common zoonotic illness in North America (Madison-Antenucci 2020; Sonenshine 2018; Nawrocki and Hinckley 2021). In recent years, there have been increasing numbers of documented cases of tick-borne illnesses across the United States (Sonenshine 2018; Nawrocki and Hinckley 2021). Humans in urban and suburban areas are vulnerable to these diseases due to their proximity to and overlap with wildlife host populations such as white-tailed deer (*O. virginianus*) (Springer and Johnson 2018). The rising prevalence of tick-borne illnesses also raises significant social concerns. Springer and Johnson (2018) highlighted health equity issues in the distribution of these diseases, examining the relationship between tick-borne illness incidence and social factors such as race, ethnicity, and socioeconomic status. Their study found that while Lyme disease incidents were higher in counties with a greater proportion of Caucasians, while marginalized, minority communities bore a disproportionate burden of the physical health impacts of zoonotic diseases (Springer and Johnson 2018). Studying tick abundances and distribution is crucial for understanding the mechanisms behind the spread of tick-borne illnesses and promoting health equity in affected communities.

Hard ticks have a unique life cycle consisting of three distinct phases: larval, nymph, and adult (Eisen 2022). To progress to the next life stage, a tick requires a blood meal (Eisen 2002). However, the organisms on which ticks feed varies by life stage. For example, larval ticks are known to feed primarily on small mammals, such as white-footed mice (*P. leucopus*) and birds (Randolph 2004), while nymphal and adult ticks typically feed on larger hosts like humans and

white-tailed deer (*O. virginiana*) (Randolph 2004). It has been hypothesized that Eastern wild turkeys (*Meleagris gallopavo silvestris* hereafter; turkey) may influence tick populations within ecosystems and serve as a tick host in certain situations (Ostfeld and Lewis 1999).

Wild turkeys are upland game birds native to the United States, with a home range of approximately 2 km² (Niedzielski and Bowman 2016). Adult males typically weigh around 7.6 kg (17 lbs) and measure between 100 and 125 cm in length, while adult females average 4.26 kg and are smaller, measuring 76 to 95 cm (Dickson 1992). The Eastern wild turkey occupies hardwood forests and mixed conifer-hardwood habitats, with scattered openings such as pastures and fields (Pollentier et al. 2021). In recent years, there has been an increase in anecdotal sightings of turkeys in urban and suburban areas throughout the Mid-Atlantic region, particularly in Maryland (MDDNR 2022a).

As potential hosts to ticks, turkeys in the Mid-Atlantic region may be contributing to the ongoing range expansion of several tick species (Mock et al 2001). However, factors driving turkey presence and their distribution in urban and suburban areas remain poorly understood and understudied. Therefore, it is important to examine how this host species may impact the presence and abundance of various tick species and the implications for the spread of tick-borne illnesses. Specifically, turkeys are associated with two native tick species in Maryland: Blacklegged ticks (*Ixodes scapularis*) and Lone star ticks (*Amblyomma americanum*) (Ostfeld and Lewis 1999; Mock et al. 2001). Existing literature has primarily focused on turkeys' relationship with *A. americanum* (Mock et al. 2001), but there is limited research examining how turkey populations influence tick abundances. There is even less understanding of turkeys' role as tick hosts in urban and suburban areas, which could facilitate understanding of urban tick ecology and the dynamics of zoonotic disease transmission.

Two hypotheses exist regarding the potential turkey-tick relationship. One hypothesis suggested that turkeys increase tick abundance on a landscape through their role as hosts (Ostfeld and Lewis 1999; Lane et al. 2006; Mock et al. 2001). After a blood meal, ticks detached from turkeys and fell onto the ground, potentially increasing tick populations in areas with established turkey populations. Conversely, another hypothesis suggested that turkeys reduced tick abundance by consuming ticks from a landscape, and studies have documented turkeys feeding on adult and nymph ticks (Steffen et al. 2022). According to that hypothesis, higher turkey abundance could decrease tick populations (Ostfeld and Lewis 1999).

Here, I aimed to better understand the relationship between turkeys and ticks in urban and suburban areas, specifically in Rock Creek Stream Valley, Cabin John Regional, Sligo Creek, Great Seneca, and Upper Paint Branch parks during the year 2023. I asked the following research questions: (1) How do total tick counts vary with site-specific vegetation metrics, independent of turkey presence? (2) How does the presence of turkey foraging/open and forested habitats affect total tick counts? (3) How does turkey relative abundance during the brood-rearing and breeding seasons impact total tick counts? (4) How do the total number and maximum number of turkeys observed influence total tick counts? I hypothesized that locations with higher turkey relative abundances would also have greater tick abundances, supporting the idea that turkeys are suitable hosts for ticks. I also analyzed how turkey counts and habitat impacted the abundance of *Ixodes scapularis* and *Amblyomma americanum* ticks to determine if these factors were influencing specific tick populations.

I hypothesized that leaf litter depth (Linske et al. 2019; Brunner et al. 2014) would positively influence total tick counts, as ticks have been documented bedding in areas with high leaf litter to avoid desiccation. In contrast, I predicted that total tick counts would be negatively

related to shrub height (Tack et al. 2012), as ticks tend to inhabit low-vegetation areas near the forest floor, where they are more likely to encounter small mammal hosts. Both hypotheses reflect existing research on tick ecology.

I hypothesized that turkey abundances and counts would have different effects on total tick counts depending on the season. During the brood-rearing season (July-August), hens feed alongside poults, potentially exerting greater foraging pressure (Dickson 1992). I predicted that if turkeys were actively consuming ticks during this period, tick abundances would be lower. In contrast, during the breeding season (April-May), ticks emerged from dormancy and were seeking a host for a blood meal (Randolph 2004). Turkeys, particularly males, are highly mobile during that time as they were traveling between mating or foraging sites (Dickson 1992). I expected that while turkeys may have acquired ticks, their mobility could have caused ticks to fall off in different areas, potentially leading to varied tick counts across ecosystems. So, I hypothesized that during the breeding season, turkeys may increase tick presence in certain ecosystems by acting as transportation, resulting in a positive correlation between turkey and tick abundances.

For the models that examined species specific counts in relation to turkey habitats, I hypothesized that as turkey foraging/open habitat increased, the abundance of *Amblyomma americanum* ticks would also increase, as they inhabit areas where forests meet meadows—areas frequently used by turkeys for foraging (Richardson et al. 2002). Additionally, I anticipated that an increase in turkey roosting locations would result in a higher abundance of *Ixodes scapularis* ticks, as these ticks are commonly found in these forested areas (Estrada-Peña and de la Fuente 2014). These findings help better understand how turkey abundances may be related to the

presence and abundance of ticks. The species-specific tick analysis offers detailed insights into how turkeys may influence the populations of certain tick populations.

METHODS

Camera Trapping

Please see Chapter 2 "Methods" Section for Camera Array Deployment Throughout Cabin John Regional, Rock Creek Stream Valley, Sligo Creek, Upper Paint Branch and Great Seneca parks.

Landscape Metrics

Please see Chapter 2 "Methods" Section.

Turkey Relative Abundance

For a description of the study areas where each analysis was conducted, please see Chapter I, and for a description of how turkey relative abundance was calculated using a camera array please see Chapter II.

Tick Sampling

To better examine turkey-tick dynamics, population data for tick species, including *Ixodes scapularis* and *Amblyomma americanum*, were collected through drag sampling. Tick collection occurred from April-November 2023 at 10 turkey camera sites in each of Cabin John Regional and Rock Creek Stream Valley Parks, with additional sampling at three sites in Great Seneca, Sligo Creek, and Upper Paint Branch parks (See Table 12). This resulted in 29 unique tick sampling locations at turkey camera sites across five suburban-urban parks. To tick sample,

circle plots with a 100m radius (200m diameter) were created around each camera site (Figure 10). Tick transects consisted of three randomly sampled 100-meter segments originating from the camera's XY location, spaced at 30-degree intervals (e.g., 0/360° N, 30°, 60°, 90° E, 120°, 150°, 180° S, 210°, 240°, 270° W, 300°, 330°) (Figure 6). Sampling was conducted during optimal weather conditions to minimize biases. Tick drags were made from 1x1 meter white denim fabric and PVC piping to collect ticks along these transects. Staff walked the first 100m transect with the drag behind them, stopping every 10 meters to check for ticks. GPS units recorded the XY of each tick or grouping of ticks. Ticks collected on the drag were placed into vials, labeled with the corresponding date, camera, angle walked, and number of ticks (e.g., 0514.RCA.90.1). After completing a transect, staff returned to the camera and repeated the procedure in the opposite direction, resulting in three randomly sampled 200-meter transects at each camera site. In the laboratory, ticks were identified by species, life stage, and sex. The number of adult and nymphal ticks collected at each camera site during the 2023 field season was summed and used as the total tick count for the corresponding grid cell. If tick sampling occurred at multiple cameras within a grid cell, the nymphal and adult counts from all cameras were summed to create a grid-level metric. For this analysis, the "Total Ticks" dependent variable included the combined counts of adult and nymph ticks from all species collected. Similarly, the "Total *Ixodes scapularis*" dependent variable was based on the total number of adult and nymphal *Ixodes scapularis* ticks, while the "Total *Amblyomma americanum*" dependent variable was based on the total number of adult and nymphal *Amblyomma americanum* ticks. For this analysis, I focused on the abundances of adult and nymphal ticks because existing literature documents their relationship with turkeys (Mock et al. 2001; Ostfeld and Lewis 1999). While there are studies exploring the connection between turkeys and larval

ticks, accurately identifying tick species and distinguishing between the nymph and adult stages is less error-prone, as nymphs and larvae are often very difficult to differentiate due to their small size and species similarities.

Vegetation Sampling

To better understand how site-specific vegetation influenced tick population abundance, independent of turkeys, vegetation sampling was conducted at each camera site. Sampling occurred at five distinct locations surrounding the camera. The first site (Site A) was always 5m in front of the camera view. The remaining four sites were randomly selected distances from the camera (25m, 50m, 75m, 100m) in each cardinal direction (N, S, E, W). The distances for each camera were randomly assigned using a number generator, where values between 0 and 25 corresponded to a 25m transect, values between 26 and 50 indicated a 50m transect, values between 51 and 75 represented a 75m transect, and values between 76 and 100 assigned a 100m transect (Figure 11). Current literature on tick ecology emphasizes the influence of microvegetation and microclimate on tick abundance and survival. For example, Linske et al. (2019) observed that ticks had a higher survival rate in areas with accumulated and undisturbed leaf litter. Litter depth increased soil relative humidity, which in turn increased tick survival (Brunner et al. 2014). At each of the five vegetation sampling locations, I recorded a GPS point and placed a meter square (constructed from PVC piping) on the ground (Stohlgren et al. 1995; Higgins et al. 1996; Dix 1961). I then measured the litter depth at three random locations within the meter square, ensuring each point was approximately 0.30 meters apart.

Shrub height is another vegetation factor known to play a role in influencing tick abundance and survival (Tack et al. 2012). Tack et al. (2012) found that abundance of larval,

nymphal, and adult ticks increased with greater shrub cover. However, shrub height tends to have a variable effect on tick abundance, varying by species (Mathisson et al. 2021). For example, *Ixodes scapularis* ticks are positively associated with dense shrub areas, whereas *Amblyomma americanum* ticks are more commonly found in less dense locations (Mathisson et al. 2021). I recorded shrub height (cm) by measuring the three tallest non-canopy plants under 5 cm diameter at breast height (DBH) within the meter square. Both shrub height and leaf litter measurements were averaged across camera sites to create a grid-level metric. This metric was then incorporated into regression models to evaluate how microscale vegetation factors influenced tick abundance, independent of turkey presence.

General Linear Mixed Models

We used ten models to assess total tick counts in relation to turkey habitat, abundance, and observations during both the breeding and brood-rearing seasons (Table 13). First, I modeled how total tick counts varied across the study parks by incorporating covariates relevant to tick ecology. Specifically, I examined total tick counts in relation to mean shrub height and mean litter depth for each grid cell. Mean shrub height and mean leaf litter depth were z-scaled. In total, I developed two single-covariate models to examine the relationship between total tick counts and microscale vegetation characteristics, independent of turkey presence (See Table 13).

I hypothesized that turkey counts, abundances, and habitat would influence the total tick counts. To test this, I developed models for total tick counts that incorporated turkey-specific covariates, including relative abundance, the maximum number of turkeys present, and the total number of turkeys observed at the grid cell level during both the breeding and brood-rearing seasons. For models that included the maximum number of turkeys present and the total number

of turkeys observed, the number of cameras in each grid cell was added as an additional covariate to account for variation in detection (See Table 13).

I also analyzed how different turkey habitats could impact total tick counts. To do this, I created two models that incorporated the proportion of the “Turkey Food/Open” and the “Turkey Forest” covariates. We treated the previously created “Turkey Food/Open” and “Turkey Forest” land cover variables as fixed effect variables. The "Turkey Food/Open" variable included Cropland, Pasture/Hay, Turf Grass, Tree Canopy over Turf, Pervious, and other land cover types. The “Turkey Forest” variable encompassed both forest and tree canopy/other land cover types. Both covariates were generated at the grid cell level. Each model included only one covariate to assess their individual effects on tick counts. All land cover and turkey metric covariates were z-scaled (See Table 13).

To analyze species-specific counts of *Ixodes scapularis* and *Amblyomma americanum* ticks, I followed a similar approach to the total tick models. I examined *Ixodes scapularis* and *Amblyomma americanum* counts in relation to the maximum number of turkeys present and the total number of turkeys observed in a grid cell during both the breeding and brood-rearing seasons. For these models, the number of cameras in each grid cell was included as an additional covariate to account for variation in detection. I also modeled *Ixodes scapularis* and *Amblyomma americanum* counts in relation to the proportion of “Turkey Food/Open” and “Turkey Forest” land cover types. Like the total tick models, each model included only one variable to assess its individual effect on *Ixodes scapularis* and *Amblyomma americanum* counts, with all covariates z-scaled. This resulted in a total of six models for each tick species (See Table 13).

All models in this analysis included "Park" as a random effect to account for inherent differences in tick counts across the study locations. All models were created using the “lme4” (Bates et al. 2015a) and “Matrix” (Bates et al. 2015b) packages in R Studio.

To examine the potential relationship between total tick counts and species-specific tick counts with turkey habitat, observations, and estimates of relative abundance (Chapter 2 results) at the grid cell level, I employed generalized linear mixed models (GLMMs) (Tables 18 and 19). I also utilized marginal R-squared (R^2m) values to assess the proportion of variance explained by the fixed effects. The generalized linear mixed model equation is the following:

$$\log(y_{ij}) = x_{ij}\beta + z_{ij}u_j + \epsilon_{ij}$$

Where y_{ij} represents the expected count of ticks in grid cell (*i*) in park (*j*). Across three independent analyses, we considered total tick counts, *Amblyomma americanum* counts, and *Ixodes scapularis* counts. I assumed tick counts would be best described by a Poisson distribution, applying a log link to restrict the response variable to positive whole numbers. Coefficient values were represented by β and x_{ij} represented land cover covariates across which we assumed response varied. The term z_{ij} represented random intercept predictors, which was the park location and $u_j$is a random effect. Lastly, ϵ_{ij} represented the residual error, which is variability not explained by fixed or random effects.

RESULTS

Most models demonstrated statistically significant relationships. As expected, shrub height was negatively correlated with total tick counts (β = -0.6395, SE = 0.2456, p = 0.009, R^2m = 0.104) (Table 14), and average litter depth was positively associated (β = 0.3475, SE = 0.1156, p =

0.002, R^2m = 0.032) (Table 14). Both turkey habitat models, which included the "Turkey Forest" and "Turkey Food/Open" variables, showed positive associations with total tick counts (Table 14). Additionally, turkey abundance, the maximum number of turkeys observed, and the total number of turkeys observed during both the breeding and brood-rearing seasons were all positively associated with total tick abundances (Tables 15).

The habitat model examining *Ixodes scapularis* counts in relation to the presence of the "Turkey Forest" covariate showed a negative relationship (β = -0.655, SE = 0.1351, p = 1.24e-06, R^2m = 0.060). In contrast, the "Turkey Food/Open" model exhibited a positive relationship (β = 0.8752, SE = 0.1567, p = 2.33e-08, R^2m = 0.072) (See Table 18). Models examining *Ixodes scapularis* counts in relation to total turkey observations and maximum turkey counts during both the brood-rearing and breeding seasons all showed a positive relationship (see Table 16). The same pattern was seen with *Amblyomma americanum* models; the "Turkey Forest" model showed a negative relationship to *Amblyomma americanum* counts (β = -0.3055, SE = 0.0022, p = <2e-16, R^2m = 0.023). On the other hand, the "Turkey Food/Open" model demonstrated a positive relationship (β = 0.8324, SE = 0.0023, p = <2e-16, R^2m = 0.083) (Table 18). When examining *Amblyomma americanum* counts in relation to the maximum number of turkeys present and the total number of turkeys observed, only the maximum number of turkeys observed during the breeding season demonstrated a significant positive relationship (See Table 17).

DISCUSSION

A positive relationship between total tick counts and mean litter depth aligns with ticks utilizing locations of dense leaf litter throughout their life cycle (Linske et al. 2019; Brunner et al. 2014).

During the spring, female ticks lay their eggs in leaf litter, so areas with high densities of leaf litter are associated with increased tick abundance. (Tietjen et al. 2019). This has implications for zoonotic disease spread particularly for the urban and suburban areas surrounding my study area. For example, some residences leave leaf litter on their lawns to increase soil moisture, return micronutrients back to the soil, and encourage invertebrate habitat (Jordan and Schulze 2020). Additionally, leaf litter accumulates in large densities during the fall season and is commonly found on single-family lawns (Jordan and Schulze 2020). This leaf litter in urban and suburban areas can provide ideal habitat for ticks (Jordan and Schulze 2020). Given that urban and suburban areas are often characterized by high-density human populations, there is an increased risk of exposure to tick-borne illnesses in these communities (Springer and Johnson 2018). Ultimately, proactive and preventative tick management strategies that include vegetation and leaf litter control are essential to mitigate the risk of tick-borne illnesses in human-dominated landscapes.

I also identified a negative relationship between total tick counts and mean shrub height, which is consistent with tick ecology and existing literature surrounding ticks and microscale vegetation (Mathisson et al. 2021). Ticks inhabit locations of low-lying shrubs because this offers humidity and moisture for survival (Mathisson et al. 2021). These shrubs also promote questing, a behavior in which ticks climb to the top of plants or shrubs and extend their appendages to search for a blood meal (Mejlon and Jaenson 1997). Questing is vital for tick survival, as they cannot progress to the next life stage without consuming a blood meal (Anderson and Magnarell 2008). The microenvironment created by low-lying shrubs is particularly important, as it is high in moisture and relative humidity (Mathisson et al. 2021). The negative correlation between ticks and shrub height has important implications for urban and

suburban areas, particularly those with single-family homes located near or adjacent to shrubby areas. These findings suggest that urban and suburban locations with abundant low-lying shrubs may support a greater abundance of ticks or serve as suitable future tick habitats, thereby increasing the risk of tick-borne illnesses. One potential limitation of the mean leaf litter and mean shrub height covariates is the scale at which these metrics were created. Leaf litter and shrub height were measured at the five random locations surrounding each camera site. These measurements were averaged to create a single metric for each grid cell. As a result, the final metrics for mean leaf litter and mean shrub height may only broadly reflect the true composition of the landscape. The shift from a fine-scale, camera-level measurement to a broader grid-level scale could introduce variability, potentially affecting accuracy and influencing the results.

A statistically significant relationship was observed between total tick counts and turkey abundance during both the brooding-rearing and breeding seasons. However, the effect size for both the turkey brood-rearing and breeding seasons is very small, indicating a weak relationship. Therefore, it is difficult to draw any conclusions about the tick-turkey relationship based on these results. Instead, both species may just occupy similar habitat types. To further investigate whether turkeys and ticks are utilizing the same habitats, a multi-species occupancy model could be conducted at the grid level. This model could help determine if turkey abundance influences tick abundances. However, there are significant challenges with this analysis. To collect tick data on the same temporal and spatial scale as turkey photos, daily tick sampling would be most relevant. Unfortunately, daily tick sampling efforts would be both costly and impractical. In addition to the financial and logical constraints, such frequent tick sampling could impact tick populations in parks and degrade habitat quality over time. Furthermore, daily tick sampling

could disturb turkey presence as turkeys typically avoid areas of high levels of human use and anthropogenic noise (Miller 2018).

It is important to note that variations in the tick life cycle could have an impact on my model results. For example, tick populations are naturally cyclical, with the abundance of ticks in one year being influenced by climatic conditions and the population demographics of the previous year (Paul et al. 2016). The overall low number of ticks collected in the 2023 field season may have impacted the results of the GLMMs, potentially limiting the ability to effectively model the tick-turkey relationship. Therefore, incorporating tick data from 2024 into a follow-up analysis may offer more reliable insight into the tick-turkey relationship.

The species-specific models showed statistical significance between *Amblyomma americanum* counts and the "Turkey Food/Open" and "Turkey Forest" variables. In general, *Amblyomma americanum* counts increased with increasing turkey foraging areas and decreased with increasing forest. This supports the hypothesis that turkeys and ticks might share similar habitats. In fact, *Amblyomma americanum* typically inhabit areas characterized by low-density canopy coverage but are considered habitat generalists (Mathisson et al. 2021). Therefore, I expected *Amblyomma americanum* ticks would be observed in a variety of land cover types.

Like *Amblyomma americanum*, *Ixodes scapularis* ticks also had a positive relationship with the turkey foraging/food variable and a negative relationship with the forest variable. However, the wide range of cover types in the "Turkey Food/Open" covariate may have influenced my results. This covariate includes Cropland, Pasture/Hay, Turf Grass, Tree Canopy over Turf, and Pervious Other. While *Ixodes scapularis* ticks are not typically abundant in Cropland or Pasture/Hay land cover types, they do inhabit forested areas (Hook et al. 2021; Springer and Johnson 2018). Therefore, the presence of "Tree Canopy over Turf" in this

covariate could explain the positive correlation. Simplifying the variable to include fewer land cover types, especially classic edge types, could clarify which specific land cover types had the greatest influence on *Ixodes scapularis* ticks. This is also important given the inclusion of turf grasses in this covariate. If the presence of *Ixodes scapularis* ticks increases with the presence of turf grass, this could increase the risk of zoonotic diseases, such as Lyme disease, in urban and suburban areas. Ultimately, areas with high human population density and high tick abundances are most vulnerable to tick-borne illnesses (Springer and Johnson 2018). Therefore, it is essential to consider land cover types and human population density when developing *Ixodes scapularis* management strategies.

In contrast, comparing *Ixodes scapularis* counts to the presence of the "Turkey Forest" covariate showed a negative correlation, which contradicts existing general tick findings. Classically, *Ixodes scapularis* ticks were most abundant in mixed forests, which provide suitable conditions for tick survival due to increased densities of vegetation and leaf litter (Tietjen et al. 2019). However, *Ixodes scapularis* also typically occupy forest edges, which has implications for urban and suburban areas where residences border forested regions (Hook et al. 2021). In my analysis of land cover types, the primary edge class was included in the "Food/Open" covariate, which captured turkey foraging habitats. It is possible that the “Turkey Forest” covariate, while relevant for turkeys and all ticks, was not as relevant for *Ixodes scapularis* specifically. Other landscape metrics that quantify forest edge and interspersion may have been more relevant for *Ixodes scapularis* (Mathisson et al. 2021). Therefore, the generalized "Turkey Forest" covariate included in this analysis may be too broad and may not account for other non-traditional forest structures commonly found in urban and suburban landscapes. Ultimately, it is imperative to consider a variety of habitat types when managing *Ixodes scapularis* ticks and how urban tick

habitats may differ from traditional ones. Examining forest edges is crucial to understanding how these transitional areas may influence tick distributions and abundances in human dominated landscapes.

My results indicate that both *Amblyomma americanum* and *Ixodes scapularis* ticks are influenced by the presence of the "Turkey Food/Open" and "Turkey Forest" variables, suggesting that ticks and turkeys may occupy similar habitats. This hypothesis is further supported by a statistically significant relationship between the total number of turkeys present and the maximum number of turkeys observed, particularly when examining total tick counts and *Ixodes scapularis* counts. To gain a better understanding of the tick-turkey relationship, simultaneous monitoring of both ticks and turkeys could help determine whether they share habitats or if turkey populations actively influence tick abundances. Examining the stomach contents of turkeys from the Maryland Spring Harvest season would provide valuable insight into whether turkeys are consuming ticks in sufficient quantities to actively reduce their population. Additionally, collecting ticks from turkeys during routine bird banding efforts in the state would offer further understanding of the parasitism rates in turkey populations.

CHAPTER 4: CONCLUSION

In Maryland, there is a growing need for more accurate estimates of wild turkey populations based on systematically collected data. These improved estimates will enable wildlife managers to make more informed decisions, particularly in suburban areas, to prevent turkeys from becoming a nuisance. I successfully implemented camera surveys to assess turkey space use and relative abundance in human-dominated landscapes. Compared to current estimates from MDDNR based on opportunistic surveys, I think the camera survey-derived estimates are more precise as they account for variations in detection across different land cover types. Turkey occupancy during the brood-rearing and breeding seasons in my study parks was most strongly influenced by building density. In both seasons, the probability of turkey occupancy decreased as building density increased. As a result, rural parks showed the highest probability of turkey occupancy during both the breeding and brood-rearing seasons, aligning with established patterns of turkey occupancy in traditional agricultural habitats. The relative abundance of turkeys was most strongly associated with forested areas during the brood-rearing season and with foraging/open locations during the breeding season. Surprisingly, the analysis indicated that turkey populations were more abundant in some suburban parks than in some rural areas. This increase in abundance within suburban parks could potentially heighten the risk of human-wildlife conflicts. Notable human-wildlife conflicts associated with turkeys include automobile collisions and landscape damage resulting from turkey foraging, grooming, and mating behaviors. In Maryland, the primary method of regulating turkey populations in rural areas is through the spring harvest season. Despite the increased abundance of turkeys in suburban areas, the state of Maryland lacks a framework for effectively managing turkeys in these suburban environments. To address this potential issue, ongoing camera monitoring

strategies could be employed to monitor turkey use. Specifically, a camera survey targeting suburban areas in Montgomery County would provide wildlife managers with the necessary information to manage these populations more effectively. Camera surveys offer a cost-effective alternative to traditional mark-recapture methods. While there are initial costs associated with the purchasing and deploying camera devices, the primary ongoing expense is data collection and analysis. Additionally, reducing the number of cameras or the frequency of surveys could still yield accurate population estimates, further lowering costs. Ultimately, camera surveys serve as a valuable tool for wildlife managers to assess turkey populations across different levels of human development and to develop effective management practices

I also examined turkey and tick populations in urban and suburban parks. With the growing concern over tick-borne illnesses, it is crucial to understand how various wildlife species, including turkeys, may influence the presence and abundance of ticks. Currently, there are two conflicting hypotheses regarding the tick-turkey relationship. One hypothesis suggests that turkeys are increasing tick populations in an ecosystem by serving as hosts, while the other suggests that turkeys are reducing tick populations through their foraging behavior. While little is known about the potential relationship between ticks and turkeys, my research helps to address this gap by exploring the habitat use of both species. My results indicated that *Amblyomma* and *Ixodes* ticks are influenced by the presence of the "Turkey Food/Open" and "Turkey Forest" variables, suggesting that ticks and turkeys may simply occupy similar habitats. However, to more accurately capture tick habitat, it is essential to incorporate models of edge density for forested landcover types, as current literature suggests that this landcover metric influences tick presence and abundance. Ultimately, the results of my research do not indicate turkeys directly influencing tick populations. To answer this question, simultaneous monitoring of both ticks and

turkeys is required to determine whether they share habitats and if turkey populations actively influence tick abundances. Examining the stomach contents of turkeys from the Maryland Spring Harvest season would provide valuable insight into whether turkeys are consuming ticks in sufficient quantities to actively reduce their population. Additionally, collecting ticks from turkeys during routine bird banding efforts in the state would offer further understanding of the parasitism rates in turkey populations. Ultimately, continued monitoring and research on the turkey-tick relationship are important for gaining a better understanding of the dynamics of this relationship. By gaining a better understanding of the dynamics of the tick-turkey relationship, wildlife managers can assess how turkey populations may be influencing tick loads in an ecosystem. This, in turn, will allow them to develop mitigation plans to prevent the spread of tick-borne illnesses, particularly in human-dominated landscapes.

TABLES

Table 1. *Number of Cameras and Urbanization Classification Across Study Parks*

Park Name	# of Cameras in Array	Urbanization Classification
Rock Creek Stream Valley	25	Urban
Cabin John Regional	25	Urban
Sligo Creek	7	Urban
Muddy Branch	6	Suburban
Great Seneca	6	Suburban
Upper Paint Branch	8	Suburban
Little Bennett Regional	9	Rural
Woodstock Equestrian	6	Rural

Table 2. *Models of Occupancy (Ψ) Results During Brood-Rearing Seasons*

Model Name	WAIC	WAIC weight	ΔWAIC	Number of Parameters (K)
Building Density	764.84	0.781	0.00	5
Turkey Food/Open	768.05	0.157	3.20	5
Road Density	771.23	0.032	6.39	5
Mean Elevation	771.62	0.026	6.78	5
Null	778.04	0.001	13.19	4
Turkey Forest	778.18	0.000	13.33	5

Table 3. *Models of Occupancy (Ψ) Results During Breeding Seasons*

Model Name	AIC	AIC weight	ΔAIC	Number of Parameters (K)
Building Density	289.85	0.614	0.00	5
Turkey Food/Open	292.16	0.193	2.31	5
Turkey Forest	293.77	0.086	3.92	5
Road Density	294.37	0.064	4.52	5
Null	296.53	0.022	6.68	4
Mean Elevation	296.56	0.021	6.71	5

Table 4. *Probability of Occupancy (Ψ) Across Seasons and Years*

Season	Year	Weighted (Ψ)	SE
Brood-Rearing	2022	0.016	3.219
Brood-Rearing	2023	0.028	4.157
Breeding	2022	0.222	7.882
Breeding	2023	0.112	6.313

Table 5. *2022 and 2023 Weighted Average Probability of Occupancy (Ψ) Across Study Parks During Brood-Rearing Season*

Park	Urbanization	Weighted Avg Ψ 2022	Weighted Avg SE 2022	Weighted Avg Ψ 2023	Weighted Avg SE 2023
CJ	Urban	**0.025**	0.889	**0.040**	1.206
GS	Suburban	**0.043**	0.273	**0.069**	0.339
LB	Rural	**0.148**	0.677	**0.217**	0.812
MB	Suburban	**0.036**	0.188	**0.059**	0.237
RC	Urban	**0.015**	0.500	**0.024**	0.702
SC	Urban	**0.006**	0.054	**0.010**	0.081
UPB	Suburban	**0.038**	0.195	**0.061**	0.252
WE	Rural	**0.144**	0.438	**0.212**	0.526

Table 5.1. *2022 and 2023 Probability of Occupancy (Ψ) Tertiles Based on Weighted Average (Brood-Rearing)*

Year	Mean Ψ	Ranking
2022	$\Psi < 0.025$	Low
2022	$0.025 < \Psi < 0.043$	Average
2022	$\Psi > 0.043$	High
2023	$\Psi < 0.040$	Low
2023	$0.040 < \Psi < 0.069$	Average
2023	$\Psi > 0.069$	High

Table 6. *2022 and 2023 Weighted Average Probability of Occupancy (Ψ) Across Study Parks During Breeding Season*

Park	Urbanization	Weighted Avg Ψ 2022	Weighted Avg SE 2022	Weighted Avg Ψ 2023	Weighted Avg SE 2023
CJ	Urban	**0.232**	2.754	**0.129**	2.084
GS	Suburban	**0.337**	0.581	**0.196**	0.499
LB	Rural	**0.571**	0.905	**0.399**	0.897
MB	Suburban	**0.307**	0.415	**0.174**	0.350
RC	Urban	**0.173**	1.831	**0.092**	1.30
SC	Urban	**0.091**	0.285	**0.046**	0.184
UPB	Suburban	**0.299**	0.500	**0.174**	0.406
WE	Rural	**0.565**	0.598	**0.393**	0.589

Table 6.1. *2022 and 2023 Probability of Occupancy (Ψ) Tertiles Based on Weighted Average (Breeding)*

Year	Mean Ψ	Ranking
2022	$\Psi < 0.232$	Low
2022	$0.232 < \Psi < 0.307$	Average
2022	$\Psi > 0.307$	High
2023	$\Psi < 0.129$	Low
2023	$0.129 < \Psi < 0.174$	Average
2023	$\Psi > 0.174$	High

Table 7. *Models of Relative Abundance (N) Results During Brood-Rearing Seasons*

Model Name	WAIC	WAIC weight	ΔWAIC	Number of Parameters (K)
Turkey Forest	465.67	4.5e-01	0.00	5
Turkey Food/Open	466.28	3.3e-01	0.61	5
Building Density	467.04	2.2e-01	1.37	5
Road Density	475.60	3.1e-03	9.94	5
Mean Elevation	481.56	1.6e-04	15.90	5
Null	486.35	1.4e-05	20.68	4

Table 8. *Models of Relative Abundance (N) Results During Breeding Seasons*

Model Name	WAIC	WAIC weight	Δ WAIC	Number of Parameters
Turkey Food/Open	979.70	1.0e+00	0.00	5
Building Density	997.85	1.1e-04	18.15	5
Road Density	1004.51	4.1e-06	24.81	5
Mean Elevation	1009.47	3.4e-07	29.77	5
Turkey Forest	1028.36	2.7e-11	48.66	5
Null	1031.28	6.3e-12	51.58	4

Table 9. *Relative Abundance (N) Across Seasons and Years*

Season	**Year**	**Weighted N (Turkeys / 2km^2)**	**Weighted SE**
Brood-Rearing	2022	0.037	4.701
Brood-Rearing	2023	0.058	5.473
Breeding	2022	0.323	15.862
Breeding	2023	0.249	13.609

Table 10. *2022 and 2023 Weighted Average Relative Abundance (N) Across Study Parks During Brood-Rearing Season*

Park	Urbanization	Weighted Avg N 2022	Weighted Avg SE 2022	Weighted Avg N 2023	Weighted Avg SE 2023
CJ	Urban	**0.042**	0.621	**0.065**	0.737
GS	Suburban	**0.087**	0.679	**0.131**	0.771
LB	Rural	**0.058**	1.024	**0.108**	1.110
MB	Suburban	**0.081**	0.224	**0.118**	0.278
RC	Urban	**0.035**	1.405	**0.052**	1.664
SC	Urban	**0.022**	0.112	**0.031**	0.154
UPB	Suburban	**0.042**	0.220	**0.062**	0.284
WE	Rural	**0.060**	0.414	**0.093**	0.473

Table 10.1. *2022 and 2023 Relative Abundance (N) Tertiles Based on Weighted Average (Brood-Rearing)*

Year	Mean (N)	Ranking
2022	N < 0.042	Low
2022	0.042 < N < 0.060	Average
2022	N > 0.060	High
2023	N < 0.062	Low
2023	0.062 < N < 0.093	Average
2023	N > 0.093	High

Table 11. *2022 and 2023 Weighted Average Relative Abundance (N) Across Study Parks During Breeding Season*

Park	Urbanization	Weighted Avg N 2022	Weighted Avg SE 2022	Weighted Avg N 2023	Weighted Avg SE 2023
CJ	Urban	**0.335**	1.773	**0.259**	1.531
GS	Suburban	**0.304**	0.777	**0.234**	0.675
LB	Rural	**0.200**	0.780	**0.157**	0.664
MB	Suburban	**0.352**	0.596	**0.275**	0.487
RC	Urban	**0.389**	2.884	**0.303**	2.501
SC	Urban	**0.448**	0.820	**0.351**	0.708
UPB	Suburban	**0.419**	5.087	**0.327**	4.305
WE	Rural	**0.464**	3.167	**0.356**	2.736

Table 11.1. *2022 and 2023 Relative Abundance (N) Tertiles Based on Weighted Average (Breeding)*

Year	Mean (N)	Ranking
2022	N < 0.335	Low
2022	0.335 < N < 0.389	Average
2022	N > 0.389	High
2023	N < 0.259	Low
2023	0.259 < N < 0.303	Average
2023	N > 0.303	High

Table 12. *Total Ticks Collected and Turkey Relative Abundances (N) By Park in 2023*

Park	Urban	Num of Sites	N Ticks	Weighted Avg N Brood-Rearing	Brood-Rearing SE	Weighted Avg N Breeding	Breeding SE
CJ	Urban	10	155	**0.065**	0.737	**0.259**	1.531
GS	Suburban	3	10	**0.131**	0.771	**0.234**	0.675
RC	Urban	10	4	**0.052**	1.664	**0.303**	2.501
SC	Suburban	3	4	**0.031**	0.154	**0.351**	0.708
UPB	Suburban	3	2	**0.062**	0.284	**0.327**	4.305

Tabe 13. *GLMM Models for Total Tick Counts, Ixodes scapularius counts and Amblyomma americanum counts. 'Analyses' refers to the model set categorized by the response variable, while 'covariate' denotes the landcover variable included in the model. Any model that included 'Total Number of Turkeys Observed' or 'Maximum Count of Turkeys' also incorporated 'Number of Cameras in Grid Cell' to account for variations in detection. All models included 'Park Location' as a random effect.*

Analyses	Covariate
Total Tick Counts	Mean Leaf Litter Depth (cm)
	Mean Shrub Height (cm)
	Turkey Food/Open
	Turkey Forest
	Turkey Abundance, Brood-Rearing
	Turkey Abundance, Breeding
	Maximum Count of Turkeys, Brood-Rearing
	Maximum Count of Turkeys, Breeding
	Total Number of Turkeys Observed, Brood-Rearing
	*Total Number of Turkeys Observed, Breeding
Amblyomma americanum Counts	Turkey Food/Open
	Turkey Forest
	*Maximum Count of Turkeys, Brood-Rearing
	*Maximum Count of Turkeys, Breeding
	*Total Number of Turkeys Observed, Brood-Rearing
	*Total Number of Turkeys Observed, Breeding
Ixodes scapularis Counts	Turkey Food/Open
	Turkey Forest

	*Maximum Count of Turkeys, Brood-Rearing
	*Maximum Count of Turkeys, Breeding
	*Total Number of Turkeys Observed, Brood-Rearing
	*Total Number of Turkeys Observed, Breeding

Table 14. *Total Tick Counts in Relation to 6 Models at the Grid Level*

Model	Predictor	Estimate	Standard Error	Z value	P >z	R squared
1	Intercept	1.278	0.860	1.485	0.137	C: 0.986 M:0.032
	Mean Litter Depth	0.347	0.115	3.003	0.002	
2	Intercept	1.273	0.851	1.497	0.134	C: 0.987 M: 0.104
	Mean Shrub Height	-0.639	0.245	-2.604	0.009	
3	Intercept	1.357	0.747	1.817	0.069	C: 0.977 M:0.030
	Turkey Food/Open	0.446	0.061	7.286	3.19e-13	
4	Intercept	1.306	0.758	1.722	0.084	C:0.977 M:0.010
	Turkey Forest	0.168	0.0578	2.913	0.003	
5	Intercept	1.281	0.759	1.687	0.091	
	Breeding Season Turkey Relative Abundance	0.188	0.038	4.875	< 0.001	C:0.977 M:0.012
6	Intercept	1.272	0.784	1.622	0.105	C:0.979 M:0.004
	Brooding Season Turkey Relative Abundance	-0.110	0.109	-1.01	0.312	

Table 15. *Total Tick Counts in Relation to Turkey Counts at Grid Cell Level*

Model	Predictor	Estimate	Standard Error	Z value	P >z	R squared
1	Intercept	1.038	0.693	1.498	0.134	C: 0.977 M:0.169
	Maximum Turkeys (Brood-Rearing)	0.457	0.116	3.940	8.14 e-05	
	Number of Cameras	0.396	0.035	11.286	< 2e-16	
2	Intercept	1.174	0.674	1.742	0.081	C: 0.974 M: 0.130
	Maximum Turkeys (Breeding)	0.280	0.078	3.576	< 0.001	
	Number of Cameras	0.424	0.034	12.290	< 2e-16	
3	Intercept	1.0500	0.6872	1.528	0.1265	C: 0.976 M: 0.162
	Total Turkeys (Brood-Rearing)	0.439	0.113	3.880	< 0.001	
	Number of Cameras	0.397	0.035	11.317	< 2e-16	
4	Intercept	1.104	0.674	1.638	0.101	C: 0.975 M: 0.147
	Total Turkeys (Breeding)	0.370	0.097	3.798	< 0.001	
	Number of Cameras	0.411	0.034	11.852	< 2e-16	

Table 16. *Ixodes scapularis Counts in Relation to Turkey Counts at Grid Cell Level*

Model	Predictor	Estimate	Standard Error	Z value	P >z	R squared
1	Intercept	-0.735	1.039	-0.708	0.047	C:0.966 M:0.109
	Maximum Turkeys (Brood-Rearing)	0.521	0.184	2.823	0.004	
	Number of Cameras	0.270	0.087	3.102	0.001	
2	Intercept	-0.649	1.005	-0.646	0.518	C: 0.964 M: 0.016
	Maximum Turkeys (Breeding)	0.456	0.152	3.000	0.002	
	Number of Cameras	0.314	0.084	3.714	<0.001	
3	Intercept	-0.752	1.039	-0.723	0.469	C: 0.966 M: 0.112
	Total Turkeys (Brood-Rearing)	0.536	0.190	2.816	0.004	
	Number of Cameras	0.270	0.087	3.104	0.001	
4	Intercept	-0.704	1.017	-0.693	0.488	C: 0.965 M:0.108
	Total Turkeys (Breeding)	0.501	0.176	2.847	0.004	
	Number of Cameras	0.290	0.085	3.386	<0.001	

Table 17. *Amblyomma americanum Counts in Relation to Turkey Counts at Grid Cell Level*

Model	Predictor	Estimate	Standard Error	Z value	P >z	R squared
1	Intercept	-1.149	1.067	-1.077	0.281	C:0.928 M:0.106
	Maximum Turkeys (Brood-Rearing)	0.641	0.335	1.914	0.055	
	Number of Cameras	0.141	0.102	1.385	0.166	
2	Intercept	-0.773	0.002	-343.31	< 2e-16	C:0.907 M:0.034
	Maximum Turkeys (Breeding)	0.244	0.002	108.60	< 2e-16	
	Number of Cameras	0.185	0.002	82.44	< 2e-16	
3	Intercept	-1.156	0.106	-1.086	0.277	C: 0.927 M:0.106
	Total Turkeys (Brood-Rearing)	0.6398	0.333	1.920	0.054	
	Number of Cameras	0.142	0.102	1.387	0.165	
4	Intercept	-0.929	0.952	-0/976	0.329	C:0.912 M:0.066
	Total Turkeys (Breeding)	0.432	0.236	1.832	0.067	
	Number of Cameras	0.167	0.100	1.663	0.096	

Table 18. *Ixodes scapularis and Amblyomma americanum Tick Counts in Relation to Turkey/Food and Turkey Forest Variables at Grid Level*

Model	Predictor	Estimate	Standard Error	Z value	P >z	R squared
Ixodes scapularis	Intercept	-0.402	1.112	-0.362	0.717	C: 0.970 M: 0.072
	Turkey Food/Open	0.875	0.156	5.586	2.33e-08	
Ixodes scapularis	Intercept	-1.002	1.443	-0.694	0.487	C: 0.982 M:0.060
	Turkey Forest	-0.655	0.135	-4.849	1.24e-06	
Amblyomma americanum	Intercept	-0.594	0.002	-250.6	<2e-16	C:0.906 M:0.083
	Turkey Forest	0.832	0.002	351.1	<2e-16	
Amblyomma americanum	Intercept	-0.8493	0.002	-383.1	<2e-16	C:0.921 M:0.023
	Turkey Food/Open	-0.3055	0.002	-137.8	<2e-16	

FIGURES

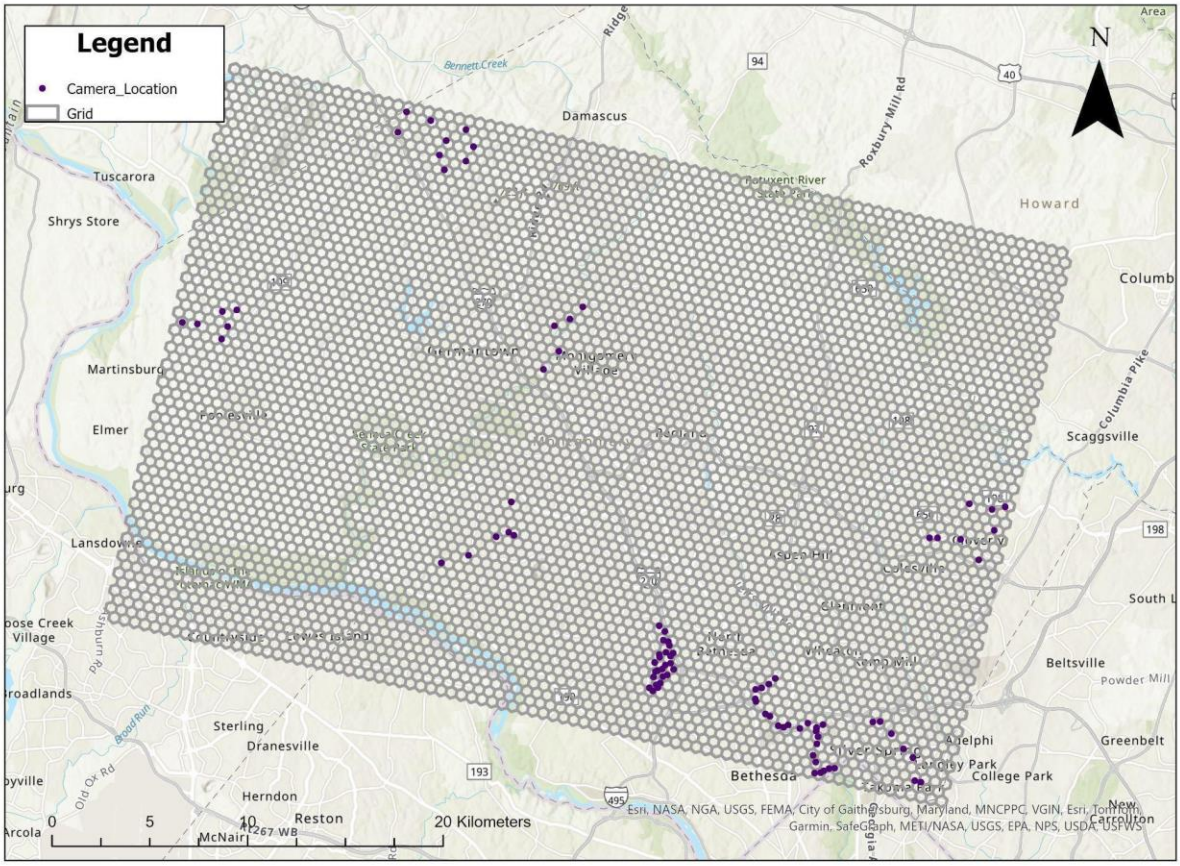

Figure 1. *Grid Overlay Across Camera Locations*

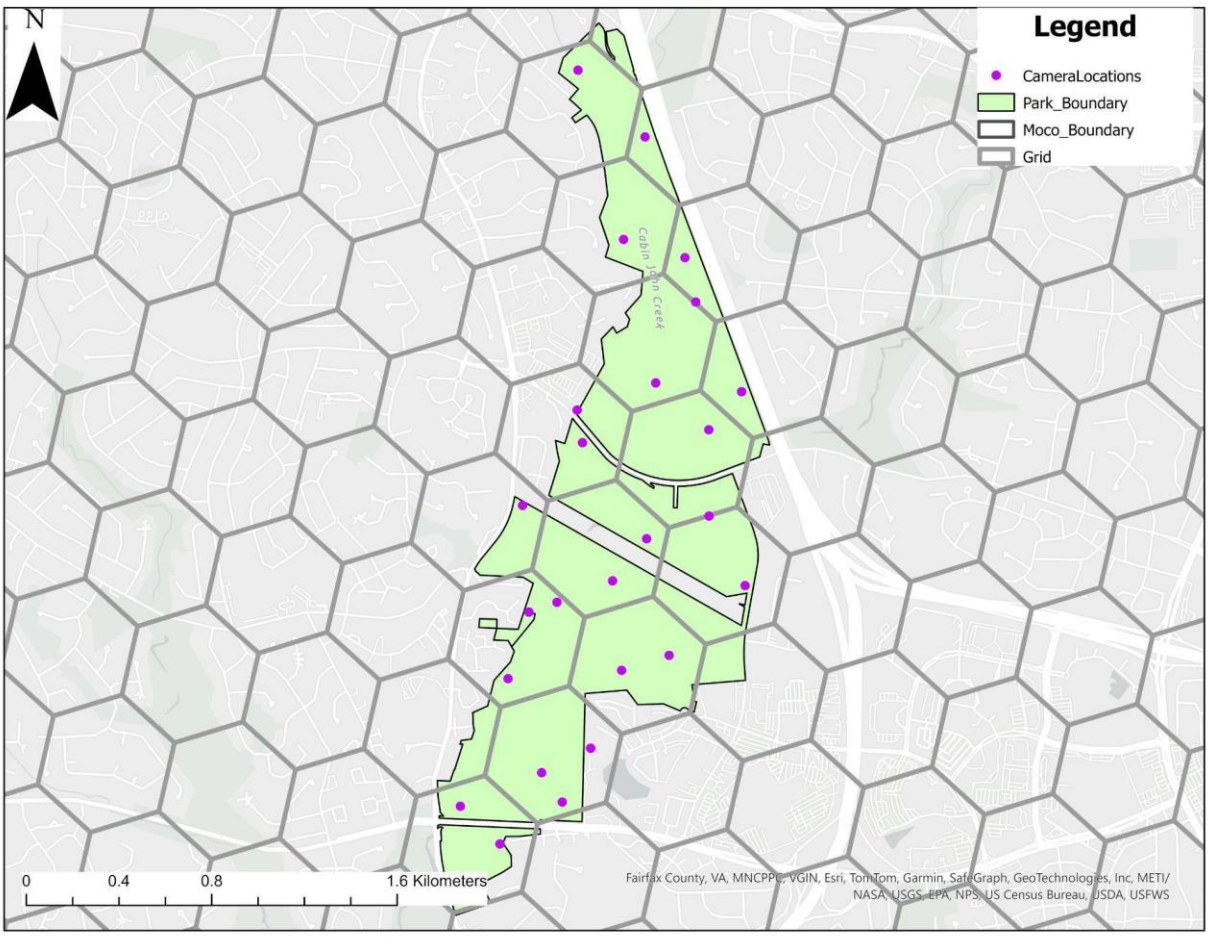

Figure 2. *Cabin John Regional (Urban) and Grid Overlay Close-Up.*

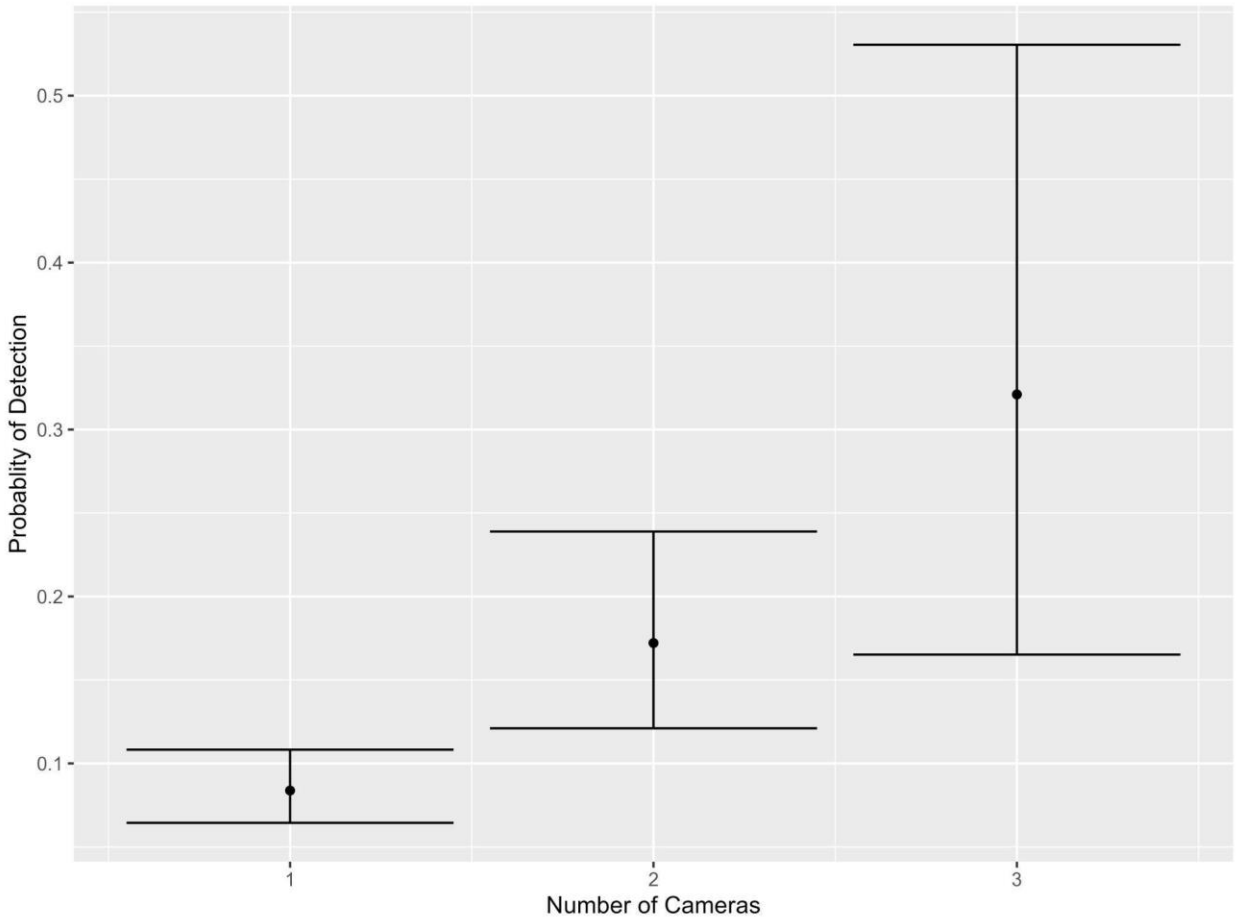

Figure 3. *Probability of Detection Based on Number of Cameras in Grid Cell During the Brood-Rearing and Breeding Seasons*

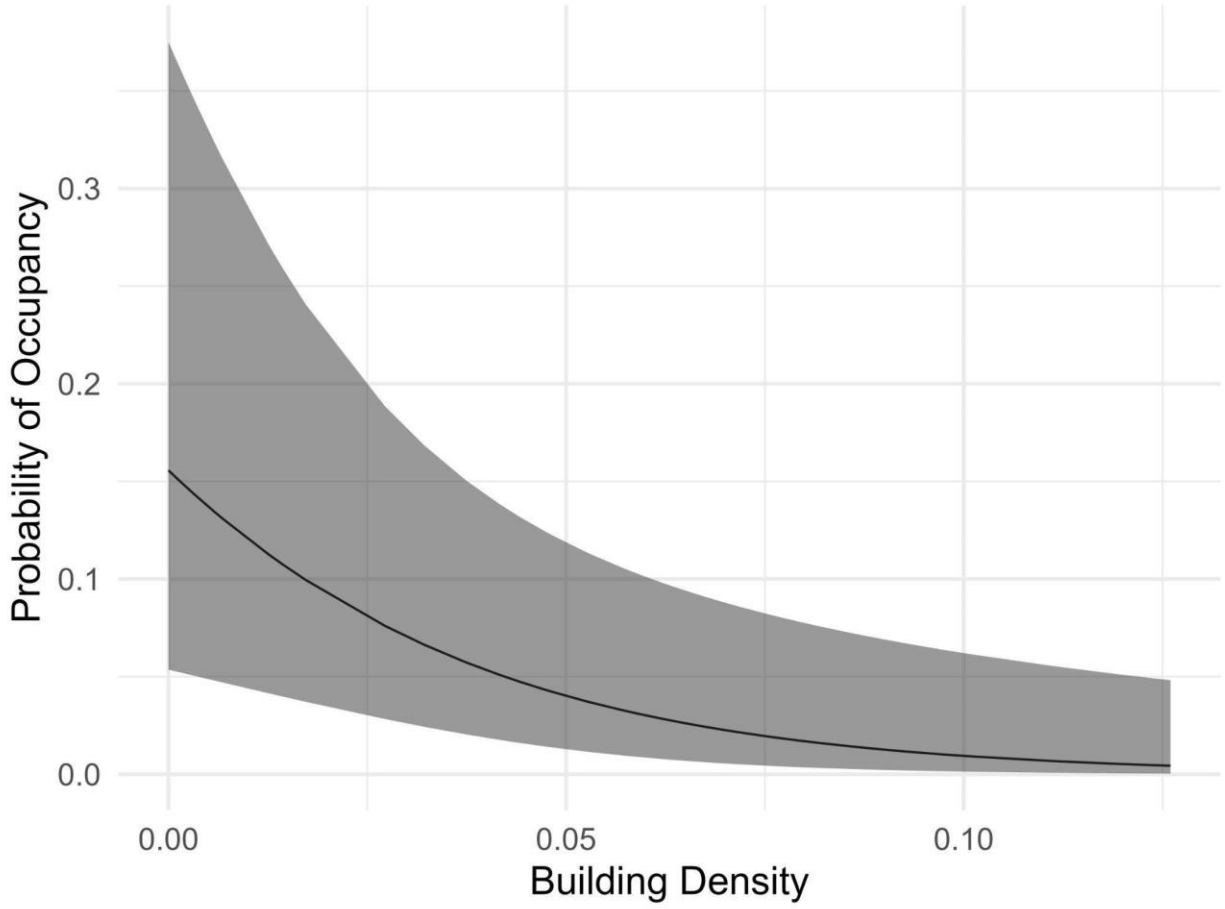

Figure 4. *The Effect of Building Density on Probability of Occupancy (Ψ) During the Brood-Rearing Season*

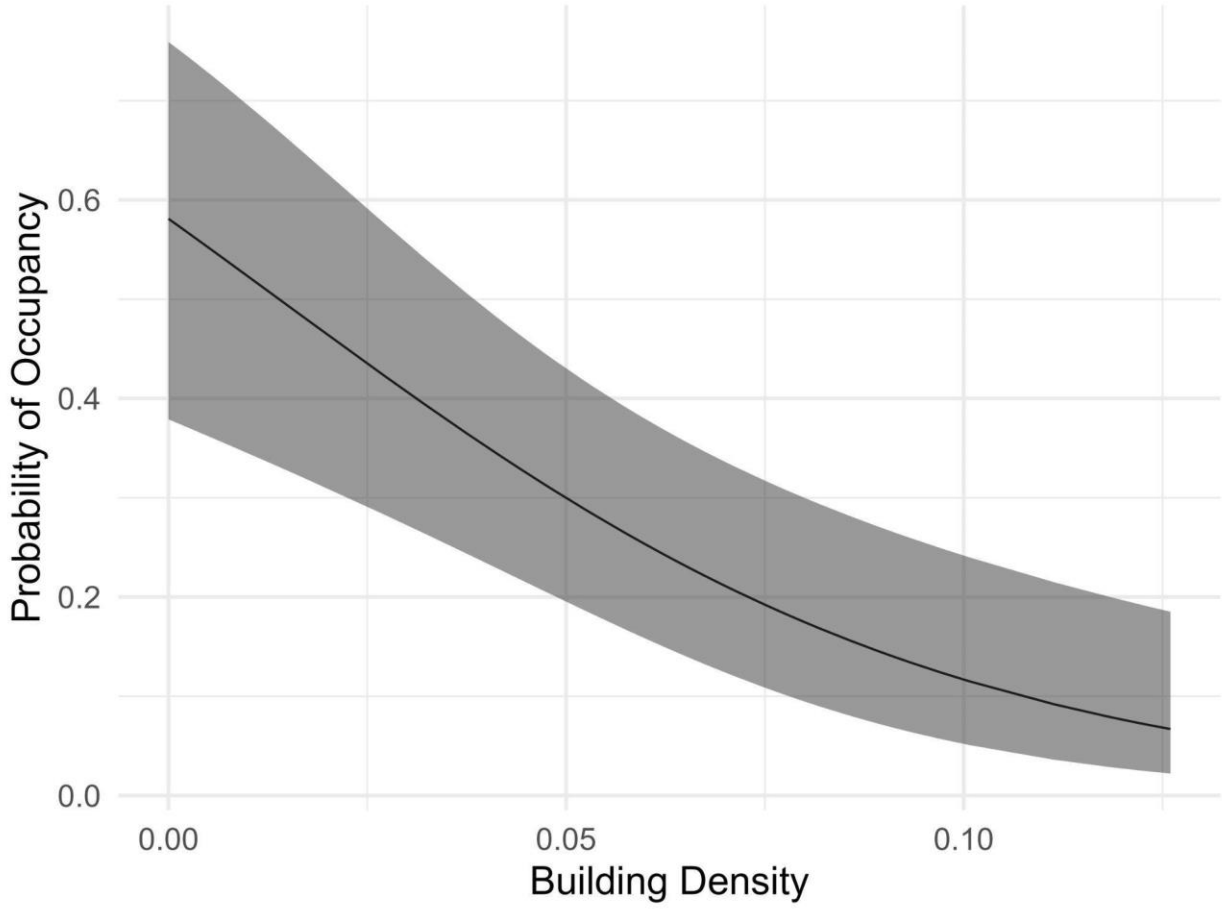

Figure 5. *The Effect of Proportion of Turkey Food/Open on Probability of Occupancy (Ψ) During the Breeding Season*

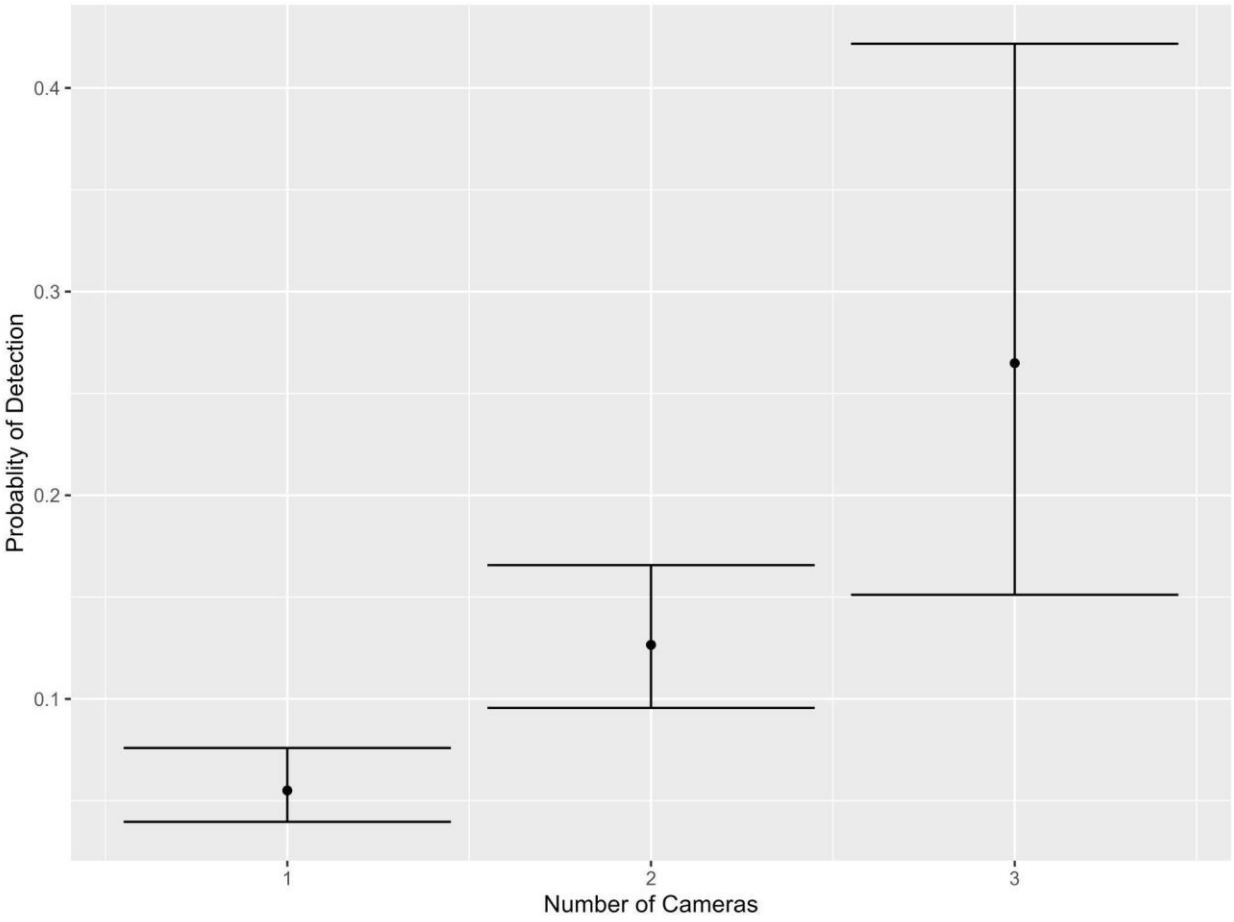

Figure 6. *N-mixture- Probability of Detection Based on Number of Cameras in Grid Cell During Brood-Rearing Season*

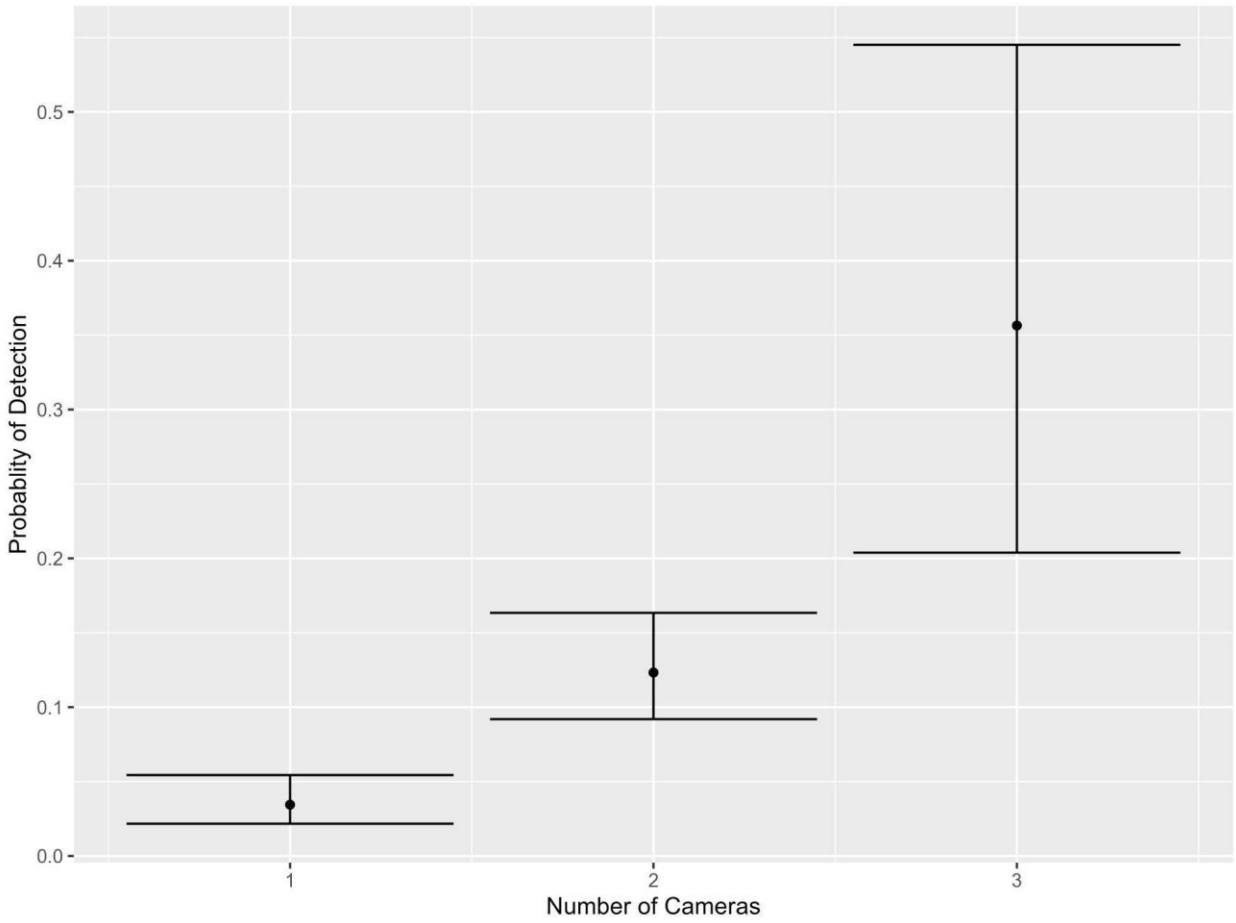

Figure 7. *N-mixture- Probability of Detection Based on Number of Cameras in Grid Cell During Breeding Season*

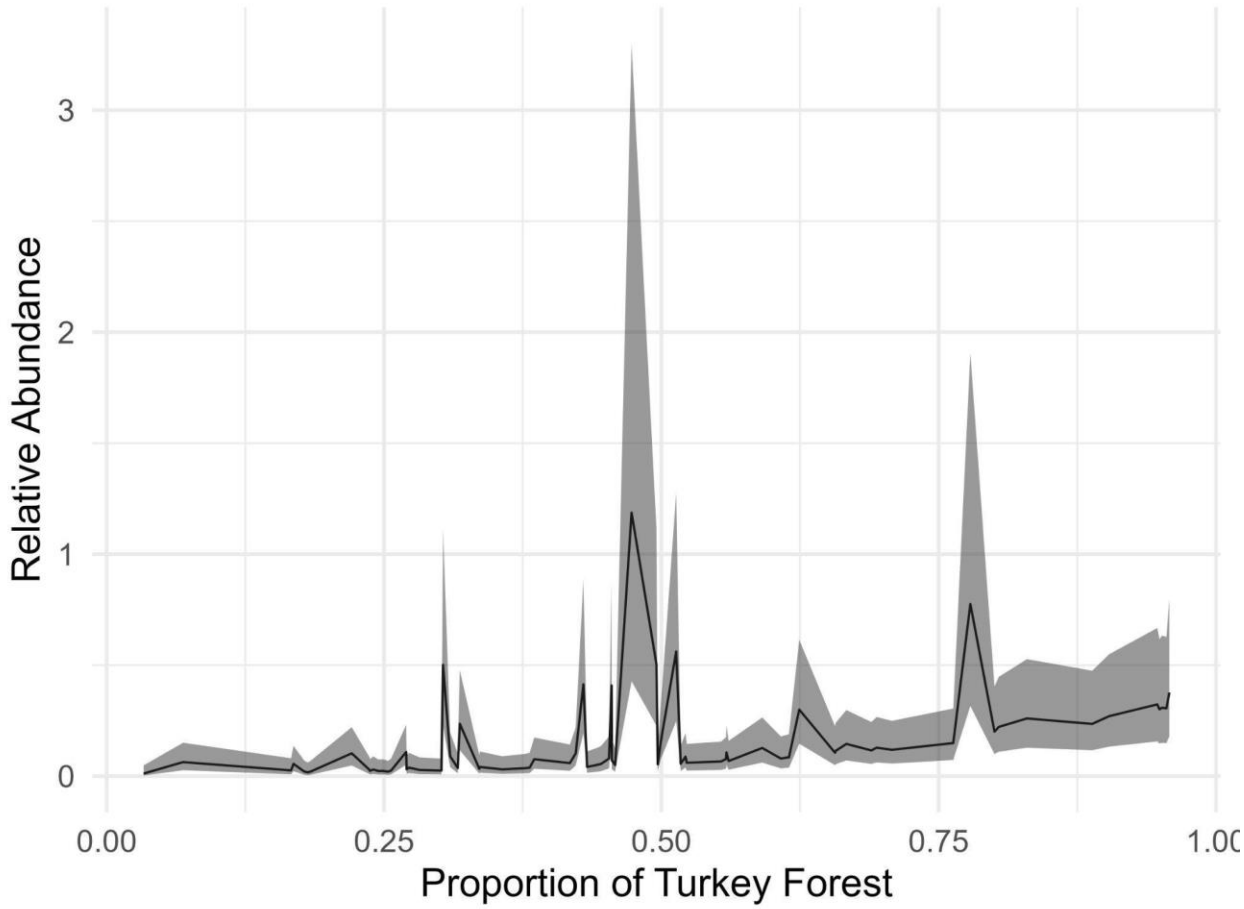

Figure 8. *The Effect of Proportion of Turkey Food/Open Variable on Relative Abundance (N) During the Brood-Rearing Season*

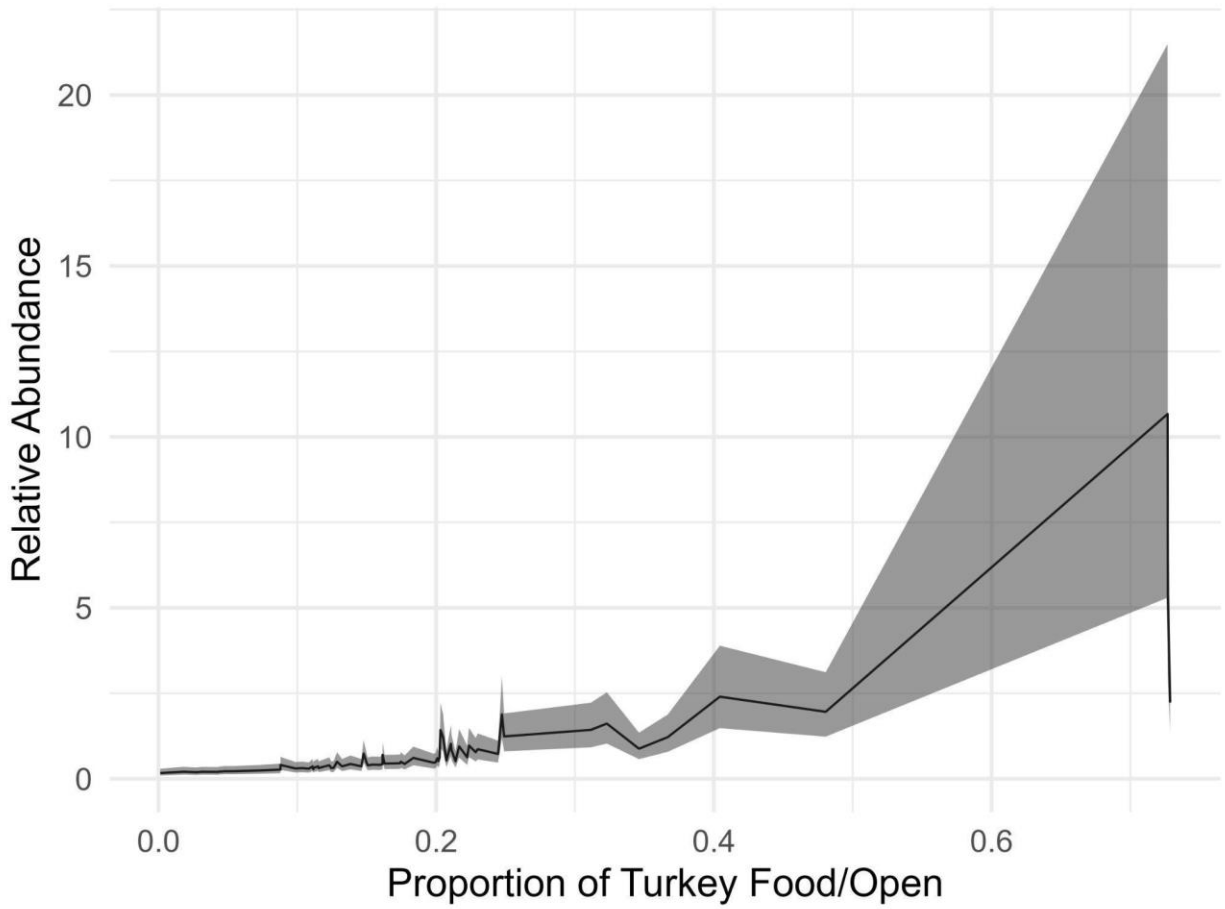

Figure 9. *The Effect of Proportion of Turkey Food/Open Variable on Relative Abundance (N) During the Breeding Season*

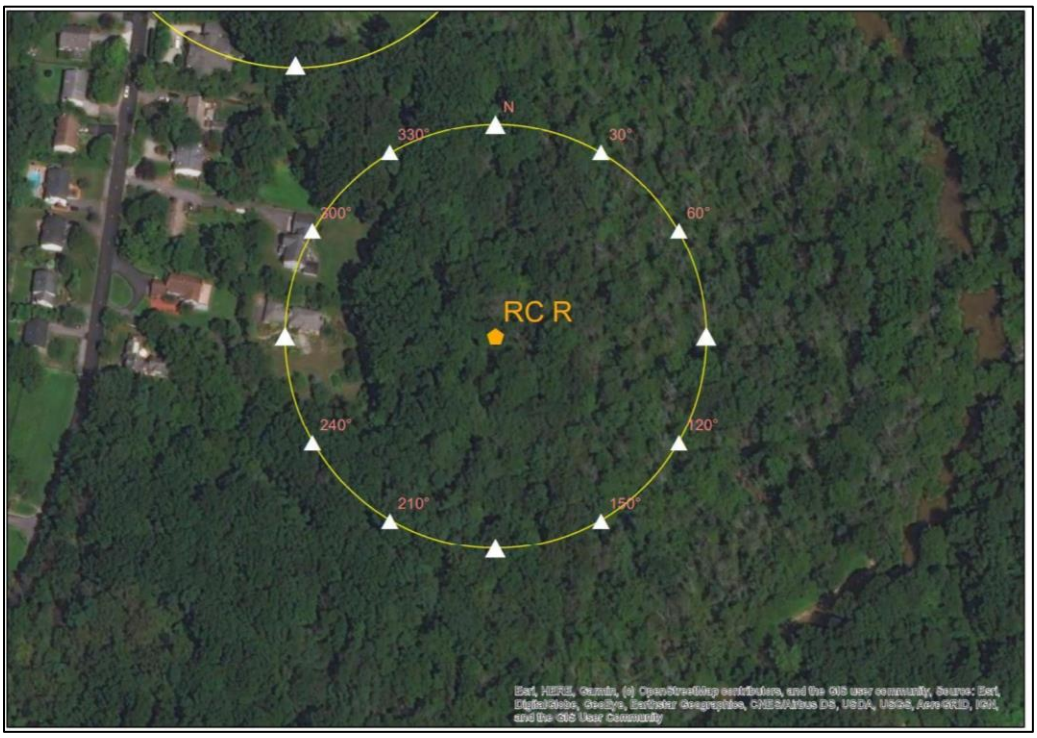

Figure 10. *Tick Sampling Plot Example. Where RCR is a Camera Location.*

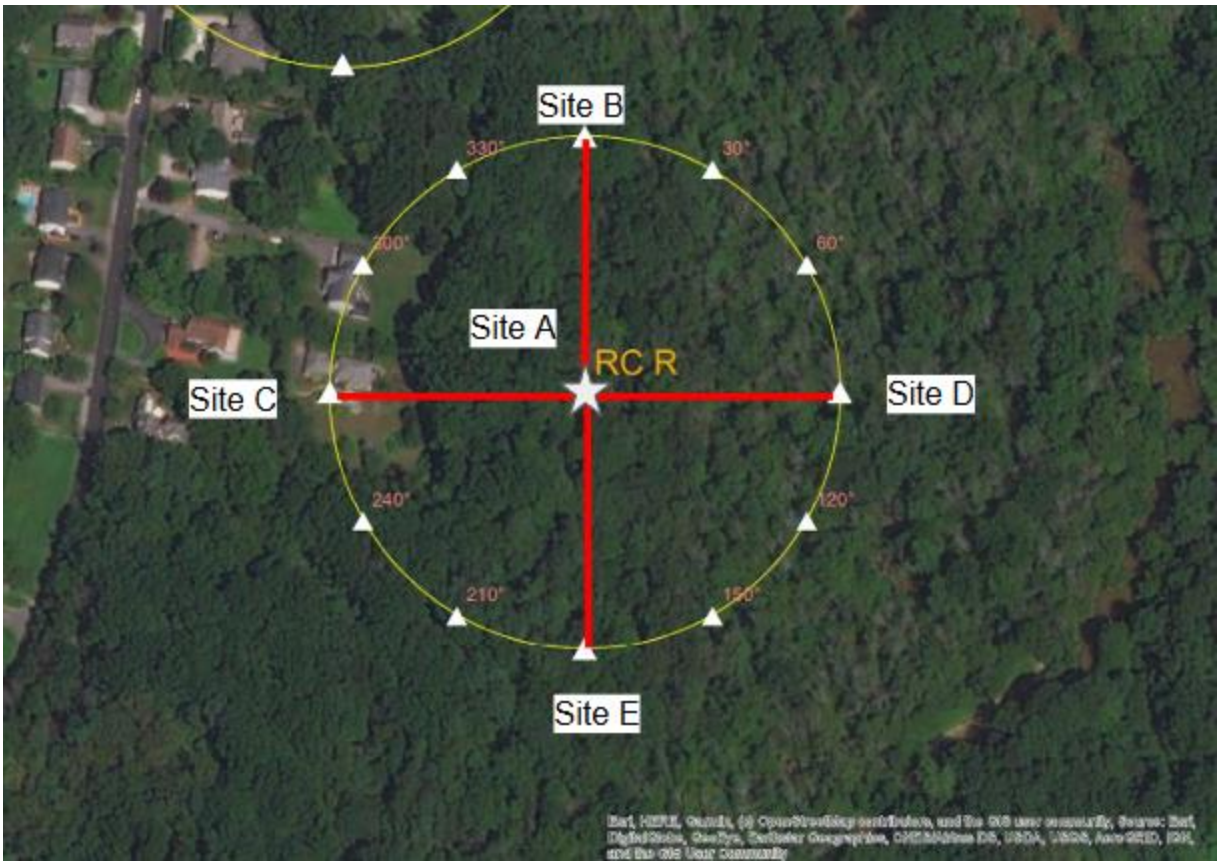

Figure 11. *Vegetation Sampling Plot Example. Where RCR (star) indicates a camera location. Site A was five meters in front of the camera. Sites B, C, D and E were randomly selected distances (25, 50, 75 or 100m) away from the camera in each cardinal direction.*

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