Using Automated Cameras to Estimate Wildlife Populations

by

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Abstract

Precise and accurate estimates of demographics such as age structure, productivity, and density are necessary in determining habitat and harvest management strategies for wildlife populations. The importance of incorporating detection rates into these demographic estimates cannot be overstated, as failure to include detection can lead to underestimated parameters. Following some introductory material in chapter one, we describe a modeling exercise to explain heterogeneity in detection for passive-infrared (PIR) triggered cameras in chapter two. This chapter illustrates the necessity of modeling camera detection when using PIR sensors in surveying populations for estimating demographics. We then describe a method for estimating Eastern wild turkey (*Meleagris gallopavo sylvesteris*) population size and structure in Alabama at a relatively large scale using time lapse cameras in chapter three. Through estimating turkey abundance, we determined and estimated important sources of variation within counts relating to detection, distribution, and density. Prior to implementing this method as a monitoring tool, modeling of hypotheses should be improved for fitting turkey count data. Additional density hypotheses should be modeled to explain extra variation in counts. With the proper survey design and hypotheses, this method should provide unbiased and precise estimates of wild turkey populations. In the final chapter, we provide some comprehensive thoughts on using cameras to survey wildlife populations and on population demographics estimation.

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CHAPTER I: INTRODUCTION

Precise and accurate estimates of demographics such as age structure, productivity, and density are necessary in determining habitat and harvest management strategies for wildlife populations. Information on such demographics has previously been acquired through indices including transect sampling (Silveira et al. 2003), mark-recapture (Soisalo and Cavalcanti 2006), aerial sampling (Amstrup et al. 2004), and automated camera surveys (Cobb et al. 1995). These surveys often are opportunistic, and poor sampling design can lead to biased estimates from surveys because the counted portion of the population may not be representative of the entire population. The importance of incorporating detection rates into these demographic estimates cannot be overstated, as failure to include detection can lead to parameter underestimation (MacKenzie et al. 2002). In addition, much of this research is executed only on public lands, where population characteristics may be quite different from those on private lands; thus, extrapolating results to other areas may only provide biased estimates of population size and structure.

Automated camera systems have evolved rapidly since methods to photograph wildlife were described by Gysel and Davis (1956). Advanced camera technology coupled with the proper survey design has now been used to estimate population demographics (Cobb et al. 1996, Martorello et al. 2001, Soisalo and Cavalcanti 2006). An added benefit of automated camera surveys is they can easily and relatively inexpensively be repeated across space and time. However, despite increasing use of cameras to survey wildlife, few researchers have explicitly estimated detection rates for cameras, or more specifically, passive-infrared (PIR) sensors (Swann et al. 2004, Rowcliffe et al. 2008). Automated cameras show great promise for estimating large-scale population demographics precisely and accurately, providing detection is accounted for and surveys are representative.

Wild turkeys are an ideal candidate for exploration of large scale population estimation techniques using automated camera surveys because they are relatively abundant and are easily attracted using bait. Large turkey populations and increasing numbers of hunters in Alabama have arguably resulted in increased harvest, and questions have arisen as to the sustainability of this harvest. In addition to suspected declines in productivity (Steve Barnett, pers. comm.), increased harvest may have negative impacts on Alabama turkey populations and hunter satisfaction. Previous wild turkey surveys have largely been opportunistic and failed to incorporate detection into estimates. With a rigorous sampling design and ample observations, estimates from automated camera surveys should provide more accurate large-scale estimates than other methods of surveying wild turkey populations.

We estimated detection rates of one commercially available PIR camera and described variability in detection rates based on taxonomic groups and body sizes of animals photographed to assess effects of variation in PIR sensors on demographic estimation. Issues with incorporating detection of cameras led us to pursue use of time-lapse triggered cameras for future research and surveys. For a wild turkey population in Alabama, we estimated abundance, productivity, and age and sex structure of wild turkeys on an eco-region scale using spatially and temporally replicated time-lapse trail camera surveys. We modeled important sources of heterogeneity in detection of turkeys in counts related to environmental factors and placement of cameras to improve the precision of our estimates. We also determined and estimated important sources of heterogeneity in the density and distribution of turkeys related to landscape scale habitat variables.

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CHAPTER II: MODELING VARIATION IN DETECTION AMONG PASSIVE INFRARED TRIGGERED-CAMERAS IN WILDLIFE RESEARCH

Abstract

Precise and accurate estimates of demographics such as age structure, productivity, and density are necessary in determining habitat and harvest management strategies for wildlife populations. Surveys using automated cameras are becoming an increasingly popular tool for estimating these parameters. However, most camera studies fail to incorporate detection probabilities, leading to parameter underestimation. The objective of this study was to determine the sources of heterogeneity in detection for trail cameras that incorporate a passive infrared (PIR) triggering system sensitive to heat and motion. Images were collected at four baited sites within the Conecuh National Forest, Alabama using three cameras at each site operating continuously over the same seven-day period. Detection was estimated for four groups of animals based on taxonomic group and body size. Our hypotheses of detection considered variation among bait sites and cameras. The best model (w = 0.99) estimated different rates of detection for each camera in addition to different detection rates for four animal groupings. Factors that explain this variability might include poor manufacturing tolerances, variation in PIR sensitivity, animal behavior, and species-specific infrared radiation. Population surveys using trail cameras with PIR systems must incorporate detection rates for individual cameras. Incorporating time-lapse triggering systems into survey designs should alleviate issues associated with PIR systems.

Introduction

Precise and accurate estimates of population demographics such as age structure, productivity, and abundance are necessary to determine habitat and harvest management strategies for most wildlife species. Knowledge of these parameters has been acquired through various indices including transect sampling (Silveira et al. 2003), mark-recapture (Soisalo and Cavalcanti 2006), aerial sampling (Amstrup et al. 2004), and automated cameras (Cobb et al. 1996). Surveys using automated cameras are an increasingly popular tool for estimating these parameters; however, many studies fail to incorporate detection rates. Variation in detection rates may bias parameter estimates (MacKenzie et al. 2002), and failure to incorporate detection may lead to parameter underestimation. Three general sources of bias in camera surveys can be identified: those associated with differences among the species of interest, those associated with survey site characteristics, and those directly related to camera function.

The use of automated cameras to photograph wildlife was first described by Gysel and Davis (1956). Automated camera systems have evolved rapidly since that time and have been used to study avian nest predation (Lehman et al. 2008), foraging ecology (Weckel et al. 2006), nesting behavior (Margalida et al. 2006), activity patterns (Wong et al. 2004) and estimating population demographics (Soisalo and Cavalcanti 2006, Martorello et al. 2001, Cobb et al. 1996). Despite increasing use of automated cameras to survey wildlife, few researchers have explicitly estimated detection rates for cameras or more specifically, PIR sensors (Swann et al. 2004, Rowcliffe et al. 2008; see Swann et al. 2004 for a detailed description of PIR). Researchers applying forward looking infrared (FLIR) in aerial surveys have more frequently noted problems with infrared sensors than researchers using automated cameras. Examples of sources for these problems included snow depth, airborne moisture, sunlight and background structure temperature (e.g., Kingsley et al. 1990, Amstrup et al. 2004, Bernatas and Nelson 2004, Locke et al. 2006, respectively).

Our objective was to determine sources of heterogeneity in detection for a commercially available trail camera incorporating a PIR triggering system. We estimated detection rates of one commercially available PIR camera and described variability in PIR detection rates based on taxonomic group and body size. Our hypotheses of detection considered variation among bait sites and differences among individual cameras additive to effects of taxonomic group and body size. Based on our results, we offer explanations of potential contributing factors to variability in detection rates. We also suggest methods of incorporating detection rates into demographic estimates. Finally, we propose an alternative that eliminates differences in detection among cameras.

Methods

We performed this research in conjunction with a wild turkey (*Meleagris gallopavo*) survey on the Conecuh National Forest (73,311 ha) in southern Alabama from 23 August to 6 September 2006. For this analysis, camera bait stations were established in areas consisting of small openings or dirt roads surrounded by managed pine forest. The average high temperature for the survey period was 33 °C, and the average low was 19 °C. Humidity averaged 76% and one rain event occurred during the study. To ensure cameras had the opportunity to trigger, sites for this research were chosen where turkeys were observed during the survey. A tree at least 20-cm DBH was selected to attach the cameras for each site, and a 10 m semicircle north of the tree was cleared of tall vegetation and overhanging branches to limit camera lens obstruction and unintended camera activation. All cameras were oriented north in order to avoid sun-blurred images. Each site was pre-baited with 4 L of cracked corn for 7 days prior to camera deployment, and bait was replenished only on the day of deployment if necessary. Bait was broadcast from directly in front of the camera to 3 m out. Three PIR activated Penn's Woods model DS-04 cameras (Penn's Woods Products, Inc., Export, PA; use of trade names or products does not imply endorsement) were deployed at each site and operated continuously during the same seven-day period. Cameras were attached to the same tree as close to ground as possible, and all were aimed at bait center. Units were set up to operate 24 h/day with a 10-sec delay between pictures. We used settings recommended by Penn's Woods (use of trade names or products does not imply endorsement) for programming digital cameras. Sites were visited a total of 3 times during the survey: pre-baiting, camera deployment, and camera retrieval. We examined images and recorded counts of each species.

We developed hypotheses and corresponding models concerning detection rates *a priori*. Species listed within these hypotheses were added *post hoc*.

1) We hypothesized that detection varied by site, because each sites had a different vegetative background (different species, ages, vigor, etc.), and distance to background vegetation also varied. This would lead to different detection rates across sites, but cameras at each site would have the same detection rate.

2) We hypothesized detection varied by camera due to differing sensitivities of PIR sensors. (Manufacturing tolerances, quality control, etc. caused each camera to detect animals at different rates.)

3) We hypothesized differences in detection occur due to animal size, so we grouped animals accordingly. Large animals (i.e., white-tailed deer [*Odocoileus virginianus*]) have the highest detection rate because they have the larger area of infrared radiation compared to background. Medium animals (i.e., wild turkey) are detected less frequently than large animals. Small animals (i.e., raccoon [*Procyon lotor*], nine-banded armadillo [*Dasypus novemcinctus*], and cottontail rabbit [*Sylvilagus floridanus*]) are detected less than large and medium animals, but more than very small animals (i.e., gopher tortoise [*Gopherus polyphemus*] and mourning dove [*Zenaida macroura*]).

4) We also hypothesized feathers (i.e., mourning dove and wild turkey) emit less infrared radiation which results in lower detection rates for birds than other animals.

5) We hypothesized birds had lower detection rates than non-feathered animals, but larger sized birds (i.e., wild turkey) have higher detection rates than smaller birds (i.e., mourning dove).

6) We hypothesized that a size threshold for detection existed with the PIR sensors. Because white-tailed deer have the greatest area of infrared radiation relative to the background, they have the highest odds of detection. All other animals have the same detection rate.

We combined additive effects of animal groupings with both site and camera models, respectively, to determine the best approximating model.

We used the Huggins closed population estimator (Huggins 1989, 1991) in Program MARK (White and Burnham 1999) to estimate the probability of detection (*p*) because it allowed us to include individual covariates. We treated each camera as a potential capture event, therefore probability of initial capture and recapture were constrained to be equal. An event occurred when at least one camera was triggered during any 9-sec interval. We created a capture history for each event. The initial capture was the image resulting from the camera that triggered first. Recaptures consisted of the image(s) resulting from the other two camera(s) subsequently triggering within 9-sec of the first camera. This interval was long enough to exclude multiple images of the same event from an individual camera and was enough time to allow potential recapture cameras to initialize, focus, and capture an image. Models were compared in Program MARK using AIC corrected for small sample sizes (AICc, Burnham and Anderson 2002). We estimated recapture probability in the Huggins model as a surrogate for detection; therefore, assessing goodness-of-fit (White and Burnham 1999) was not appropriate. Actual detection rates were not important for this exercise, so we compared odds ratios (βs) among cameras and animal groups. We used indicator variables for sites and animal groups and a logit link to estimate log odds of detection. To compare among sites and animal groups, we calculated the relative odds of detection as the inverse natural log of the differences in the βs for each group. We did not present animal group-specific detection rates because they were different for each camera. We compared the camera with the highest odds of detection to other cameras, and the animal group with the highest odds of detection to other groups. Model averaging was not incorporated into these results, since model selection was unequivocal (*w*AICc = 0.9998).

Results

Data at one site were discarded because only one camera at the fifth site recorded any images. Even prior to modeling, the number of events triggered by individual cameras at each site varied considerably. The PIR sensors detected a total of 868 events, 701 of which resulted in an image of an animal (81%). Variation in the number of events was high at each site (Table 2.1). Two sites (1 and 4) had a high percentage of images with animals present and low variability between cameras (83-93% and 97-100%, respectively). The other two sites (2 and 3) had greater variation (34-62% and 50-83%, respectively) and a greater number of images that did not include any animals.

The most parsimonious and best approximating model was p(camera+size) (Table 2.2). This model estimated detection rates for individual cameras at each site and four size covariates. It had the largest model probability (w = 0.9998), and best fit (Dev = 1845). The next best approximating model was p(camera+threshold) (ΔAICc = 18), but had negligible model probability (w = 0.0002). Odds of detection ranged from 0.02 to 0.66 among cameras (Figure 1). Therefore the camera with the smallest detection rate was 0.02 times as likely to detect an animal as the one with the largest detection. Large animals were most likely to be detected followed by small, medium, and very small animals, respectively (Figure 2). Despite large differences in relative odds of detection, 95% confidence intervals overlapped in most cases (Figures 1 and 2).

Discussion

One potential cause of variation in detection rates among different animal groups is the variation in intensity of infrared radiation a species emits. Most commercially available trail cameras operate using PIR, which only detects changes in background infrared radiation wavelengths. Therefore, if species have different body temperatures and insulative properties (feathers, fur, shell, scales, etc.), then differences in PIR sensitivity would contribute to variability in detection rates between animal groups. For example, Butler et al. (2006) could not detect turkeys on the roost with a FLIR camera unless their featherless heads were exposed. Counter to our size hypothesis, the odds of detecting medium-sized animals (turkeys) were lower than some smaller animals (small group). Perhaps due to their feathered covering, turkeys might emit less infrared radiation than small mammals. Although the feather hypotheses were not supported by our data, lack of fit for these models could have been caused by limited sample size and clustering non-feathered animals into a single detection group. Ideally, we would have modeled detection rates for each species, but some species were detected infrequently.

Both background temperature and environmental conditions (rain, snow, wind, cloud cover, etc.) are potential causes of lower detection rates. If differences in background temperature and the target species are not large enough, the PIR sensor will not trigger the automated camera to capture an image. Swann et al. (2004) found some models of commercially available automated cameras were more sensitive to changes in background temperature than others. Bernatas and Nelson (2004) determined overcast skies allowed for greater detection of bighorn sheep (*Ovis canadensis*) than sunny skies in aerial FLIR surveys. They also determined that flat rock surfaces emitted more infrared radiation than soil, grass, and sagebrush vegetation; therefore, sheep were detected less frequently in these areas. Kingsley et al. (1990) reported problems with detecting ringed seal (*Pusa hispida*) lairs on ice using FLIR that were related to snow depth, ambient temperature, wind, and sunlight. Known polar bear (*Ursus maritimus*) dens were missed in a FLIR survey due to fresh snow, wind, and airborne moisture (Amstrup et al. 2004). Locke et al. (2006) found external temperatures of turkeys and background structure (roost and ground) to be too close, regardless of other weather conditions, which made detecting wild turkeys with FLIR difficult. While these variables could contribute to lower or varied detection rates, we controlled for them by placing sites in similar habitats, aiming all three cameras at the same focal point, and by collecting data at the four sites at the same time.

Manufacturing tolerances of camera components could also contribute to variability in detection rates and could be linked to several sources. The PIR components could have varied in sensitivity, which may have led to variable detection rates. Swann et al. (2004) demonstrated leveling a camera may not align the PIR sensor detection zone perfectly to the area of interest. This misalignment could lead to presumed false detections where an animal is present on site, missed by the camera, but detected by the sensor. Therefore, the direction in which the sensor is facing when mounted inside the camera housing could influence detection rates. Because our intent was to examine performance of the cameras under field conditions, we did not test the aim or sensitivity of PIR sensors in our units; thus, they are plausible explanations for at least some variation we observed. However, we did aim cameras at the same focal point at each site. If our PIR sensors were mounted within the cameras similarly, aim should not have contributed to variability in detection.

Detection rates for individual cameras should be incorporated into population estimation methods to minimize the effects of PIR sensor variability. Failure to account for detection reduces the reliability of estimates. The use of variance inflation factors such as $\hat{c}$ in model selection favors simpler models when model fit is poor, but does not eliminate or reduce the bias in parameter estimates (Burnham and Anderson 2002). An "observer" effect could be included into the models that would account for variability in PIR sensitivity of individual cameras. This method could complicate analyses because a parameter for each camera would be added to the model, potentially increasing amount of data needed to yield reasonable precision. Mixture or random effects models would be more parsimonious than observer effects models and could estimate detection based on groups of cameras with similar rates (Pledger 2000). They also allow for the use of covariates and can be fitted using Program MARK. However, the lack of ability to distinguish among sources of variation is inherent within these models.

Much of the literature that addresses use of trail cameras to estimate population parameters is based on the assumption that a direct relationship exists between the number of images captured over time and density of the species being surveyed (e.g., Jacobson et al. 1997, Main and Richardson 2002, Silveira et al. 2003, McKinley et al. 2006). These approximations do not include measures of detection for individual cameras or for environmental factors. Proper use of mark-recapture methods circumvents these issues; however, for estimating population size, they are particularly sensitive to un-modeled heterogeneity in detection rates (White et al. 1982). Thus, differences in detection rates among cameras must be estimated to avoid biased estimates of population parameters. Swann et al. (2004) explored measuring zones of detection for several models of trail cameras. Rowcliffe et al. (2008) used animal group sizes and movement rates to accurately estimate density of three of four ungulate species. If PIR triggering systems are used for population estimation, identifying these zones of detection for individual cameras and controlling for group size and environmental conditions may reduce the effect of heterogeneity in animal detection caused by PIR sensors (Swann et al. 2004). This identification would in turn reduce bias in population estimates, but could not fully account for large differences in detection among cameras.

Time-lapse systems provide more reliable estimates and require fewer parameters because they eliminate the need to estimate detection rates for individual cameras. With a time-lapse system, the camera captures an image on a fixed interval, irrespective of species presence, location, or environmental conditions. Digital trail cameras have great advantages over 35mm cameras that allow them to function for several weeks in the field and store thousands of images, thus making surveys using a time-lapse triggering system more feasible than in the past. Depending on the time interval, the number of images that must be analyzed could be increased substantially by using time-lapse systems. However, eliminating the effects of PIR sensor variability outweighs this cost because of more parsimonious model selection (fewer parameters and more data) and less biased demographic estimates (less un-modeled variation in detection). Using a time-lapse system would further standardize surveys because they would be performed on a fixed interval. Because of the inherent variability associated with PIR systems, time-lapse systems reduce the potential sources of variation in abundance estimation from repeated count (e.g., Royle et al. 2005) or mark-recapture methods.

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Table 2.1. Number of events triggered by each camera at each site and percentage of images with animals present from a wildlife survey of Conecuh National Forest, summer 2006.

Site	Camera	Total images	% images w/animals
1	1	86	83 %
1	2	49	86 %
1	3	107	93 %
2	4	110	62 %
2	5	98	59 %
2	6	56	34 %
3	7	48	83 %
3	8	6	67 %
3	9	4	50 %
4	10	121	98 %
4	11	26	100 %
4	12	157	97 %

Table 2.2. Comparison of models for estimating detection rates of PIR-activated cameras from Conecuh National Forest, summer 2006. Values for AICc, relative difference in AICc, model probability (*w*), likelihood (Lik), number of parameters in each model (*K*), and deviance (Dev) are shown.

Model	Hypotheses[1]	AICc[2]	Δ[3]	w[4]	Lik[5]	*K*	Dev[6]
p(camera+size)	1,3	1877	0	0.9998	1.00	16	1845
p(camera+threshold)	2,6	1895	18	0.0002	0	13	1868
p(camera)	2	1904	27	0	0	12	1880
p(camera+feathers)	2,4	1905	28	0	0	13	1879
p(camera+feathersize)	2,5	1906	29	0	0	14	1878
p(site+size)	1,3	2126	249	0	0	8	2109
p(site+threshold)	1,6	2142	265	0	0	5	2132
p(site)	1	2151	274	0	0	4	2143
p(site+feathers)	1,4	2152	275	0	0	5	2142
p(site+feathersize)	1,5	2153	276	0	0	6	2141
p(.)	Intercept	2184	307	0	0	1	2182

[1]Indicates hypothesis(es) supported by the model; see text for descriptions.

[2]Akaike's Information Criterion corrected for small sample size.

[3]$AICc_i - \min(AICc)$.

[4] $\exp(-0.5\Delta_i) / \sum_{i=1}^{R} \exp(-0.5\Delta_i)$

[5] $\exp(-0.5\Delta_i)$

[6]-2ln(Lik(model|data))

Figure 2.1. Odds of detection of automated cameras relative to the camera with the highest estimated detection (9) and 95% confidence intervals.

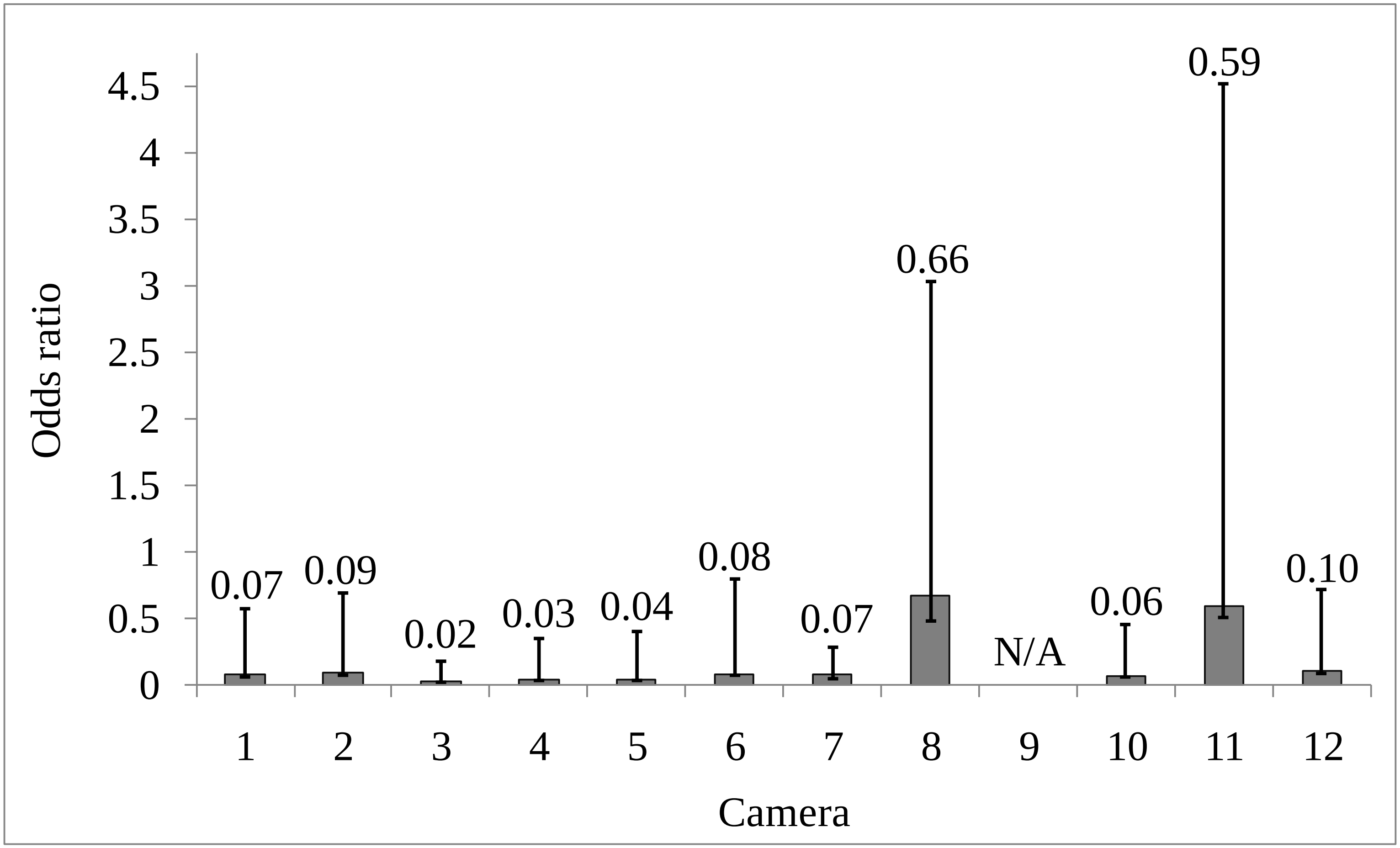
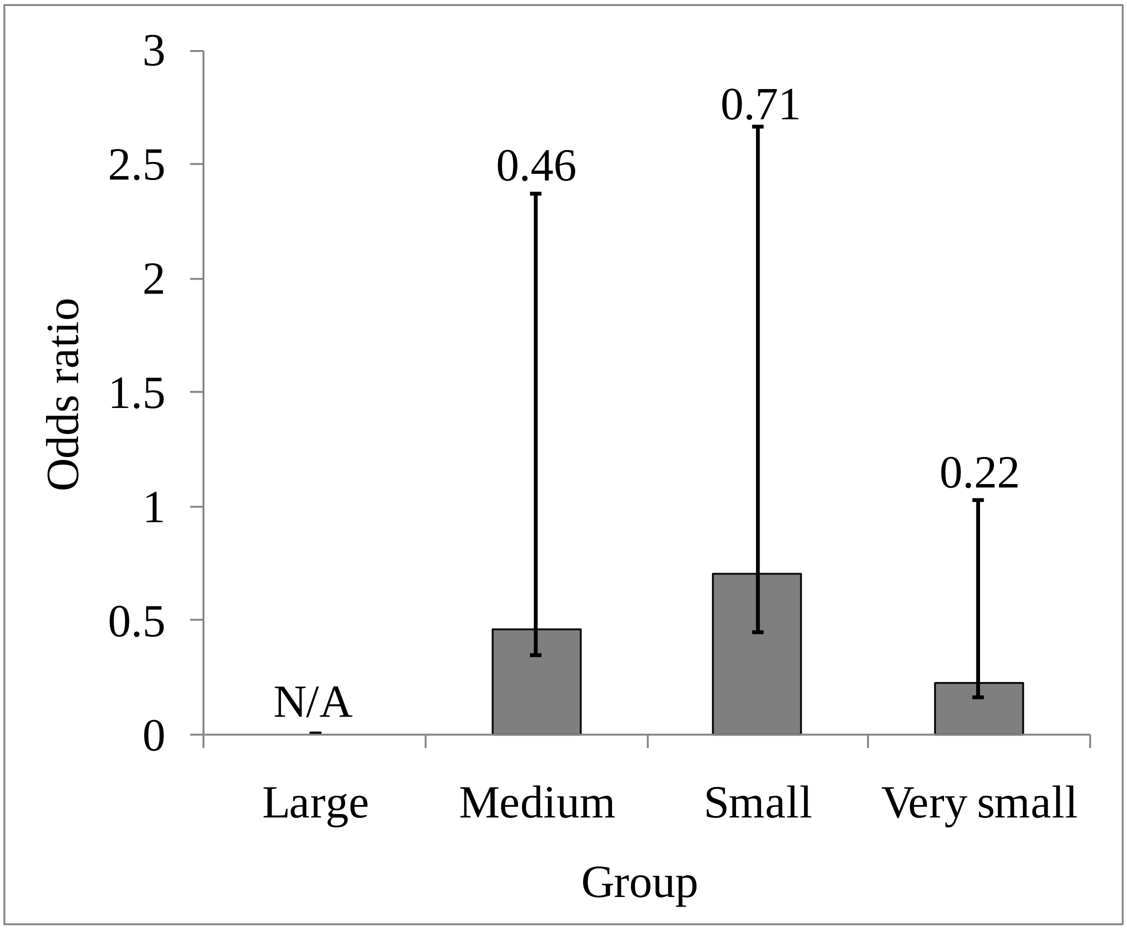


Figure 2.2. Odds of detection relative to the most frequently detected size of animal (large) and 95% confidence intervals.



CHAPTER III: USING TIME-LAPSE CAMERAS TO ESTIMATE ABUNDANCE AND POPULATION STRUCTURE OF EASTERN WILD TURKEYS IN SOUTHWEST ALABAMA

Abstract

Unbiased population size and structure estimates are lacking for wild turkeys (*Meleagris gallopavo*), particularly at large scales and for reasonable costs. Large scale estimates are required when harvest management occurs at the state level. In this study, we estimated abundance, productivity, and age and sex structure of wild turkeys on a larger scale in southwest Alabama using replicated time-lapse trail camera surveys. We determined and estimated important sources of heterogeneity in detection of turkeys related to environmental factors and placement of cameras. We also determined and estimated important sources of heterogeneity in the density and distribution of turkeys related to landscape scale variables. Estimates of density were similar to those found in previous literature in similar habitats. However, in addition to problems associated with extrapolation, model fit was poor for both adult gobblers and poults, which resulted in imprecise estimates. A *post hoc* weighting system was used to reduce effects of extrapolation. After weighting, population estimates were reasonable and comparable to population size gleaned by state biologists. To increase precision, we suggest improving modeling of hypotheses for fitting wild turkey count data. We also suggest modeling alternative density hypotheses to explain extra variation in counts. We believe with

proper survey design, hypotheses modeling, and some additional research, repeated count density models could provide un-biased and precise estimates of wild turkey populations.

Introduction

The southeastern United States contained an abundance of wild turkeys in pre-colonial times (Kennamer et al. 1992). Turkey populations declined to all time lows due to unregulated hunting and timber harvest by the early 1900s (Mosby 1975). Restocking efforts were unsuccessful until the development of the cannon net for capturing wild turkeys (Holbrook 1952). Populations have increased dramatically throughout the remainder of the century (Mosby 1959 and 1975, Bailey 1980, Kennamer and Kennamer 1996, Tapley et al. 2001). Today hunted turkey populations thrive in every state except Alaska, much of the southern Canada, and Mexico. The resurgence of turkey populations has resulted in increased harvest, and questions have arisen as to the sustainability of this harvest. Current population estimation techniques are potentially fraught with bias and too inaccurate for managers to make well-informed management decisions for populations at large spatial scales (e.g. Main and Richardson 2002, McKinley et al. 2006, Jacobson et al. 1997, Silveira et al. 2003).

Poor sampling design can lead to biased estimates from surveys because the counted portion of the population may not be representative of the entire population. Wild turkey surveys have largely been opportunistic and have included roadside counts (Bartush et al. 1985, Cobb et al. 1995), automated camera surveys at bait stations (Cobb et al. 1995), aerial surveys (Locke et al. 2006), roost surveys (Butler et al. 2006), and gobble counts (Lint et al. 1995). Many of these surveys are conducted on public lands, where densities might be quite different from those on private lands. Thus, extrapolating these results to other areas may provide only biased estimates of population size and structure. Variation in detection rates (relationship between the counted and uncounted portions of the population) may bias parameter estimates (MacKenzie et al. 2002), and failure to incorporate detection may lead to underestimation of parameters. Surveys using automated cameras are an increasingly popular tool for estimating population parameters (Rowcliffe and Carbone 2008); however, many surveys fail to incorporate detection rates into estimates. Using passive infrared triggered cameras may introduce additional heterogeneity into estimates of detection, but this issue is eliminated using a time-lapse system (see Chapter I, Damm et al. unpublished).

With an appropriate sampling design and intensity, estimates from time-lapse camera surveys may provide more accurate estimates of wild turkey density at large spatial scales. Estimates of density that account for detection can be obtained from repeated count surveys (Royle 2004), and survey replication across space and time is attainable with time-lapse cameras. With adequate temporal and spatial replications, this approach could be used to minimize bias in estimates of population size and structure of turkeys by modeling heterogeneity in density and detection at landscape scales. With repeated count surveys, uncertainty regarding the sources of heterogeneity can be incorporated using multi-model inference (Burnham and Anderson 2002). Potential sources of variation in counts are modeled from *a priori* hypotheses concerning detection and density. After correcting for differences in detection, estimates of density based on landscape characteristics could be used to estimate populations over large areas (Borchers et al. 2002).

Alabama's population of Eastern wild turkeys (*M. g. sylvesteris*) is approximated at over 500,000 birds by Alabama Department of Conservation and Natural Resources (ADCNR). Harvest averages 62,500 gobblers per year (51,600 combined fall 2007 and spring 2008 gobbler harvest; Barnett and Barnett 2008). Liberal spring hunting seasons and higher bag limits probably have caused increased harvest (Kurzejeski and Vangilder 1992). Current Alabama wild turkey population figures are based on land cover classifications and regional wildlife biologists' knowledge of habitat quality, brood-rearing success, and other factors, while the number of harvested gobblers is estimated through a mail survey (Barnett and Barnett 2008). In reality, the actual size and structure (e.g. sex and age ratios) of the turkey population changes annually and seasonally as a result of variations in reproductive success, availability of suitable habitat, and survival.

Reliable estimates of population demographics such as age and sex structure, productivity, and abundance are especially critical, given the large harvest in Alabama. If harvest is too large or occurs at the wrong time of year, it may have adverse effects on productivity that year in the form of illegal hen kill (Whitaker et al. 2005) and hens potentially not reproducing. Estimating turkey populations is important for evaluating and recommending management practices and in determining future research needs (Kurzejeski and Vangilder 1992). The most recent studies of wild turkeys in Alabama were conducted ~25 years ago. These studies examined both historical and re-stocked turkey populations in southern (Speake et al. 1969, Gardner et al. 1972, Speake et al. 1975, Fleming and Speake 1976, and Speake 1980) and northern (Everett et al. 1978, Everett et al. 1980, Speake 1980, Metzler and Speake 1985, and Speake et al. 1985) Alabama. Information from these studies and others in similar habitats could be used to develop a population model, but estimates of survival, reproductive success, suitable habitat, and harvest rates probably do not represent current conditions. Therefore, a monitoring tool is necessary to improve the accuracy of abundance estimation and reproductive success and for informing decisions regarding harvest rates, habitat management, and conservation.

Information on population demographics has been acquired through indices including transect sampling (Silveira et al. 2003), mark-recapture (Soisalo and Cavalcanti 2006), aerial sampling (Amstrup et al. 2004), and automated camera surveys (Cobb et al. 1995). Methods of automated camera photography for wildlife were first described by Gysel and Davis (1956). Automated camera systems have evolved rapidly since that time and have been used to study avian nest predation (Lehman et al. 2008), foraging ecology (Weckel et al. 2006), nesting behavior (Margalida et al. 2006), activity patterns (Wong et al. 2004), and for estimating population demographics (Soisalo and Cavalcanti 2006, Martorello et al. 2001, Cobb et al. 1995). Using automated cameras in wildlife research is not a new idea; however, technological advances allow for easier data retrieval, longer battery life, increased data storage space, and reduced maintenance (Bolton et al. 2007). These advances allow researchers to obtain larger sample sizes with lower disturbance to surveyed species than were previously possible.

The goal of this research was to develop and test a method for achieving relatively unbiased estimates of population size and structure of wild turkeys at reasonable cost using time-lapse cameras. Our specific objectives were to estimate abundance, productivity, and age and sex structure of wild turkeys on a large scale in southwest Alabama using replicated time-lapse trail camera surveys. We determined and estimated important sources for variation in detection of turkeys in counts related to environmental factors and placement of cameras. We investigated and estimated important sources for variation in density and distribution of turkeys related to landscape scale habitat variables.

Methods

Our study area was located in District V of the ADCNR in southwest Alabama and spanned Choctaw, Clarke, Wilcox, Monroe, Washington, Conecuh, Escambia, Baldwin and Mobile counties (Fig. 1). The majority of the land in the district was privately owned, but was interspersed with relatively small parcels of public land. Most of the area was rural and forested, but also contained agricultural land and other open type habitats such as clear cuts and wildlife openings. The Alabama and Tombigbee Rivers flowed south through the study area, which resulted in corridors of river floodplain hardwoods. The southern portions of Mobile and Baldwin counties consisted of large-scale agriculture and vast urban areas in addition to some inaccessible land (Mobile-Tensaw Delta) and thus were removed from the scope of inference (Fig. 1).

We randomly selected 100 survey points in the study area using a two-stage cluster sample and a geographic information system (GIS). We clustered points to reduce travel time between surveys. The nine-county study area was initially subdivided into square primary units 6084 ha in size for logistical purposes (Fig. 1). A random number generator was used to select twenty primary units and five alternates. Each primary unit was subdivided into secondary units 60.8 ha in size (100 in each primary) to ensure even turkeys with the smallest home ranges had some probability of being counted. Within each of the selected primary units, five secondary units and five alternates were selected at random for surveys (Fig. 2). This number of selected sampling units allowed us to distribute cameras among observers for logistical purposes while achieving our goal of sampling 100 secondary units within a reasonable amount of time.

Land ownership in each sampling unit was determined using county plat maps that contained information regarding property boundaries, parcel size, and landowner names. These maps were compared to digital-ortho-photo quadrangles and land cover of southwest Alabama overlaid with township and range grids to locate survey points and their landowners. Contact information for landowners was researched through county courthouses, phone books, internet, and by visiting landowner residences.

Time-lapse camera field surveys were conducted 7 July through 12 September 2008 by four state-employed biologists and one graduate student. Survey plot centers were located with handheld GPS units using UTM coordinates acquired from our GIS. We arbitrarily selected camera sites within each secondary sampling unit close to plot center and in brood-rearing habitat (e.g. wildlife openings, old fields, low traffic roads, landings, or clearings). Ideal brood-rearing habitat consists of herbaceous vegetative groundcover holding abundant insects interspersed with forest (Porter 1992). At each site, we attached the camera to a tree at least 20-cm DBH, and cleared tall vegetation and overhanging branches within 10m on the north side of the tree to limit camera obstruction. Sites were established so cameras could be aimed north to avoid sun-blurred images. Seven days prior to sampling each site, we pre-baited sites with two gallons of cracked corn, and bait was replenished on the day of deployment if necessary. Bait was broadcast within 3 m directly in front of the camera and was raked into the ground to slow rate of bait consumption. Reconyx PC-85 game cameras (RECONYX, Inc., Holmen, Wisconsin; use of trade names or products does not imply endorsement) were attached on the camera tree and aimed north as close to ground as possible. All cameras operated on time-lapse, captured an image every 4 min, and were retrieved after seven days. Sites were visited a total of three times: 1) pre-baiting; 2) camera deployment; and 3) camera retrieval.

Wild turkeys were counted in each image and divided into age and sex classes using physical characteristics (e.g. plumage, beard and spur length, body size). We categorized individuals into classes of adult gobblers (males at least 2 years old), hens (females at least 1 year old), juvenile gobblers (males 1 year old), poults (young of the year of any age), or unknowns. Birds were classified as unknown if we were unable to determine their sex or age. Computer software limitations forced us to increase survey occasions to one hour instead of using each image as the interval (every 4 min). We used the maximum count for each class in any one image during one-hour intervals for our analysis. Since turkeys are diurnal, only images from between 30 min before sunrise and 30 min after sunset were used. To reduce bias associated with human disturbance during camera deployment, we allowed two-4 min images to lapse before beginning the first one-hour interval beginning after cameras were deployed.

We determined land cover characteristics for each survey point using circular buffers from the 71-class Alabama GAP data (Silvano et al. 2008) using ArcGIS (ESRI, Inc., Redlands, CA; use of trade names or products does not imply endorsement). We pooled these class data into more general groupings for habitat covariates relating to density (Table 3.1). Pooling resulted in six groups: hardwood classes, open pines, open habitat classes, forested classes, developed classes, and monoculture pine classes. We estimated habitat relationships based on the percentage of landcover of each group at two arbitrary scales: the first (100ha) represents the approximate summer home range size of a hen with a small brood (Speake et al. 1975, Porter 1980); the second (1000ha) represents the approximate largest summer home range size of gobbler turkeys (Godwin et al. 1995). We standardized all covariate data by subtracting the mean and dividing by the standard deviation. We grouped similar landcover classes for covariates to represent hypotheses of density (Table 3.2).

We defined detection as the probability of capturing turkeys in images, assuming they are present in the sampling unit, and developed a number of *a priori* hypotheses regarding detection rates.

1. Because camera stations were located in early succession type habitats, we hypothesized that detection would decrease as temperature increased. Hens with poults may select forested areas over open early succession areas to escape in periods of high heat (Rumble and Anderson 1996). As a surrogate for temperature, we modeled detection using time of day and hypothesized detection would be greater in morning and late afternoon when temperatures were lower. Cobb et al. (1995) and Wunz (1990) both found a bimodal activity pattern at bait stations during camera surveys.
2. We hypothesized that detection would increase as more turkeys found the bait station; conversely, we hypothesized detection would decrease as bait was depleted. We modeled these changes in detection using time since camera deployment.

3. We also hypothesized that detection increased with increasing amounts of precipitation, because turkeys move to more open areas during and immediately following rain events, and they spend even more time in openings during and after larger amounts of rainfall (Philip Damm, pers. obs.). Our camera locations were often located in openings likely to be used by broods, so we expected detection to increase with amount of precipitation. Daily precipitation amounts were available from the nearest weather station of the National Oceanic and Atmospheric Association (<http://www.ncdc.noaa.gov/oa/climate/stationlocator.html>; accessed June 2009).
4. We hypothesized detection increased where food resources on the landscape were lacking, and turkeys were more likely to be detected because they relied more heavily on corn bait in these areas.
5. We hypothesized detection varied by the person selecting the camera site (hereafter, observer effect), because each observer could have a different perception of the "best" location to place the camera.
6. We hypothesized detection increased as distance to nearest stream decreased. Sites that are closer to streams (i.e. roost sites) would be visited more frequently than those farther away.
7. We hypothesized detection increases with calendar date for poults. As poults age, their nutritional requirements change from mostly insects to a more diverse diet (Hurst 1992). This diverse diet would lead them to use bait more frequently as they age.

We defined density as the number of turkeys per sampling unit, and developed density hypotheses *a priori*. For models of density, we developed logical combinations of these covariates. For example, we hypothesized that increasing amounts of monoculture pine habitat would make hardwood habitats more important; therefore, we modeled an interaction between area of hardwoods and area of monoculture pine (see hypotheses 1 and 6).

1. We hypothesized that turkey density increased as percentage of hardwoods increased. Hen turkeys prefer roosting in trees near water (Chamberlain et al. 2000, Flake et al. 1996) and in the branches of trees that would grow in such areas (Flake et al. 1996). Turkeys have been observed roosting in bald cypress trees located in standing water (Wilson 2005). Several studies recognized wild turkeys, including hens with broods, used hardwoods as habitat (Phalen et al. 1986, Exum et al. 1987, Miller et al. 1999). We estimated this relationship in two ways. In the first model, we used the percentage of hardwoods through land cover classes. In the second model, we used stream length in meters as a surrogate for available hardwoods in stream bottoms. Stream bottoms are likely to be associated with older stands of hardwoods and better turkey habitat because current silvicultural methods typically avoid harvesting in streamside management zones.
2. We hypothesized density increases as available stream habitat increases. Features of quality brood-rearing habitat may occur near streams (Smith et al. 1990, Stys et al. 1992, Palmer and Hurst 1996). Miller and Conner (2005) and Burk et al. (1990) found all sex and age classes of turkeys use streams.

3. We hypothesized density increases as availability of older, managed (burned and thinned) open canopy pines increase. Both gobbler and hen turkeys select older (>30 years) pine stands as foraging and roosting habitat (Miller et al. 1999). Hens use saw timber sized pine (Chamberlain et al. 2000) and intensively managed pine (Miller and Conner 2007) for foraging. We used the AL GAP open understory longleaf pine as the only measure of open canopy pine forest.
4. We also hypothesized since turkeys have been associated with many forest types, they would be found in similar densities in all of them. Therefore, density increases as the amount of forested habitat types increases.
5. We hypothesized density increased as amount of open habitat types increased. Turkeys forage in these areas for invertebrates and seeds as well as to provide escape cover (Hurst 1981, Hurst and Dickson 1992, Rumble and Anderson 1993, Speake et al. 1975); and these characters are even more applicable to brooding hens (Phalen et al. 1986, Hurst and Dickson 1992, Porter 1992). Also, Miller and Conner (2005) found all turkeys use agriculture fields as a source of food. The open habitat covariate in this model included three classes of shrub/scrub, pasture/hay, and row crop.
6. We hypothesized that density decreased with increasing area of closed canopy pines. Once these pines reach canopy closure, foraging opportunities are limited, which results in lower densities. Exum (1985) reported relatively low turkey density on a commercial pine forest in south Alabama. This hypothesis also stems from personal observation of un-managed (absence of prescribed fire and thinning operations) pine stands in southwest Alabama. Evidence suggests wild

turkeys readily use pine plantations, although proper management (e.g. burning, thinning, etc.) in these stands is critical (Allen et al. 1996). We combined the density of plantation pine and loblolly land cover for the closed canopy pine covariate.

7. Finally, we hypothesized density decreased with increasing amounts of development. Developed areas are either unsuitable as habitat (e.g. impervious surfaces) or contain too much human disturbance for turkeys to inhabit in larger numbers.

We used binomial and Poisson mixture models based on repeated count data to estimate probability of detection, density, and relationships to covariates (Royle 2004). We used a logit link to estimate detection and a log link to estimate density. We compared models using AIC corrected for small sample size (AICc, sample size = number of sites) and model probability (*w*) (Burnham and Anderson 2002). We first compared all detection (*p*) models for each sex and age class of turkey using the average density model ($\lambda(.)$). Then, to reduce the total number of models, only the best approximating detection models were used to compare density models. We calculated effect sizes of model covariates (β) and their standard errors (SE) to determine the importance of landscape characteristics on turkey distributions.

Density was estimated using model-averaging to incorporate uncertainty in model selection (Burnham and Anderson 2002). First we calculated βs for each covariate of density for each secondary sampling unit in the study area. Then, we estimated density for each class using each *a priori* model. These estimates were multiplied by the strength of evidence for each respective model and summed across the sampling units to estimate population size. Finally, we obtained 95% confidence limits on the estimates using the variance on the βs and methods described by Dahiya and Guttman (1982) for a log-normally distributed set of predictions. Due to extreme outliers in poult and adult gobbler sampling unit densities, we weighted each density with the probability of occurrence under a log-normal distribution using the mean and variance from sampled sites (Stein 1956). In doing so, we simply imposed the log-normal distribution as an *a priori* distribution of the study area density estimates. We used the same procedure to weight 95% confidence limits on each sex and age class' density. Productivity was calculated for both weighted and un-weighted estimates by dividing the total number of poults by total number of hens. Sex ratios were calculated similarly, and both juvenile gobblers and adult gobblers were included. Due to time constraints, we did not calculate prediction intervals for productivity and sex ratios.

Results

During the survey period, 5 observers collected 178,952 images at 101 sampling units during the survey period. Turkeys were present in 2,712 (1.5%) of those images. Due to logistical constraints, surveys at 43 sites were less than 7 days. The number of survey occasions (one-hour intervals during daytime) at each site ranged from 47 to 114 ($\bar{x}$ = 93; 7 days = ~91 occasions). Hens were observed in images more frequently (70%) than any other sex or age class, followed distantly by poults (24%; Table 3.3). More hens were counted in images (n = 3,358) than other classes, followed by poults (n = 2,222; Table 3.3). Adult gobblers were conspicuously absent during surveys, both in terms of frequency (n = 279) and count (n = 397, 5%; Table 3.3). Of the surveyed points where turkeys were detected (n = 55), hens were observed at 91% and poults only 39%. Notably, we failed to sex or age 328 turkeys (4% of total count).

Detection model selection

The most parsimonious hen detection model was unequivocal (w = 0.98) and estimated detection based on time of day and amount of daily precipitation (Table 3.4). Detection increased with amount of precipitation, and we found a quartic relationship between detection and time of day (Figure 3). The most parsimonious poult detection model also was unequivocal (w = 0.99) and estimated detection based on time of day and by the person selecting the survey site (Table 3.5). Detection was different for each observer, and we found a quartic relationship between detection and time of day (Figure 4). The most parsimonious juvenile gobbler detection model estimated detection based on time of day and by each observer (Table 3.6). Detection was different for each observer, and we found a quartic relationship between detection and time of day (Figure 5). Time since camera deployment (Figure 6) and amount of daily precipitation also probably are related positively to detection of juvenile gobblers; however, evidence for these models was considerably lower (ΔAICc = 5 and 6, respectively; w = 0.09 and 0.04, respectively). The most parsimonious adult gobbler detection model estimated detection based on time of day and observer (Table 3.7). Detection was different for each observer (one observer did not detect any adult gobblers, so only 4 estimates were possible), and we found a quartic relationship between detection and time of day (Figure 7). Amount of precipitation also affected detection for adult gobblers positively (Figure 8); however, evidence for this model was lower (ΔAICc = 1; w = 0.33), and it did not explain as much variation in detection of our data.

Density model selection

Models of hen density based on land cover within 100ha were more parsimonious than 1000ha models; therefore, 1000ha models were omitted from results tables (Table 3.8). The most parsimonious hen density model estimated decreasing density with increasing area of development (Figure 3.9; Table 3.14), even though it was only slightly better than the model that included the amount of open area. All four models with model probabilities > 0 included the area of development covariate. Although the data provided strong evidence in support of the top four models (ΔAICc $\leq$ 5), adding parameters to area of development only improved model deviance only slightly.

All 100ha landscape buffer models for poults were more parsimonious than 1000ha models; therefore, 1000ha models were omitted from results tables (Table 3.9). The most parsimonious poult density model was unequivocal (w = 1.00) and estimated density by a positive interaction between area of hardwoods and monoculture pines. Both area of hardwoods and monoculture pines had positive relationships to poult density (Figure 10; Table 3.14).

All 100ha landscape buffer models for juvenile gobblers were more parsimonious than 1000ha models; therefore, 1000ha models were omitted from results tables (Table 3.10). Two juvenile gobbler density models were essentially equivocal in terms of evidence; they resulted in identical deviance and AICc and model probabilities were similar. The best model estimated density based on an interaction between length of streams and amount of monoculture pine. Both monoculture pine area (Figure 3.11) and stream length (Figure 3.12) had positive relationships to density, although the estimate of the interaction was negligible (Table 3.14). The second best model estimated density by additive positive relationships of length of streams and area of monoculture pine. While area of open pine was included in this model, the magnitude of the relationship was negligible (Table 3.14; Figure 3.13). Although nine models were at least marginally supported by our data (ΔAICc < 8), model probabilities were negligible (0.01-0.02) for all but the two best models.

Adult gobbler density model selection was more ambiguous than other classes, as the top approximating models included covariates from both 100ha and 1000ha spatial scales (Table 3.11). The top 19 models bore measurable model probabilities although most were negligible (n = 14; w = 0.01 to 0.04). The top two models of density were 1000ha scale and indicated positive relationships for open pines (Figure 14) and length of streams (Figure 15) and a negative relationship for area of development (Figure 16). The relationship of open habitat types to density was negligible (Table 3.14). The difference in model fit between the top two models resulted from differences in *p* model selection; one contained amount of precipitation and the other was the observer effect. The differences in fit of the third and fourth best models also were attributed to differences in *p* model selection. These models were at the 100ha scale and estimated density based on a positive interaction between length of streams and area of monoculture pine (Table 3.14). In both cases, the observer *p* model fit the data better than the amount of precipitation *p* model. While these interaction models were ranked below the top two, they still bore relatively large model probability (*w* = 0.13 and 0.07 v. 0.28 and 0.14).

Population estimates

Both un-weighted and weighted estimates of hen and juvenile gobbler population size (Table 3.13) and density per sampling unit (Table 3.14) appeared plausible; however, 95% CIs were quite wide for both. The width of intervals decreased considerably after weighting, as did the estimates. Estimates of poult and adult gobbler population size and density per sampling unit were unbelievably large prior to weighting, as were 95% confidence intervals. Prior to weighting, sex ratios were unbelievably large, which resulted from large population size estimates of adult gobblers (Table 3.12). Productivity (poults per hen) was believable prior to weighting (4.23), but was quite low after (0.19; Table 3.12). As a measure of performance of our weighting technique, we compared weighted average estimates of density to estimates from the intercept only density model ($\lambda(.)$; Table 3.13).

Discussion

We estimated bimodal detection rates for poults, hens, and juvenile gobblers with peaks near 0900h and 1730h. Similarly, in a study examining relationships of turkeys to clearings, Wunz (1990) found broods used bait at the clearings mostly from 0700h to 0930h and 1300h to 1930h. While attempting to validate a road-based transect survey, Cobb et al. (1995) found peak turkey bait use was 1000h and 1800h. We also fit a quartic model to estimate adult gobbler detection rates, and the greatest detection occurred near 0900h. However, the second peak in detection was estimated to occur after dark, which was probably attributable to poor model fit and could have been an artifact of the quartic model. Adult gobblers may also have preferred roosting adjacent to easily accessible food resources (bait stations).

We observed evidence for differences in detection by observers for poults, juvenile gobblers, and adult gobblers. The effects of observers detecting birds at varying efficiencies during point counts have been shown widely (Cunningham et al. 1999);

however, we have not observed this in the turkey literature. In our case, this effect could be explained by observers' ability to select sites where turkeys were most likely to be counted. Or, some observers might have placed bait stations farther from the sampling unit's center to locate sites where turkeys would be more likely detected, while others might have sacrificed better sites for proximity to the sampling unit's center. Our observers were all considered highly qualified in recognizing turkey habitat, so training was likely not an issue. Differences in site selection by observers would be negligible if camera bait stations were placed precisely at the sampling plot's center, and cameras were all aimed in the same direction. Reasonably, surveying a species having the ability to locate food by olfaction using bait stations at exactly plot center would be feasible. However, for turkey surveys, bait stations must be located where use by turkeys is likely, because they visually locate potential food items (Hurst 1992). Turkey's use of randomly or systematically selected sites would probably be much less frequent, further decreasing detection rates and reducing the precision of density estimates. However, if detection were high enough to use randomly selected sites, bias attributed to bait station placement should not exist.

Even though precipitation data were sparse and potentially inaccurate (daily precipitation amounts were not available as for all areas, and were only available from the nearest weather station), evidence still suggested it affected visitation to bait stations. Surprisingly, estimated detection rates for adult gobblers approached 70% when bait site activity was maximized and amount of daily precipitation was highest. Additionally, daily precipitation levels were associated with greater detection of hens. Turkeys were likely moving to openings (therefore, camera bait stations) immediately following rain events to dry their feathers in the sun (Philip Damm, pers. obs.). Confounding factors causing increased detection in relation to precipitation could have included increased wind speed, weather fronts, and invertebrate activity. Precipitation obviously cannot be controlled for within survey design, but it must be recognized as a potential contributor to variation in turkey detection.

Although turkey densities for all sex and age classes have not previously been estimated across such a relatively large area and variety of conditions, we compared our weighted and un-weighted estimates to some small-scale studies. Our weighted estimate of density for all classes was 6.5/km^2 (95% CI: 2.3-26.0), and our un-weighted estimate was 127.1 /km^2 (95% CI: 1.8-785.0). Speake et al. (1969) determined a turkey population in southeast Alabama reached 4.0/km^2 three years after re-stocking using a "direct count" method. Gardner et al. (1972) estimated 4.8/km^2 after five years for the same population using the same methods. Three areas in southwest Alabama within the spatial extent of our study were estimated ≥12.4 turkeys/km^2 using total counts of separate flocks (Speake et al. 1975). In northwest Florida Cobb et al. (2001) used several mark-recapture estimators to obtain estimates ranging from 1.7 to 19.0/km^2, but most estimates were <10/km^2. In all cases, our un-weighted estimates were greater than other estimates in the literature; however, several of these published estimates were within our 95% confidence limits. Our weighted density estimate was close to most estimates presented in the literature, except for the three sites in southwest Alabama. Our weighted estimate of density for gobblers (0.88/km^2; 95% CI: 0.28-11.5) is comparable to those found on a wildlife management area in Mississippi using mark-recapture methods by Lint et al. (1996); they estimated gobbler densities at 0.3 to 0.7/km^2. Our weighted

($3.7/km^2$; 95% CI: 1.2-4.5) and un-weighted ($5.2/km^2$; 95% CI: 0.77-18.1) hen density estimates were comparable to those found by Weinstein et al. (1995) in Mississippi using mark-recapture methods (0.95 and 3.21/ km^2). We must point out although our results are comparable to literature, methods we used at arriving at our densities were quite different from those presented in literature. Also, aside from mark-recapture studies modeling recapture rates, other studies did not incorporate detection rates into their estimates, which likely led to under-estimates of density.

Our estimates of productivity seemed plausible prior to weighting. Productivity in 2008 for District V using un-weighted and weighted estimates was 4.23 and 0.19 poults per hen, respectively. Estimates were found by Everett et al. (1980) in north Alabama at 1.9, 3.0, and 3.6 poults per hen for three consecutive years. Speake (1980) in southwest Alabama found 0.5-6 poults per hen on an area with predator removals and 0.5-2.5 on a control area over several years. Bartush et al. (1985) found productivity in northwest Florida using road transect surveys for two consecutive years (2.1 and 4.1 poults per hen). In all cases our weighted estimates of productivity were lower than what we found in the literature for the southeast. As in abundance estimation, the size of our study area precludes us from making detailed comparisons to other studies, and as such, productivity varied considerably across the area. We also emphasize estimates from the literature were derived ≥23 years ago. Due to the problems associated with extrapolating our models to non-surveyed sites, poult density estimates for some sites were unbelievably large; therefore, our un-weighted estimate of productivity is probably biased high and definitely lacks precision. Even with great imprecision in poult estimates our mean poult to hen ratio was plausible. That is, the mean ratio across all sites was substantially less than the maximum expected brood size for both weighted and un-weighted estimates.

We compared the average of the weighted and un-weighted estimates of density for all sampling units to the estimate of density from the intercept only model ($\lambda(.)$; Table 3.13) under the assumption that discounting the outliers would not appreciably change the mean of the estimates when models fit well. Both average estimates were similar for hens and juvenile gobblers, the classes where models fit adequately, so we felt the weighting scheme was appropriate. Large site density estimates for poults and gobblers were based on covariate values that were far beyond the range encountered at the locations we sampled. Undoubtedly, a better strategy for sampling turkey densities across the range of values for potential covariates would result in more precision and would eliminate the need for weighting due to extremes. However, these improvements could require a substantially larger number of randomly selected samples, or a less efficient sampling design than the cluster sample we used.

Assumptions

Sometimes, turkeys present in images could not be classified by age and/or sex. We likely underestimated density by not including these individuals in counts, but would rather do so instead of misclassifying individuals. Unknown turkeys occurred 328 times in 208 images (4% of the total number of birds counted, Table 3.3). These observations were limited to three situations. In some instances, distinguishing poults from adult hens based on their size was impossible, or they were partially obscured from view by other turkeys. Additionally, adult gobblers and juvenile gobblers were sometimes difficult to distinguish due to lack of defining beard, spur, or plumage characteristics. The final situation occurred when turkeys were too far from the camera to accurately classify, or when birds were obstructed by vegetation. Without better information on the magnitude of underestimation for each class, we hesitate to speculate the effects these un-classified turkeys have on estimates of population structure.

We used broad land cover class classes derived from Alabama GAP land cover in our analysis to minimize errors resulting from misclassification (Kleiner 2007). For example, development classes were often confused with one another, so we grouped all of these classes into one to eliminate this potential source of error (Table 3.1). However, Alabama GAP landcover classification was based on imagery collected in 1999-2001, while our turkey surveys were conducted in 2008, so potential for error in landcover classification still existed. A recent survey of Alabama's forests from 2000-2005 revealed increases in land area covered by pine plantations resulting from conversions of natural pine forests, oak-pine forests, and agricultural land (Hartsell and Johnson 2009). The survey also revealed decreases in land area covered by oak-hickory and oak-gum forests. From 2000 to 2005, seven of nine counties in District V showed ≥2.5% increases in forested land. One county (Conecuh) showed no change; one (Baldwin) showed a decrease of 5%. Because of intensive forest management practices (e.g. relatively frequent clear-cutting), the distribution of land cover types has also likely changed considerably. More current landcover data is essential for more precisely estimating covariate relationships and populations of turkeys in areas where land use changes are frequent.

Land development could result in diminished habitat for wild turkeys through increases in impervious surface, human disturbance, more localized hunting pressure, etc.

We found hens were negatively associated to amount of developed area. If developed area has increased since GAP data were collected, we likely overestimated hen density. Alabama census data revealed decreases in human populations for seven of nine counties in District V from 2000 to 2006; only Baldwin and Mobile counties increased in population during this time (Trent 2007). These increases probably resulted from development in the southern portions of those counties, which were not included in our scope of inference. So, using population trends as a loose correlate to developed area, in District V, hen density should not be biased as a result of using old land cover data.

An assumption of the repeated-count density estimator is all individuals within a sampling unit have some probability of being counted. Violation of this assumption leads to underestimation of detection, and therefore, density. Camera station placement within the sampling unit (~61ha square) could bias estimates of detection, because individuals whose home ranges did not overlap the bait station may not have had any probability of being counted. Since our sampling unit size was significantly smaller than the home range size of turkeys without young and was about the size of a young brood home range, on average across the landscape all turkeys had some probability of being counted.

Another assumption of the repeated-count density estimator is the number of individuals present at one sampling unit is random and independent of the number of individuals at adjacent sampling units. Since our sampling units were ~61ha and the largest turkey home ranges (gobblers) at this time of year could have been ~1000ha, counting an individual (presumably a gobbler) in one sampling unit and an adjacent sampling unit seemed likely. Since the density of turkeys was explained by differences in habitat associated with covariates, adjacency of sampling units had little to do with correlation in densities. However, because counting individuals in more than one sampling unit was possible, estimates of abundance are probably biased high. We need to determine a method for estimating the magnitude of spatial autocorrelation and incorporating it into estimates of density. Knowledge of home range size of each class of turkeys within our study area would allow for some adjustment of abundance estimates to reflect the magnitude of spatial autocorrelation.

One final assumption of the repeated-count density estimator is the population being surveyed is demographically closed (i.e., no births, deaths, immigration, or emigration). By the second week in July when the surveys began, most poults had aged at least a few weeks, allowing them to surpass the initial high mortality period (no births and few deaths), as Everett et al. (1980) found the majority of poult losses in north Alabama occurred in the first 2 weeks of life, and the latest hatch date was 24 June. Also, adults at this time of year have minimal mortality (Palmer et al. 1993, Vangilder 1995) which reduces potential for bias attributed to changes in adult demographics. Since the study area was so large, we assume emigration was relatively minimal, and immigration should be equal to it where it might occur. Also, we attempted to conduct these counts in a relatively short period of time (~2 months) to minimize effects of violating this assumption.

Recommendations

Modeling detection is important in estimating density as the relationship between the counted and uncounted portions of the population may not be consistent. While detection remains a nuisance parameter and actual estimates are not interpretable, recommendations can be made from results of these exercises in terms of survey design.

Researchers employing time lapse cameras surveys could improve detection rates by concentrating observations during periods of high detection, thus reducing the number images collected. In our case, substantial reductions in the number of images would have allowed us to use each image as a sampling occasion instead of one per hour. More occasions could have increased precision of density estimates through more precise estimates of detection, particularly for adult gobblers where counts were limiting. With any turkey survey method, researchers should observe bait stations during periods of high detection to reduce sampling effort. Survey times should be determined *a priori* and should include a range of times encompassing peaks in detection.

Turkey surveys relying on observers placing cameras and/or bait stations should investigate the effects of station location on detection. In cases where observers are un-familiar with the surveyed species habitat requirements, proper training in site selection might decrease the effect of this potential variability on detection. In addition, observers could be limited in the distance from the sampling unit's center when selecting bait station locations. In any case, all types of demographic surveys employing more than one observer should model attempt to model detection based on observer effects.

We assumed we could adequately model distribution of turkeys using landscape scale habitat data (i.e. GAP landcover), and we raised problems with landcover data as well as potential influences on our estimates. We emphasize the need for updated information at the landscape scale for added precision in both population estimates and habitat associations, particularly when land use changes are frequent. Since turkeys are most likely affected by habitat at ground level, use of spatially explicit data on vegetative structure at that level would be ideal. Recent data on percent canopy closure could provide valuable information from which habitat structure at ground level could be inferred.

A key assumption to any survey is that an appropriate sampling design is employed. As we illustrated, use of bait, placement of bait stations within the sampling units, and sampling unit size may lead to biased estimates of density. We need to determine the potential effects that using bait and bait station placement have on our estimates of density. In addition further examination of sampling unit size is warranted. These potential influences on estimates could be investigated through a study on home ranges, including home range size and spatial fidelity after introduction of bait stations.

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Table 3.1. AL-GAP land cover class (Silvano et al. 2008) aggregations used as covariates of wild turkey density on time-lapse camera surveys in southwest Alabama, summer 2008.

Hardwood
East Gulf Coastal Plain Southern Mesic Slope Forest
East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland-Offsite Hardwood Modifier
East Gulf Coastal Plain Large River Floodplain Forest-Forest Modifier
East Gulf Coastal Plain Small Stream and River Floodplain Forest
Southern Coastal Plain Blackwater River Floodplain Forest
East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods
Southern Coastal Plain Nonriverine Cypress Dome
East Gulf Coastal Plain Large River Floodplain Forest-Herbaceous Modifier
Monoculture pine
Evergreen Plantations
East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland-Loblolly Modifier
Open pine
East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland-Open Understory Modifier

Table 3.1. AL-GAP land cover class (Silvano et al. 2008) aggregations used as covariates of wild turkey density on time-lapse camera surveys in southwest Alabama, summer 2008.

Open
Successional Shrub/Scrub (Clear Cut)
Successional Shrub/Scrub (Utility Swath)
Successional Shrub/Scrub (Other)
Pasture/Hay
Row Crop
Developed
Developed Open Space
Low Intensity Developed
Medium Intensity Developed
High Intensity Developed
Bare Soil
Quarry/Strip Mine/Gravel Pit
Forest
East Gulf Coastal Plain Southern Mesic Slope Forest

Table 3.1. AL-GAP land cover class (Silvano et al. 2008) aggregations used as covariates of wild turkey density on time-lapse camera surveys in southwest Alabama, summer 2008.

East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland-Offsite Hardwood Modifier
East Gulf Coastal Plain Large River Floodplain Forest-Forest Modifier
East Gulf Coastal Plain Small Stream and River Floodplain Forest
Southern Coastal Plain Blackwater River Floodplain Forest
East Gulf Coastal Plain Southern Loblolly-Hardwood Flatwoods
Southern Coastal Plain Nonriverine Cypress Dome
East Gulf Coastal Plain Large River Floodplain Forest-Herbaceous Modifier
Evergreen Plantations
East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland-Loblolly Modifier
East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland-Open Understory Modifier

Table 3.2. List of abbreviations for density (λ) and detection (p) covariates of wild turkey density on time-lapse camera surveys in southwest Alabama, summer 2008. In model selection tables, a ‘2’ after an abbreviation indicates 100ha scale GIS data extraction, and a ‘3’ indicates 1000ha.

	Abbreviation	p covariate	Abbreviation
Open area	open	Time of day (temp.)	TOD
Open pine area	oppine	Amount of precipitation	rain
Hardwood area	hdwd	Time since deployment	TSD
Monoculture pine area	pine	Date	date
Developed area	dev	Distance to stream	strmd
Forest area	allfor	Resource limited	reslim
Stream length	strml	Site selection person	obs

Table 3.3. Uncorrected counts and percentages of wild turkeys separated into sex and age classes from time-lapse camera wild turkey density survey in southwest Alabama, summer 2008.

	Hen	Adult gobbler	Juvenile gobbler	Poult	Unknown	Total
Images with turkeys present	1885	279	557	645	208	2712
Total individuals counted	3358	397	1354	2222	328	7659
Percent of sites turkeys where counted (n = 101)	51%	13%	20%	22%	31%	56%

Table 3.4. Comparison of detection (*p*) models for wild turkey hen abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance are shown (Dev).

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(.) *p*(TOD+rain)	5698	0	0.98	1.00	7	5682
λ(.) *p*(TOD+strmd)	5707	9	0.01	0.01	7	5692
λ(.) *p*(TOD)	5708	10	0	0	6	5696
λ(.) *p*(TOD+reslim)	5709	11	0	0	7	5694
λ(.) *p*(TOD+TSD)	5710	12	0	0	7	5695
λ(.) *p*(TOD+obs)	5710	12	0	0	10	5687
λ(.) *p*(TOD+date)	5710	12	0	0	7	5695
λ(.) *p*(.)	5863	165	0	0	2	5859

Table 3.5. Comparison of detection (p) models for wild turkey poult abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (w), model likelihood (Lik), number of estimable parameters (K), and deviance (Dev) are shown.

Model	AICc	ΔAICc	w	Lik	K	Dev
λ(.) p(TOD+obs)	4689	0	0.99	1.00	10	4666
λ(.) p(TOD+rain)	4699	10	0.01	0.01	7	4684
λ(.) p(TOD+strmd)	4702	13	0	0	7	4687
λ(.) p(TOD+reslim)	4702	13	0	0	7	4687
λ(.) p(TOD+TSD)	4703	14	0	0	7	4688
λ(.) p(TOD)	4707	18	0	0	6	4694
λ(.) p(TOD+date)	4709	20	0	0	7	4694

Table 3.6. Comparison of detection (p) models for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (w), model likelihood (Lik), number of estimable parameters (K), and deviance (Dev) are shown.

Model	AICc	ΔAICc	w	Lik	K	Dev
λ(.) *p*(TOD+obs)	2195	0	0.87	1.00	10	2173
λ(.) *p*(TOD+TSD)	2200	5	0.09	0.10	7	2184
λ(.) *p*(TOD+rain)	2201	6	0.04	0.05	7	2186
λ(.) *p*(TOD)	2206	11	0	0	6	2193
λ(.) *p*(TOD+strmd)	2208	13	0	0	7	2193
λ(.) *p*(TOD+reslim)	2208	13	0	0	7	2193
λ(.) *p*(.)	2289	94	0	0	2	2285

Table 3.7. Comparison of detection (p) models for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (w), model likelihood (Lik), number of estimable parameters (K), and deviance (Dev) are shown.

Model	AICc	ΔAICc	w	Lik	K	Dev
λ(.) *p*(TOD+obs)	890	0	0.67	1.00	10	868
λ(.) *p*(TOD+rain)	892	2	0.33	0.50	7	877
λ(.) *p*(TOD)	908	18	0.00	0.00	6	895
λ(.) *p*(TOD+reslim)	909	19	0.00	0.00	7	893
λ(.) *p*(TOD+TSD)	909	19	0.00	0.00	7	894
λ(.) *p*(TOD+strmd)	909	19	0.00	0.00	7	894
λ(.) *p*(.)	930	40	0.00	0.00	2	926

Table 3.8. Comparison of density (λ) and detection (*p*) models for wild turkey hen abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance are shown (Dev). Only the "best" *p* model was used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(dev2) *p*(TOD+rain)	5669	0	0.52	1.00	8	5651
λ(dev2+open2) *p*(TOD+rain)	5670	1	0.39	0.74	9	5650
λ(dev2+strml2+oppine2+open2) *p*(TOD+rain)	5674	5	0.05	0.10	11	5649
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+rain)	5674	5	0.04	0.07	11	5649
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+rain)	5696	27	0	0	10	5674
λ(.) *p*(TOD+rain)	5698	29	0	0	7	5682
λ(open2) *p*(TOD+rain)	5698	29	0	0	8	5681
λ(strml2+pine2+strml2*pine2) *p*(TOD+rain)	5698	29	0	0	10	5676
λ(allfor2) *p*(TOD+rain)	5699	30	0	0	8	5682
λ(hdwd2+oppine2+pine2) *p*(TOD+rain)	5700	31	0	0	10	5678
λ(allfor2+open2) *p*(TOD+rain)	5700	31	0	0	9	5680
λ(hdwd2+oppine2) *p*(TOD+rain)	5701	32	0	0	9	5681
λ(strml2+oppine2) *p*(TOD+rain)	5702	33	0	0	9	5682
λ(hdwd2+oppine2+open2) *p*(TOD+rain)	5703	34	0	0	10	5680

Table 3.8. Comparison of density (λ) and detection (*p*) models for wild turkey hen abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance are shown (Dev). Only the "best" *p* model was used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(open2+pine2+open2*pine2) *p*(TOD+rain)	5703	34	0	0	10	5680
λ(strml2+oppine2+open2) *p*(TOD+rain)	5703	34	0	0	10	5680
λ(strml2+oppine2+pine2) *p*(TOD+rain)	5704	35	0	0	10	5681

Table 3.9. Comparison of density (λ) and detection (*p*) models for wild turkey poult abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood, number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* model was used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+obs)	4606	0	1.00	1.00	13	4576
λ(dev2+strml2+oppine2+open2) *p*(TOD+obs)	4651	45	0	0	14	4618
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+obs)	4651	45	0	0	14	4618
λ(dev2+open2) *p*(TOD+obs)	4654	48	0	0	12	4626
λ(dev2) *p*(TOD+obs)	4655	49	0	0	11	4630
λ(hdwd2+oppine2+pine2) *p*(TOD+obs)	4672	66	0	0	13	4642
λ(hdwd2+oppine2) *p*(TOD+obs)	4672	66	0	0	12	4645
λ(hdwd2+oppine2+open2) *p*(TOD+obs)	4675	69	0	0	13	4645
λ(open2+pine2+open2*pine2) *p*(TOD+obs)	4681	75	0	0	13	4651
λ(strml2+oppine2+open2) *p*(TOD+obs)	4682	76	0	0	13	4652
λ(strml2+oppine2) *p*(TOD+obs)	4683	77	0	0	12	4656
λ(strml2+oppine2+pine2) *p*(TOD+obs)	4686	80	0	0	13	4656
λ(open2) *p*(TOD+obs)	4687	81	0	0	11	4662

Table 3.9. Comparison of density (λ) and detection (*p*) models for wild turkey poult abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood, number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* model was used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(.) *p*(TOD+obs)	4689	83	0	0	10	4666
λ(strml2+pine2+strml2*pine2) *p*(TOD+obs)	4689	83	0	0	13	4659
λ(allfor2+open2) *p*(TOD+obs)	4689	83	0	0	12	4662
λ(allfor2) *p*(TOD+obs)	4690	84	0	0	11	4665

Table 3.10. Comparison of density (λ) and detection (*p*) models for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(strml2+pine2+strml2*pine2) p(TOD+obs)	2172	0	0.45	1.00	13	2142
λ(strml2+oppine2+pine2) *p*(TOD+obs)	2172	0	0.38	0.85	13	2142
λ(strml2+pine2+strml2*pine2) *p*(TOD+TSD)	2178	6	0.02	0.05	10	2155
λ(dev2+strml2+oppine2+open2) *p*(TOD+obs)	2178	6	0.02	0.05	14	2145
λ(strml2+oppine2+pine2) *p*(TOD+TSD)	2178	6	0.02	0.05	10	2156
λ(strml2+oppine2+open2) *p*(TOD+obs)	2178	6	0.02	0.04	13	2148
λ(strml2+pine2+strml2*pine2) *p*(TOD+rain)	2178	6	0.02	0.04	10	2156
λ(strml2+oppine2) *p*(TOD+obs)	2178	6	0.02	0.04	12	2151
λ(strml2+oppine2+pine2) *p*(TOD+rain)	2179	7	0.02	0.04	10	2156
λ(dev2+strml2+oppine2+open2) *p*(TOD+TSD)	2179	7	0.01	0.03	11	2154
λ(dev2+strml2+oppine2+open2) *p*(TOD+rain)	2180	8	0.01	0.02	11	2155
λ(strml2+oppine2+open2) *p*(TOD+TSD)	2181	9	0	0.01	10	2159
λ(strml2+oppine2+open2) *p*(TOD+rain)	2182	10	0	0.01	10	2159
λ(strml2+oppine2) *p*(TOD+TSD)	2182	10	0	0.01	9	2162

Table 3.10. Comparison of density (λ) and detection (*p*) models for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(open2+pine2+open2*pine2) *p*(TOD+obs)	2182	10	0	0.01	13	2151
λ(strml2+oppine2) *p*(TOD+rain)	2182	10	0	0.01	9	2162
λ(allfor2) *p*(TOD+obs)	2185	13	0	0	11	2160
λ(allfor2+open2) *p*(TOD+obs)	2186	14	0	0	12	2158
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+obs)	2186	14	0	0	14	2153
λ(open2+pine2+open2*pine2) *p*(TOD+TSD)	2190	18	0	0	10	2167
λ(dev2) *p*(TOD+obs)	2191	19	0	0	11	2166
λ(dev2+open2) *p*(TOD+obs)	2191	19	0	0	12	2163
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+TSD)	2191	19	0	0	11	2166
λ(open2+pine2+open2*pine2) *p*(TOD+rain)	2191	19	0	0	10	2169
λ(hdwd2+oppine2) *p*(TOD+obs)	2191	19	0	0	12	2164
λ(allfor2) *p*(TOD+TSD)	2192	20	0	0	8	2174
λ(allfor2+open2) *p*(TOD+TSD)	2192	20	0	0	9	2172
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+rain)	2192	20	0	0	11	2167

Table 3.10. Comparison of density (λ) and detection (*p*) models for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(allfor2) *p*(TOD+rain)	2194	22	0	0	8	2176
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+obs)	2194	22	0	0	13	2164
λ(hdwd2+oppine2+pine2) *p*(TOD+obs)	2194	22	0	0	13	2164
λ(allfor2+open2) *p*(TOD+rain)	2194	22	0	0	9	2174
λ(dev2+open2) *p*(TOD+TSD)	2194	22	0	0	9	2174
λ(hdwd2+oppine2+open2) *p*(TOD+obs)	2194	22	0	0	13	2164
λ(dev2) *p*(TOD+TSD)	2194	22	0	0	8	2177
λ(.) *p*(TOD+obs)	2195	23	0	0	10	2173
λ(dev2+open2) *p*(TOD+rain)	2195	23	0	0	9	2175
λ(dev2) *p*(TOD+rain)	2196	24	0	0	8	2178
λ(open2) *p*(TOD+obs)	2196	24	0	0	11	2171
λ(hdwd2+oppine2) *p*(TOD+TSD)	2198	26	0	0	9	2178
λ(hdwd2+oppine2) *p*(TOD+rain)	2199	27	0	0	9	2179
λ(.) *p*(TOD+TSD)	2200	28	0	0	7	2184

Table 3.10. Comparison of density (λ) and detection (*p*) models for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(open2) *p*(TOD+TSD)	2200	28	0	0	8	2182
λ(hdwd2+oppine2+open2) *p*(TOD+TSD)	2200	28	0	0	10	2178
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+TSD)	2200	28	0	0	10	2178
λ(hdwd2+oppine2+pine2) *p*(TOD+TSD)	2201	29	0	0	10	2178
λ(.) *p*(TOD+rain)	2201	29	0	0	7	2186
λ(open2) *p*(TOD+rain)	2201	29	0	0	8	2184
λ(hdwd2+oppine2+open2) *p*(TOD+rain)	2202	30	0	0	10	2179
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+rain)	2202	30	0	0	10	2179
λ(hdwd2+oppine2+pine2) *p*(TOD+rain)	2202	30	0	0	10	2179

Table 3.11. Comparison of density (λ) and detection (*p*) models for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(dev3+strml3+oppine3+open3) *p*(TOD+obs)	875	0	0.28	1.00	14	842
λ(dev3+strml3+oppine3+open3) *p*(TOD+rain)	876	1	0.14	0.51	11	851
λ(strml2+pine2+strml2*pine2) *p*(TOD+obs)	877	2	0.13	0.47	12	846
λ(strml2+pine2+strml2*pine2) *p*(TOD+rain)	878	3	0.07	0.25	9	855
λ(dev2+strml2+oppine2+open2) *p*(TOD+obs)	878	3	0.06	0.23	14	845
λ(dev2) *p*(TOD+obs)	879	4	0.04	0.15	11	854
λ(dev3+hdwd3+oppine3+open3) *p*(TOD+rain)	879	4	0.04	0.13	11	854
λ(dev2+open2) *p*(TOD+obs)	879	4	0.03	0.12	12	852
λ(strml2+oppine2+pine2) *p*(TOD+rain)	880	5	0.03	0.10	10	857
λ(dev3+hdwd3+oppine3+open3) *p*(TOD+obs)	880	5	0.03	0.10	14	847
λ(strml3+oppine3) *p*(TOD+obs)	880	5	0.03	0.09	12	852
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+obs)	880	5	0.02	0.09	14	847
λ(strml2+oppine2+pine2) *p*(TOD+obs)	880	5	0.02	0.08	13	850
λ(strml3+oppine3) *p*(TOD+rain)	881	6	0.01	0.05	9	861

Table 3.11. Comparison of density (λ) and detection (*p*) models for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(dev2+strml2+oppine2+open2) *p*(TOD+rain)	881	6	0.01	0.04	11	856
λ(dev3) *p*(TOD+obs)	882	7	0.01	0.04	11	857
λ(strml3+oppine3+open3) *p*(TOD+obs)	882	7	0.01	0.03	13	852
λ(dev2+hdwd2+oppine2+open2) *p*(TOD+rain)	882	7	0.01	0.03	11	857
λ(strml3+oppine3+pine3) *p*(TOD+obs)	882	7	0.01	0.03	13	852
λ(dev2+open2) *p*(TOD+rain)	883	8	0	0.02	9	863
λ(strml3+oppine3+open3) *p*(TOD+rain)	883	8	0	0.02	10	861
λ(dev2) *p*(TOD+rain)	883	8	0	0.02	8	866
λ(strml3+oppine3+pine3) *p*(TOD+rain)	883	8	0	0.01	10	861
λ(dev3+open3) *p*(TOD+obs)	884	9	0	0.01	12	857
λ(dev3) *p*(TOD+rain)	885	10	0	0.01	8	867
λ(hdwd3+oppine3) *p*(TOD+rain)	886	11	0	0	9	866
λ(strml2+oppine2) *p*(TOD+obs)	886	11	0	0	12	858
λ(allfor3+open3) *p*(TOD+obs)	887	12	0	0	12	859

Table 3.11. Comparison of density (λ) and detection (*p*) models for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(hdwd3+oppine3) *p*(TOD+obs)	887	12	0	0	12	859
λ(strml2+oppine2+open2) *p*(TOD+obs)	887	12	0	0	13	857
λ(dev3+open3) *p*(TOD+rain)	887	12	0	0	9	867
λ(strml2+oppine2+open2) *p*(TOD+rain)	888	13	0	0	10	865
λ(hdwd3+oppine3+open3) *p*(TOD+rain)	888	13	0	0	10	865
λ(strml2+oppine2) *p*(TOD+rain)	888	13	0	0	9	868
λ(hdwd3+oppine3+pine3) *p*(TOD+rain)	888	13	0	0	10	866
λ(strml3+pine3+strml3*pine3) *p*(TOD+obs)	888	13	0	0	13	858
λ(allfor3+open3) *p*(TOD+rain)	889	14	0	0	9	869
λ(hdwd3+oppine3+open3) *p*(TOD+obs)	889	14	0	0	13	859
λ(hdwd3+oppine3+pine3) *p*(TOD+obs)	890	15	0	0	13	859
λ(strml3+pine3+strml3*pine3) *p*(TOD+rain)	890	15	0	0	10	867
λ(.) *p*(TOD+obs)	890	15	0	0	10	868
λ(open2) *p*(TOD+obs)	891	16	0	0	11	866

Table 3.11. Comparison of density (λ) and detection (*p*) models for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(open2) *p*(TOD+rain)	891	16	0	0	8	873
λ(allfor2) *p*(TOD+obs)	891	16	0	0	11	866
λ(allfor2+open2) *p*(TOD+obs)	892	17	0	0	12	864
λ(.) *p*(TOD+rain)	892	17	0	0	7	877
λ(allfor3) *p*(TOD+obs)	892	17	0	0	11	867
λ(allfor2+open2) *p*(TOD+rain)	892	17	0	0	9	872
λ(allfor2) *p*(TOD+rain)	893	18	0	0	8	875
λ(hdwd2+oppine2+open2) *p*(TOD+rain)	893	18	0	0	10	870
λ(open2+pine2+open2*pine2) *p*(TOD+rain)	893	18	0	0	10	870
λ(open3) *p*(TOD+obs)	893	18	0	0	11	868
λ(hdwd2+oppine2+pine2) *p*(TOD+obs)	893	18	0	0	13	863
λ(hdwd2+oppine2+pine2) *p*(TOD+rain)	893	18	0	0	9	870
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+rain)	893	18	0	0	10	871
λ(allfor3) *p*(TOD+rain)	893	18	0	0	8	876

Table 3.11. Comparison of density (λ) and detection (*p*) models for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008. For each model, values for bias corrected AIC, relative difference in AICc, model probability (*w*), model likelihood (Lik), number of estimable parameters (*K*), and deviance (Dev) are shown. Only the "best" *p* models were used for λ model comparisons.

Model	AICc	ΔAICc	*w*	Lik	*K*	Dev
λ(hdwd2+pine2+hdwd2*pine2) *p*(TOD+obs)	893	18	0	0	13	863
λ(open2+pine2+open2*pine2) *p*(TOD+obs)	894	19	0	0	13	864
λ(hdwd2+oppine2+open2) *p*(TOD+obs)	894	19	0	0	13	864
λ(open3) *p*(TOD+rain)	894	19	0	0	8	877
λ(hdwd2+oppine2) *p*(TOD+obs)	895	20	0	0	12	867
λ(open3+pine3+open3*pine3) *p*(TOD+obs)	896	21	0	0	13	865
λ(hdwd2+oppine2) *p*(TOD+rain)	896	21	0	0	9	876
λ(open3+pine3+open3*pine3) *p*(TOD+rain)	897	22	0	0	9	874
λ(hdwd3+pine3+hdwd3*pine3) *p*(TOD+obs)	897	22	0	0	13	867
λ(hdwd3+pine3+hdwd3*pine3) *p*(TOD+rain)	898	23	0	0	10	876

Table 3.12. Un-weighted and weighted estimates of wild turkey abundance, sex ratio, and productivity and 95% confidence intervals by sex and age class for the scope of inference of a time-lapse camera survey in southwest Alabama, summer 2008.

Class	Un-weighted	95% LCL	95% UCL	Weighted	95% LCL	95% UCL
Poult	384,345	13,825	2,080,844	12,042	1,271	55,475
Hen	90,885	13,637	318,034	64,735	21,301	79,894
Juvenile gobbler	45,738	2,375	235,217	21,407	13,529	119,293
Adult Gobbler	1,718,817	1,755	11,193,292	15,569	4,880	203,216
Total	2,239,785	31,592	13,827,388	113,753	40,785	457,878
Gobblers/hen	19.4			0.57		
Poults/hen	4.23			0.19		

Table 3.13. Un-weighted, weighted, and intercept only model estimates of wild turkey sampling unit density (per 60.8 ha) and 95% confidence intervals by sex and age class from a time-lapse camera survey in southwest Alabama, summer 2008. Un-weighted and weighted estimates are average densities from the distribution of all potential sampling units.

Class	Weighted	95% LCL	95% UCL	Un-weighted	95% LCL	95% UCL	λ(.) model	SE
Poult	0.39	0.04	1.82	12.60	0.45	68.22	1.8	1.09
Hen	2.12	0.70	2.62	2.98	0.45	10.43	2.26	1.08
Juvenile gobbler	0.70	0.44	3.91	1.50	0.08	7.71	0.72	1.14
Adult Gobbler	0.51	0.16	6.66	56.35	0.06	366.99	0.37	1.22
Total	3.73	1.34	15.01	73.44	1.04	453.36		

Table 3.14. Relationship to log density (β) and variances (σ^2) for density covariates by wild turkey sex and age class from a time-lapse camera survey in southwest Alabama, summer 2008. Betas were averaged across models using model probabilities. Covariates with suffix '2' were extracted using 100ha circular buffers, and those with suffix '3' were 1000ha.

Covariate by class	β	σ^2
Hen		
Developed area2	-0.413	0.009
Hardwood area2	0.029	0.003
Hardwood area2 x monoculture pine area2	3.32e-07	4.56e-13
Forest area2	1.14e-08	9.35e-16
Intercept	0.729	0.019
Open area2	-0.046	0.004
Open area2 x monoculture pine area2	6.78e-10	6.25e-18
Open pine area2	0.001	6.33e-05
Monoculture pine area2	1.38e-07	9.103e-14
Stream length2	-0.003	6.74e-05
Stream length2 x monoculture pine area2	5.74e-08	1.43e-14
Poult		
Developed area2	-1.48e-10	1.27e-19
Hardwood area2	0.116	0.010
Hardwood area2 x monoculture pine area2	-0.621	0.031
Forest area2	1.47e-19	1.27e-37
Intercept	3.151	0.115
Open area2	-6.02e-11	1.80e-20
Open area2 x monoculture pine area2	-1.00e-17	4.47e-34
Open pine area2	-8.95e-11	3.62e-20
Monoculture pine area2	0.451	0.010
Stream length2	-3.25e-11	4.97e-21
Stream length2 x monoculture pine area2	-3.34e-19	4.96e-37
Juvenile gobbler		
Developed area2	-0.011	0.001

Table 3.14. Relationship to log density (β) and variances (σ^2) for density covariates by wild turkey sex and age class from a time-lapse camera survey in southwest Alabama, summer 2008. Betas were averaged across models using model probabilities. Covariates with suffix '2' were extracted using 100ha circular buffers, and those with suffix '3' were 1000ha.

Covariate by class	β	σ^2
Hardwood area2	0.000	1.77e-07
Hardwood area2 x monoculture pine area2	-2.31e-06	3.08e-11
Forest area2	0.001	1.36e-06
Intercept	-0.534	0.024
Open area2	0.016	0.001
Open area2 x monoculture pine area2	-0.001	8.10e-06
Open pine area2	0.192	0.052
Monoculture pine area2	0.505	0.053
Stream length2	0.321	0.130
Stream length2 x monoculture pine area2	0.057	0.015
Adult Gobbler		
Developed area2	-0.146	0.062
Developed area3	-0.357	0.232
Hardwood area2	-0.040	0.006
Hardwood area2 x monoculture pine area2	-0.002	9.88e-06
Hardwood area3	-0.091	0.031
Hardwood area3 x monoculture pine area3	-6.55e-06	1.75e-10
Forest area2	6.18e-05	1.99e-08
Forest area3	0.004	6.55e-05
Intercept	-1.346	0.103
Open area2	-0.046	0.008
Open area2 x monoculture pine area2	-2.05e-06	1.78e-10
Open area3	0.005	0.012
Open area3 x monoculture pine area3	4.44e-06	9.78e-11
Open pine area2	0.031	0.007
Open pine area3	0.357	0.135

Table 3.14. Relationship to log density (β) and variances (σ^2) for density covariates by wild turkey sex and age class from a time-lapse camera survey in southwest Alabama, summer 2008. Betas were averaged across models using model probabilities. Covariates with suffix '2' were extracted using 100ha circular buffers, and those with suffix '3' were 1000ha.

Covariate by class	β	σ^2
Monoculture pine area2	0.159	0.063
Monoculture pine area3	0.006	0.000
Stream length2	0.049	0.026
Stream length2 x monoculture pine area2	0.129	0.050
Stream length3	0.197	0.054
Stream length3 x monoculture pine area3	0.000	1.31e-07

Figure 3.1. Study area covering 9 counties in southwest Alabama showing the distribution of primary sampling units used for clustering time-lapse camera surveys for estimating abundance of wild turkeys, summer 2008. Shaded units were used first, and diagonal-hatched units were used as alternates.

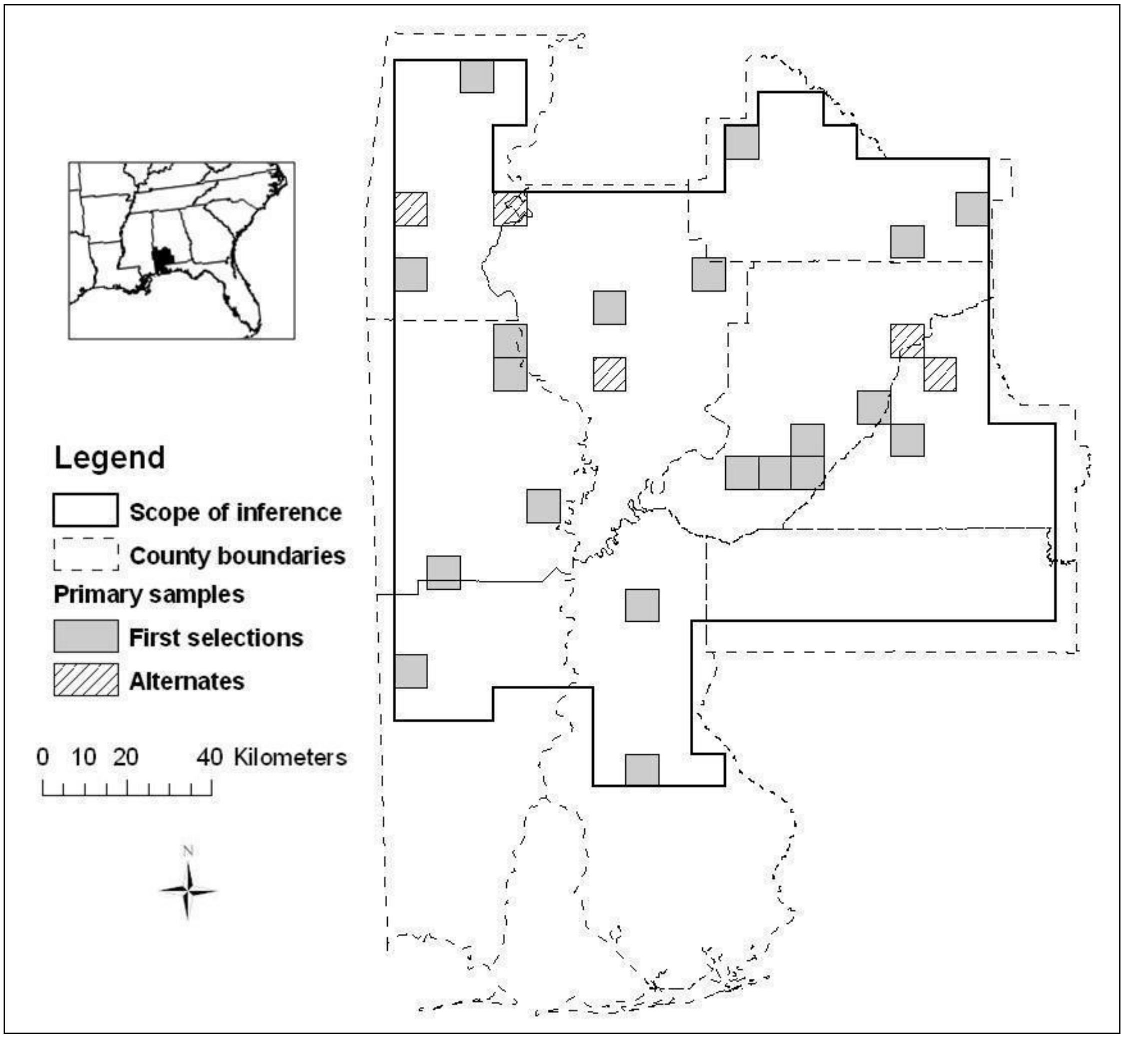


Figure 3.2. Example of a cluster of secondary sampling units from a wild turkey survey to estimate abundance using time-lapse cameras in southwest Alabama, summer 2008. Primary sampling units consisted of 10 randomly chosen square secondary sampling unit (60.8 ha). Units indicated with solid lines were used first, and those indicated with dashed lines were used as alternates.

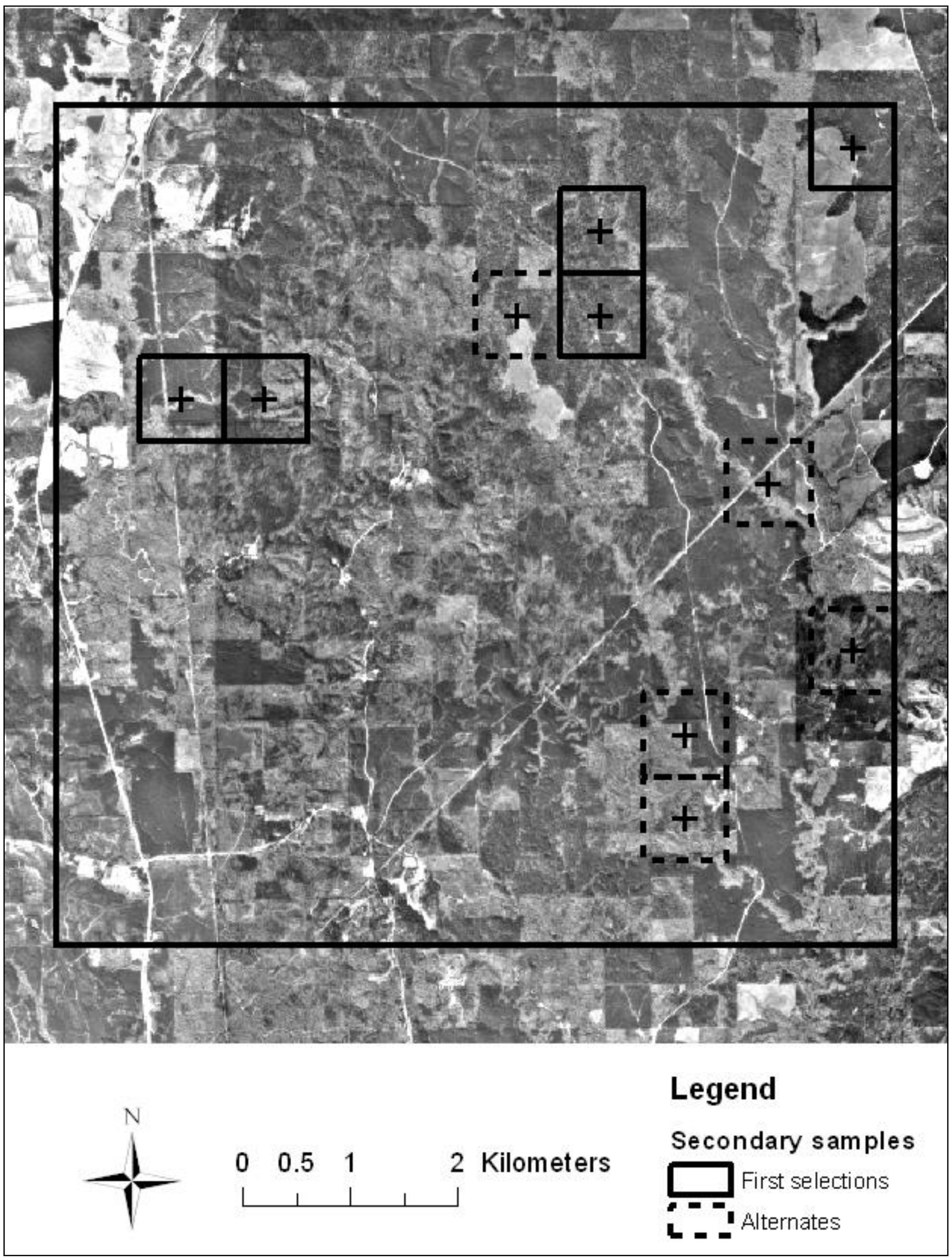


Figure 3.3. Relationships among time of day and daily rainfall, and detection for wild turkey hen abundance estimation using time-lapse cameras in southwest Alabama, summer 2008.

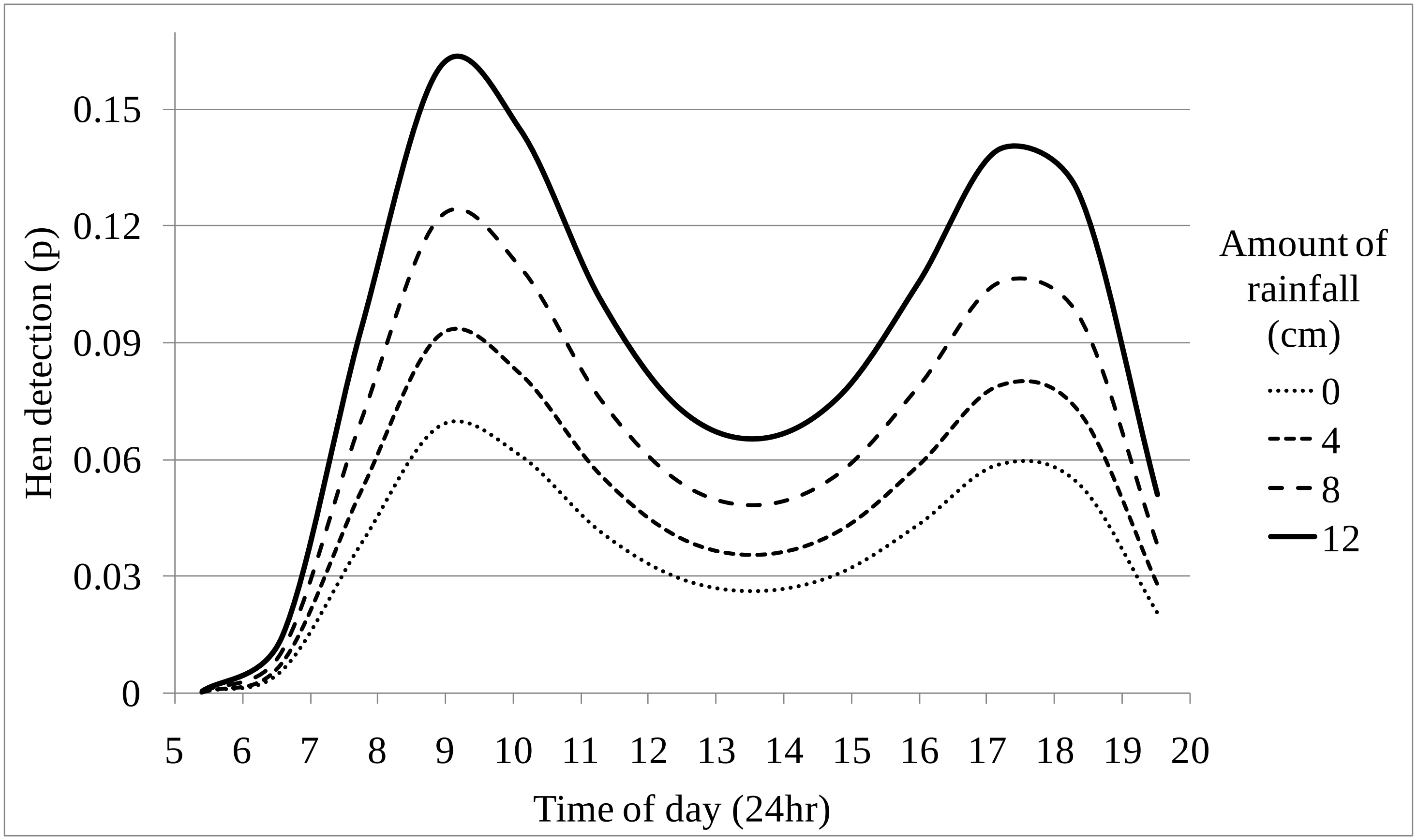


Figure 3.4. Relationships among time of day, observer, and detection for wild turkey poult abundance estimation using time-lapse cameras in southwest Alabama, summer 2008.

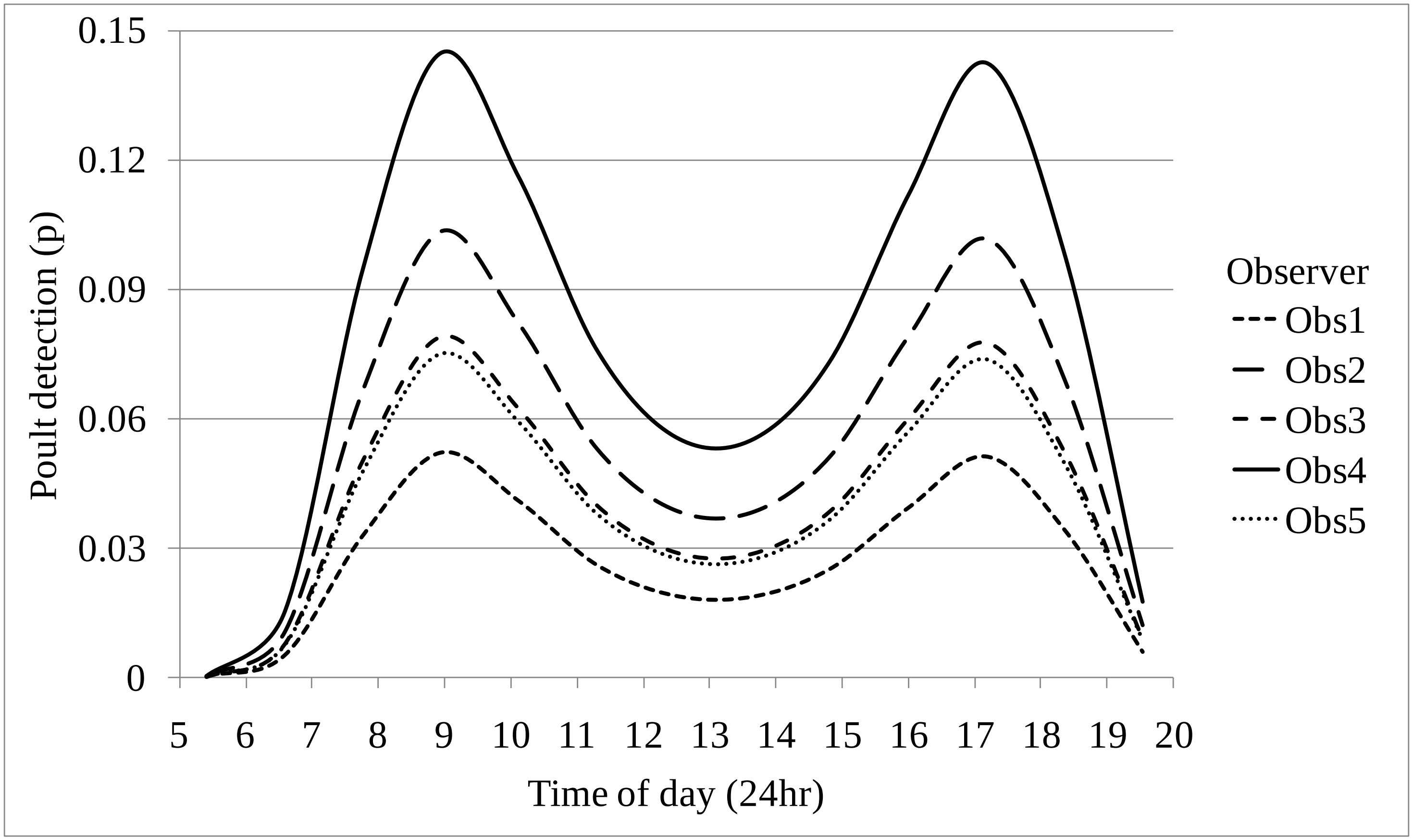


Figure 3.5. Relationships among time of day, observer, and detection for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008.

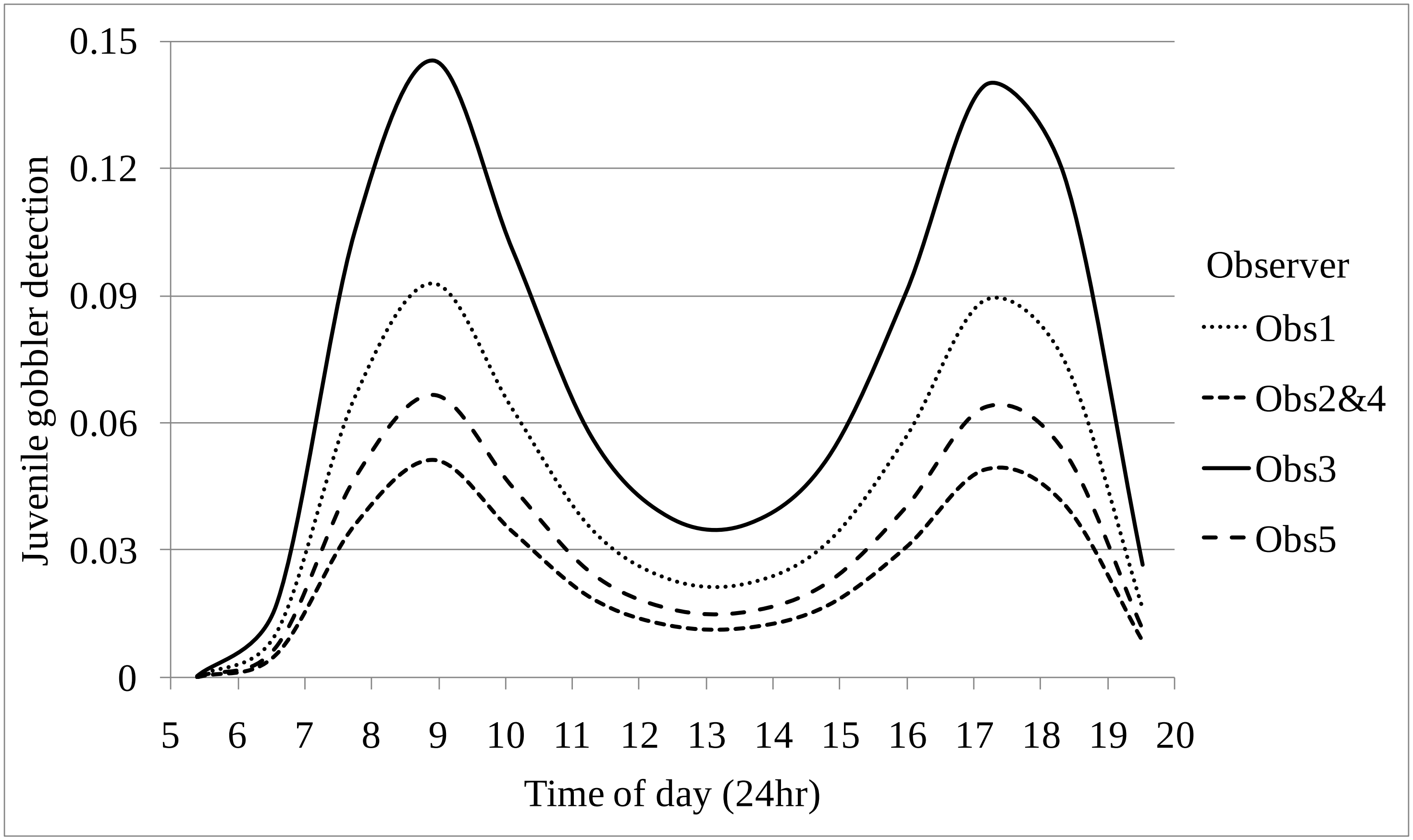


Figure 3.6. Relationships among time of day, time since camera deployment, and detection for wild turkey juvenile gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008.

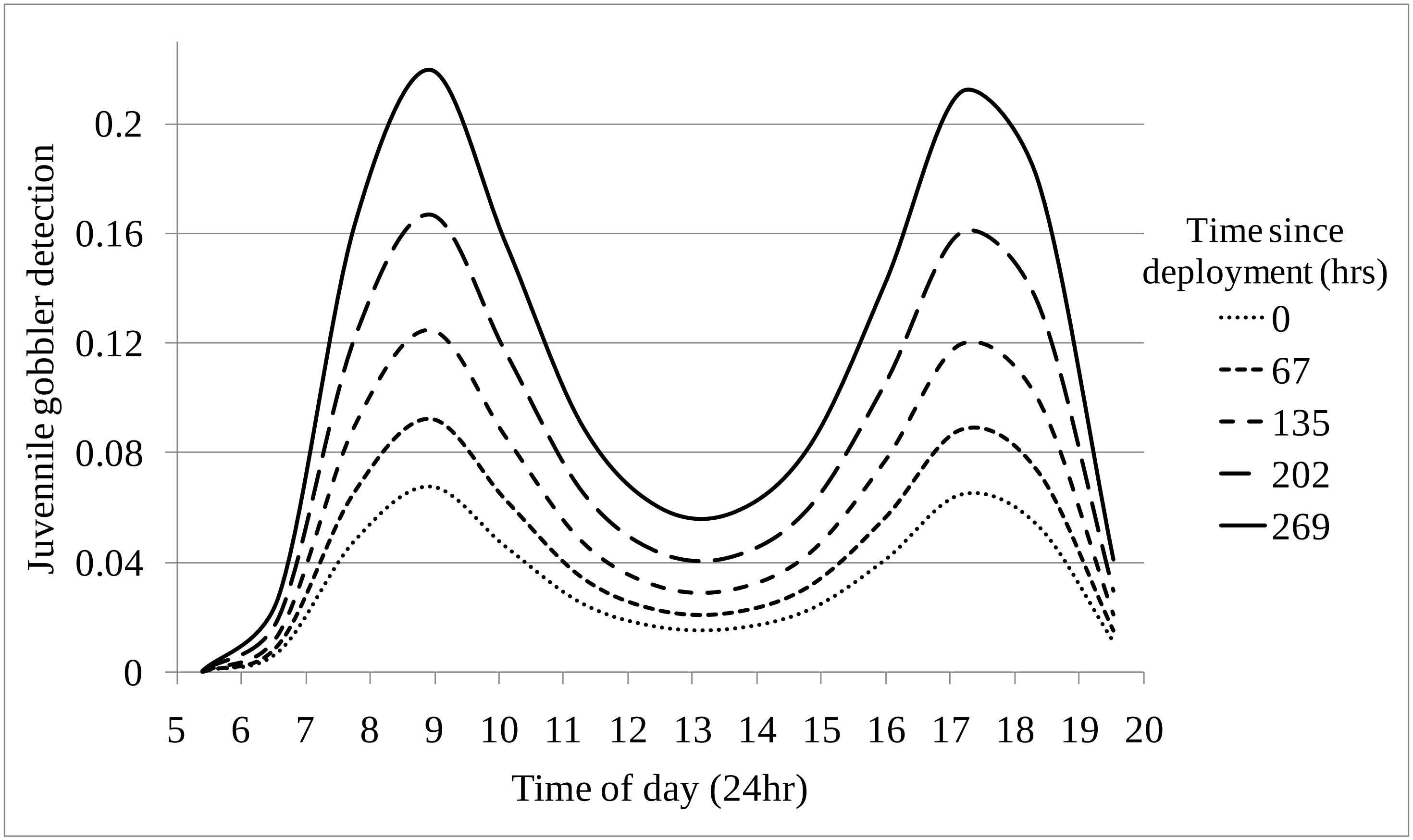


Figure 3.7. Relationships among time of day, observer, and detection for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008.

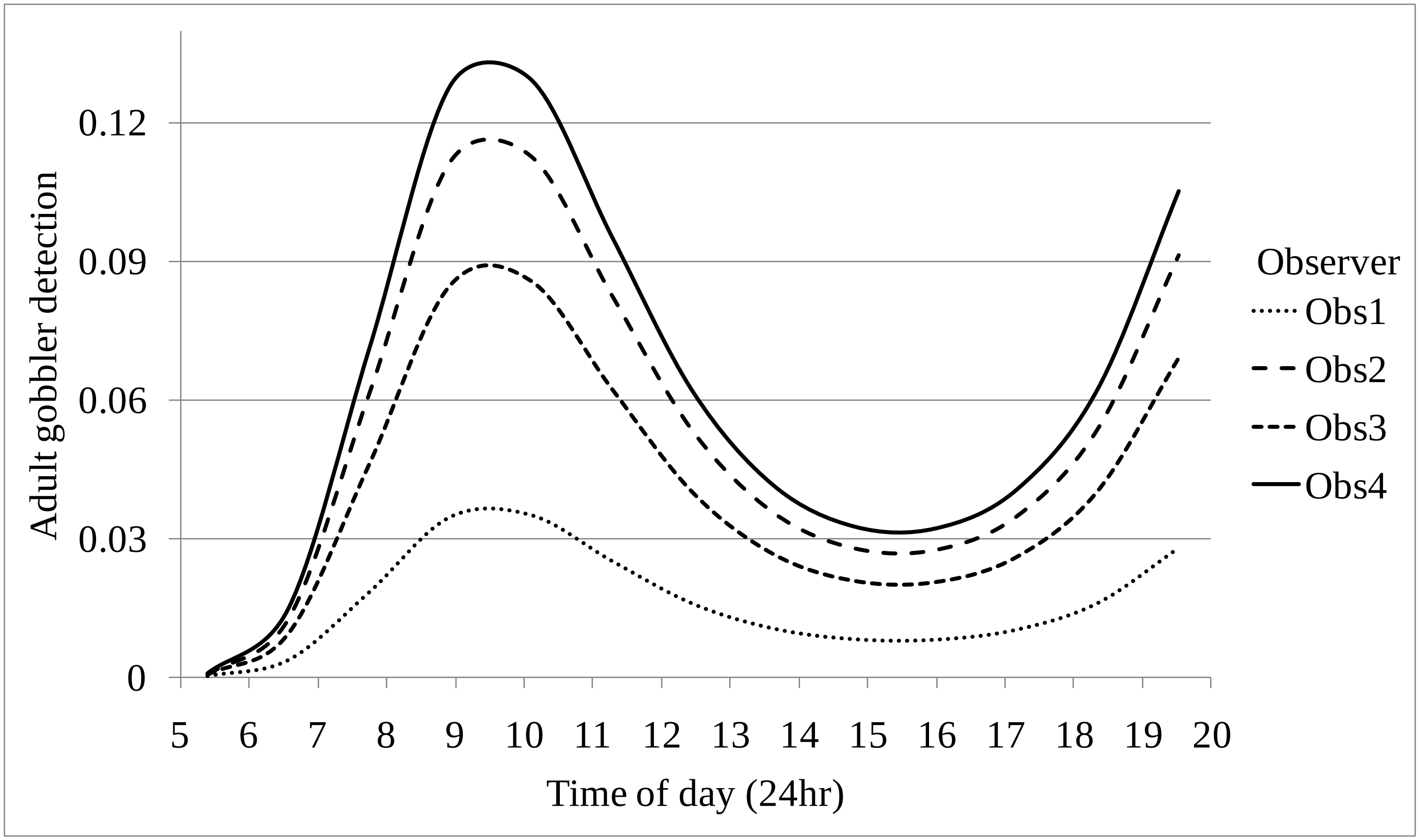


Figure 3.8. Relationships among time of day, daily rainfall, and detection for wild turkey adult gobbler abundance estimation using time-lapse cameras in southwest Alabama, summer 2008.

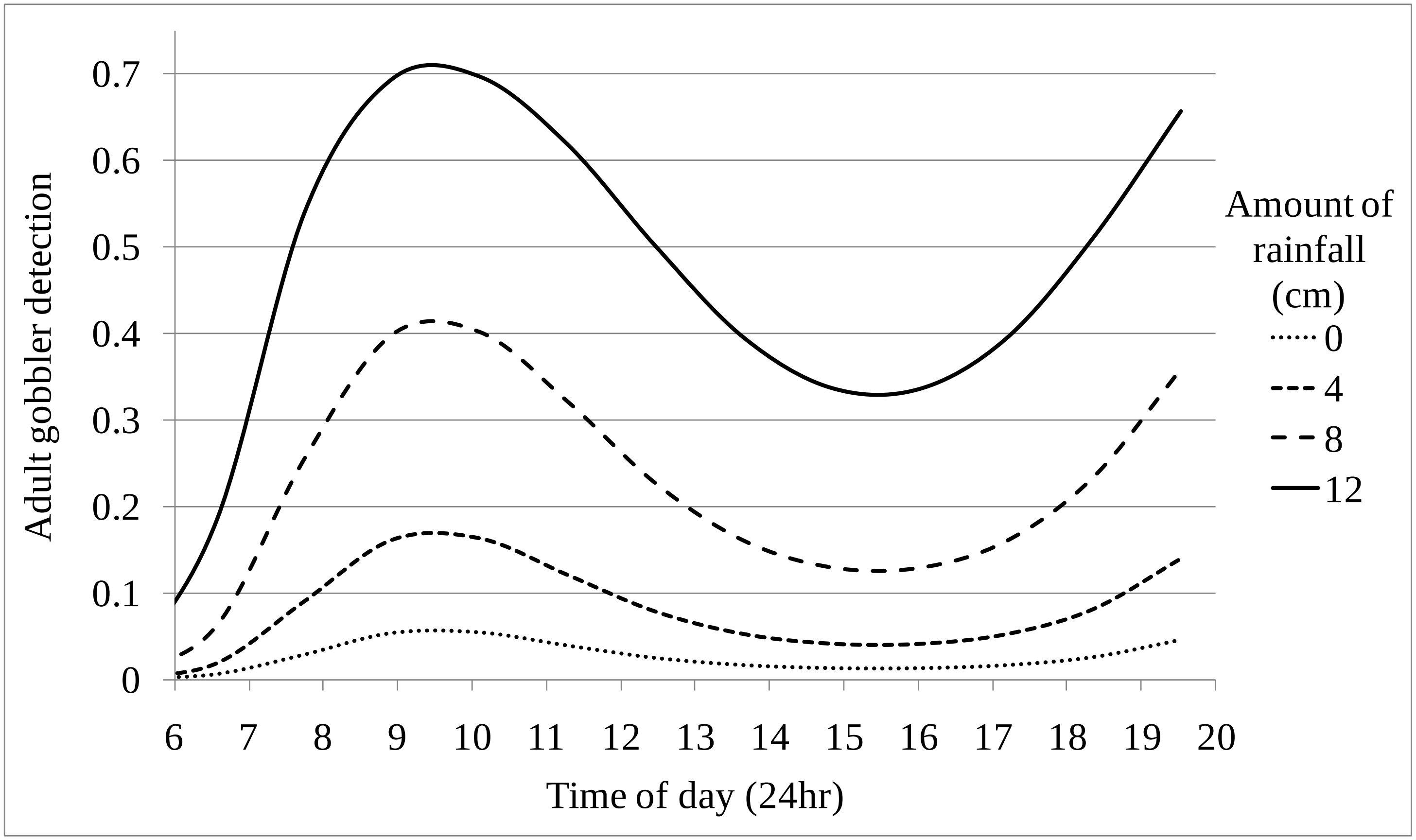


Figure 3.9. Relationship of wild turkey hen density to percent of developed area within a 100ha circular buffer around time-lapse cameras in southwest Alabama, summer 2008.

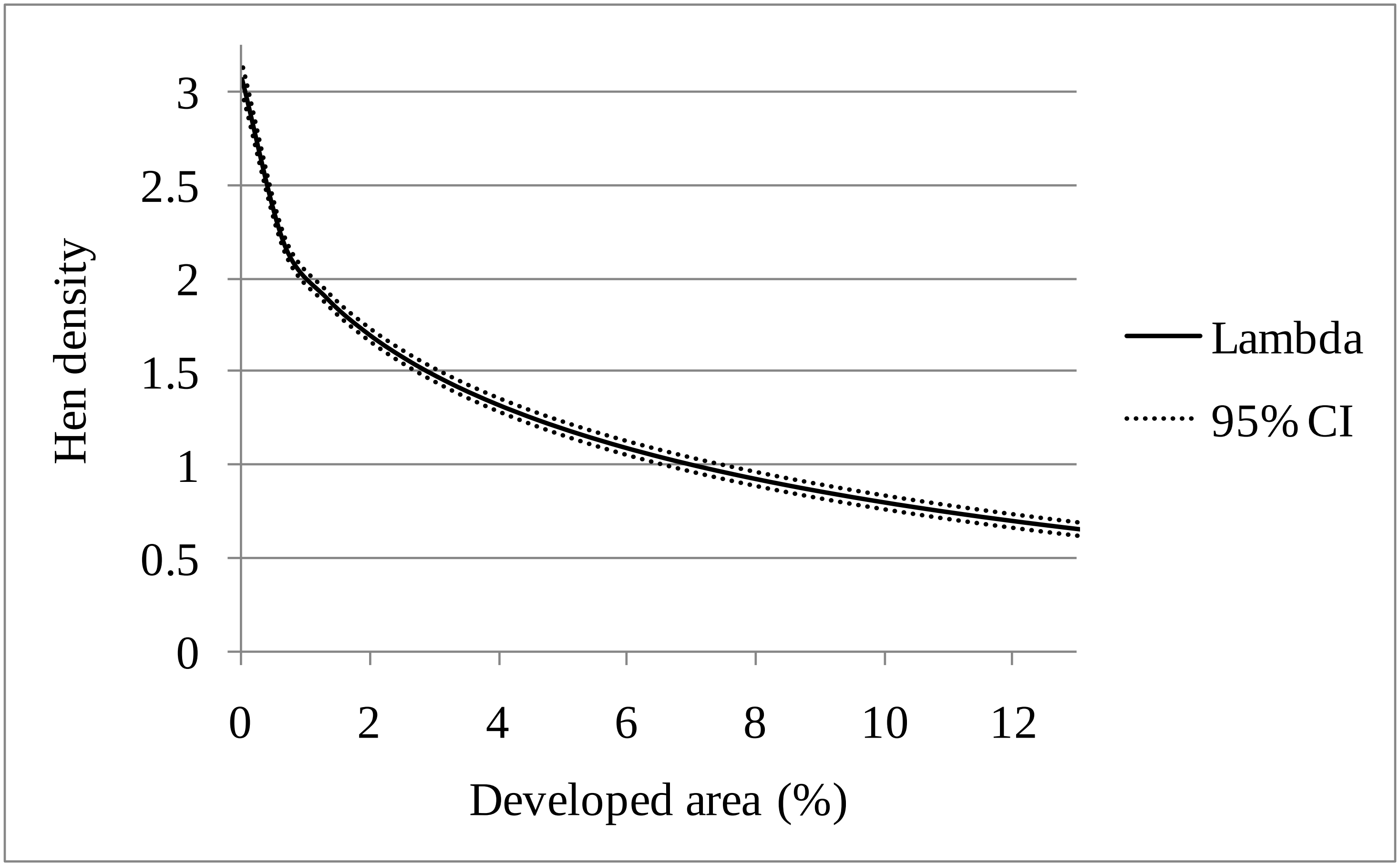


Figure 3.10. Relationship of wild turkey poult abundance to percentage of hardwoods and percentage of monoculture pines within a 100ha circular buffer surrounding time-lapse cameras in southwest Alabama, summer 2008. The effect of percent of hardwoods is shown at varying percentages of monoculture pines as labeled.

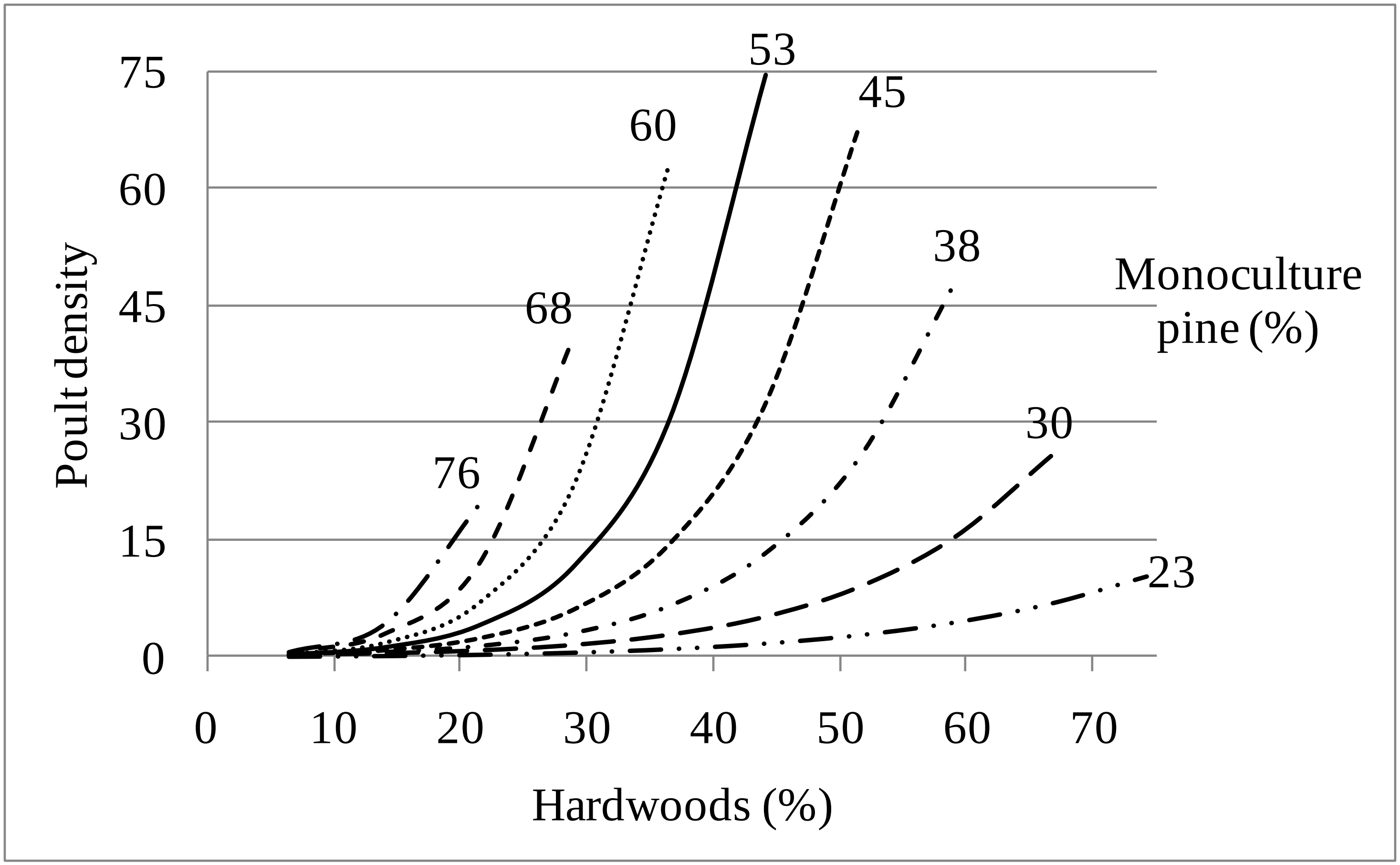


Figure 3.11. Relationship of wild turkey juvenile gobbler abundance to percentage of monoculture pine within a 100ha circular buffer around time-lapse cameras in southwest Alabama, summer 2008.

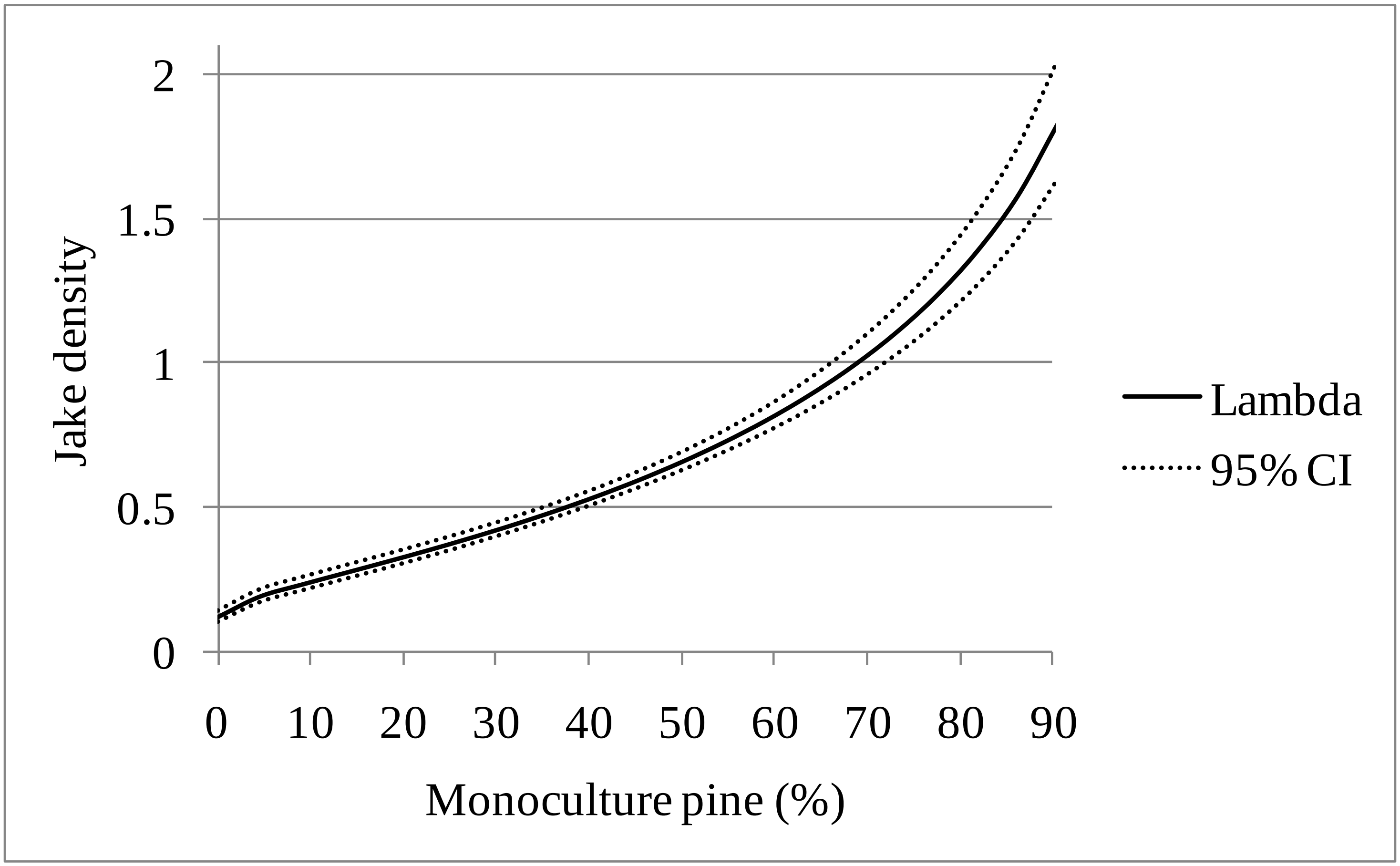


Figure 3.12. Relationship o f wild turkey juvenile gobbler density to length of streams within a 100ha circular buffer surrounding time-lapse cameras in southwest Alabama, summer 2008.

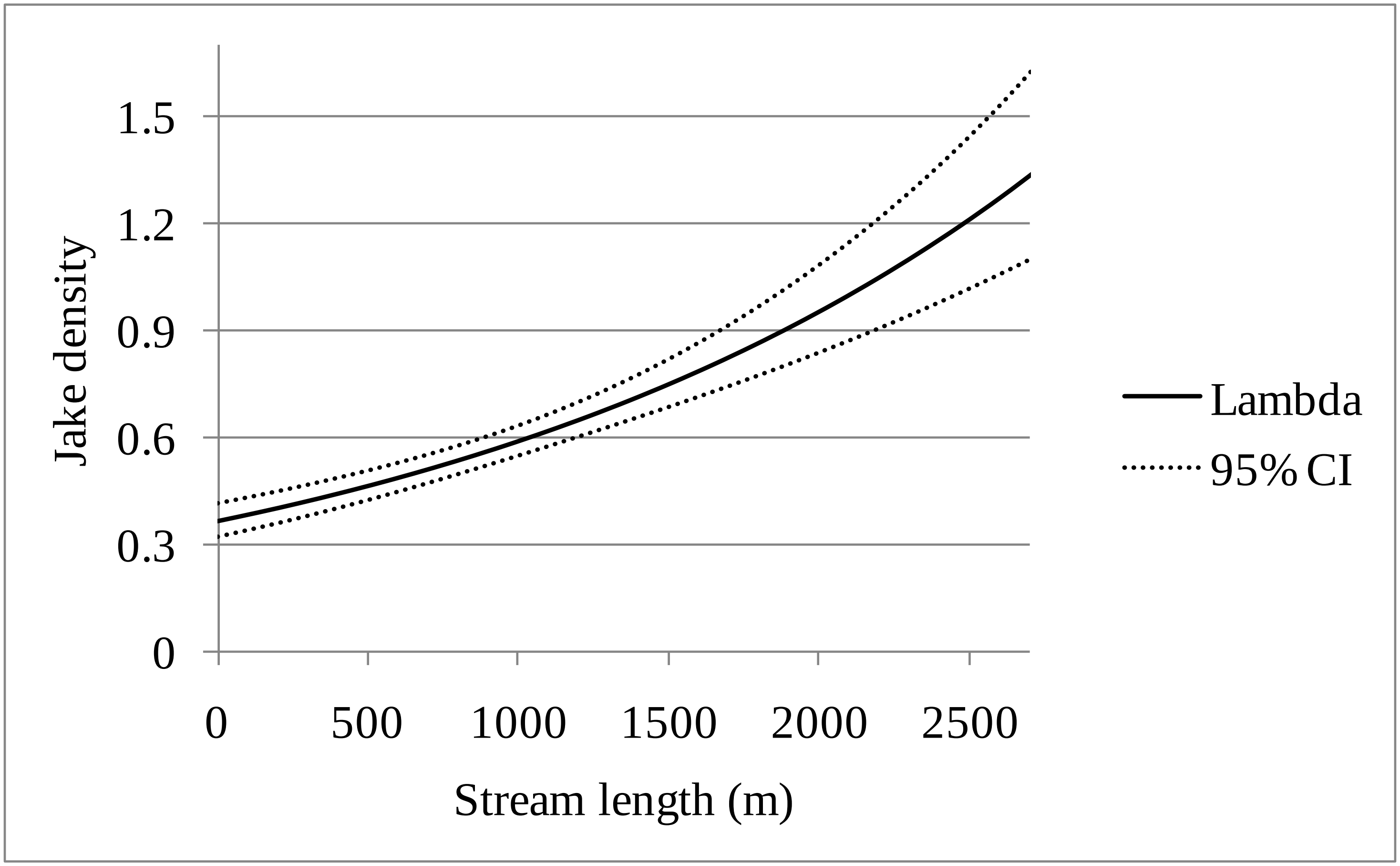


Figure 3.13. Relationship of wild turkey juvenile gobbler density to percentage of open pine within a 100ha circular buffer surrounding time-lapse cameras in southwest Alabama, summer 2008.

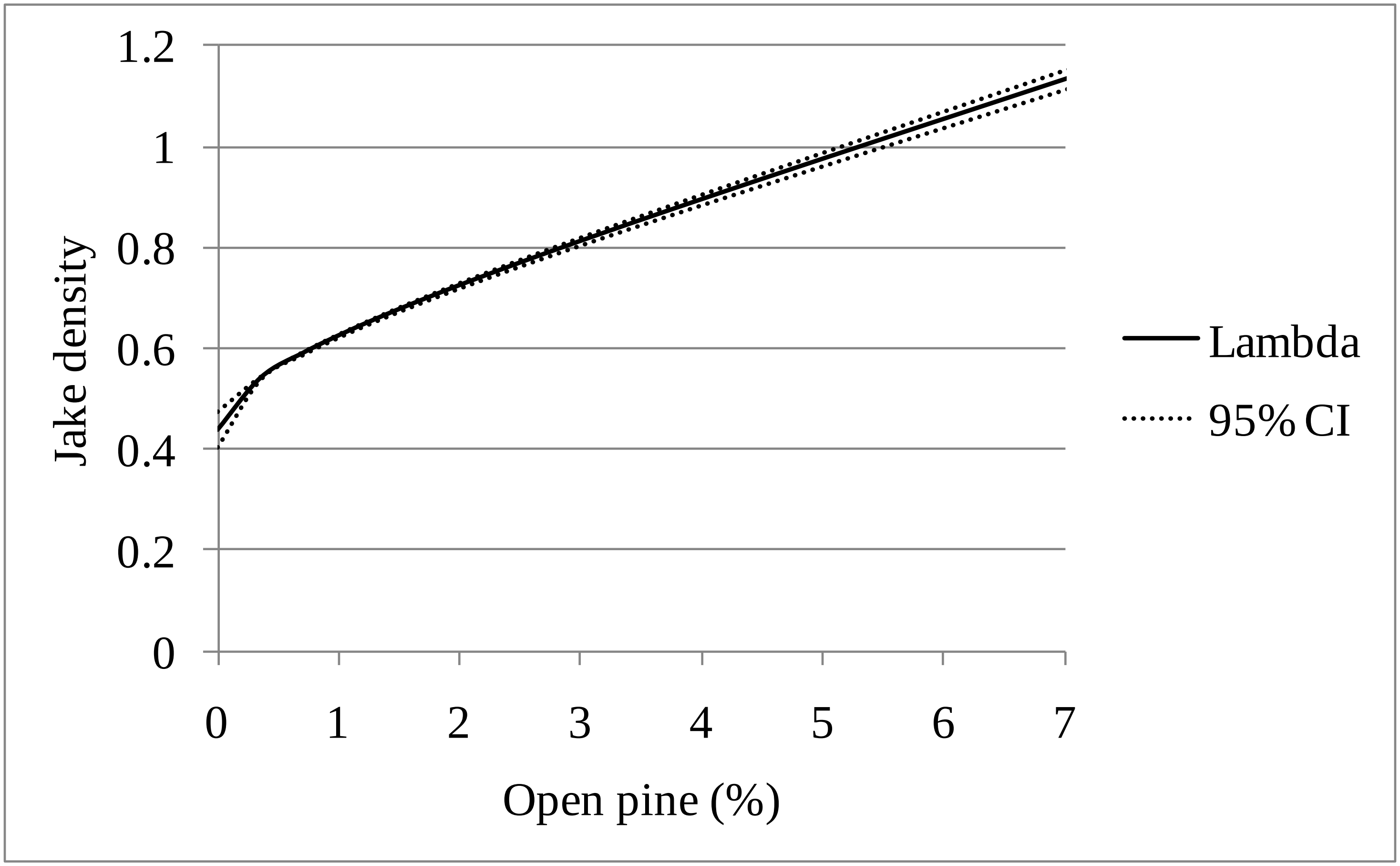


Figure 3.14. Relationship of wild turkey adult gobbler density to percentage of open pine within 100ha and 1000ha circular buffer surrounding time-lapse cameras in southwest Alabama, summer 2008.

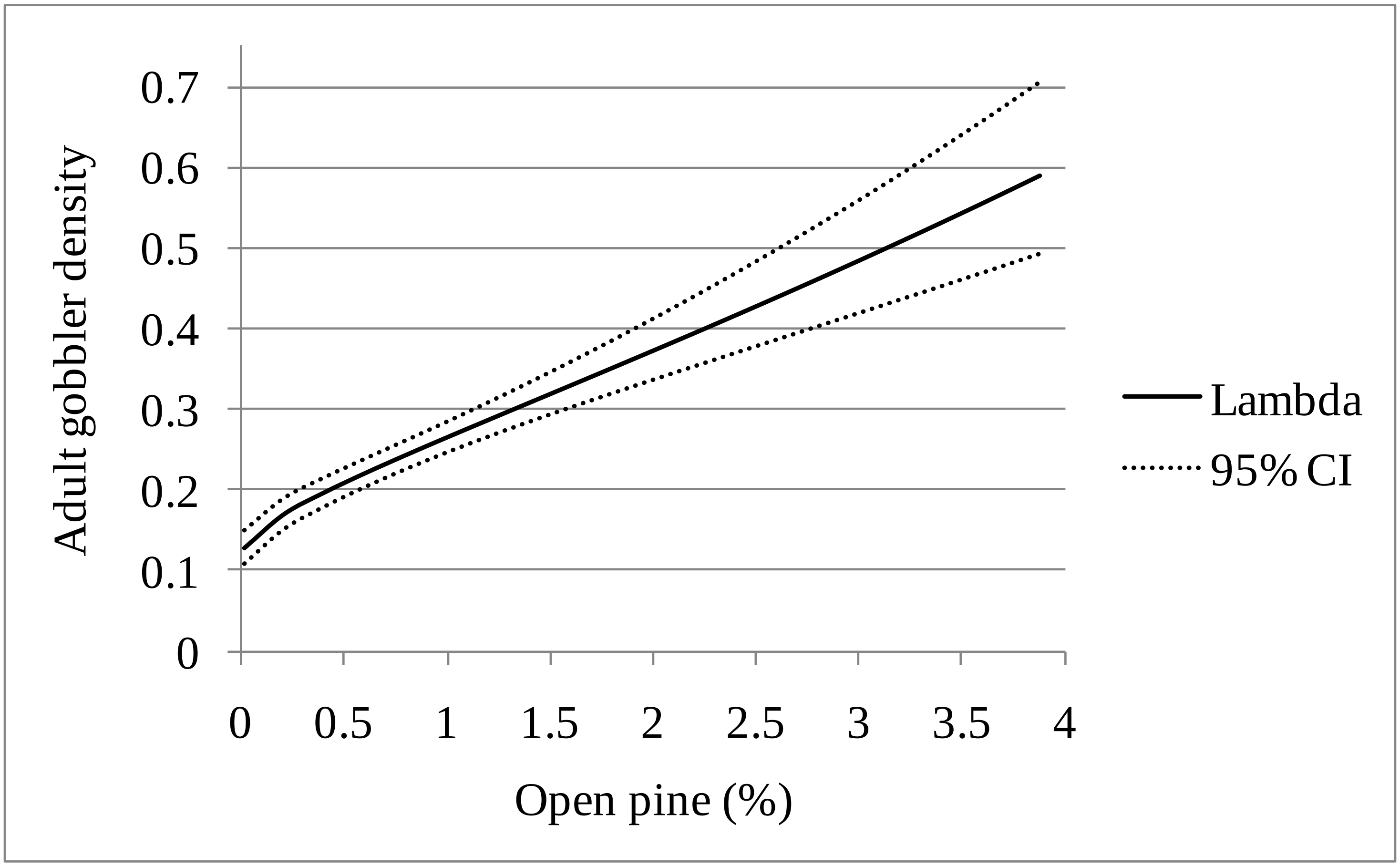


Figure 3.15. Relationship of wild turkey adult gobbler density to stream length within a 100ha and 1000ha circular buffer surrounding time-lapse cameras in southwest Alabama, summer 2008.

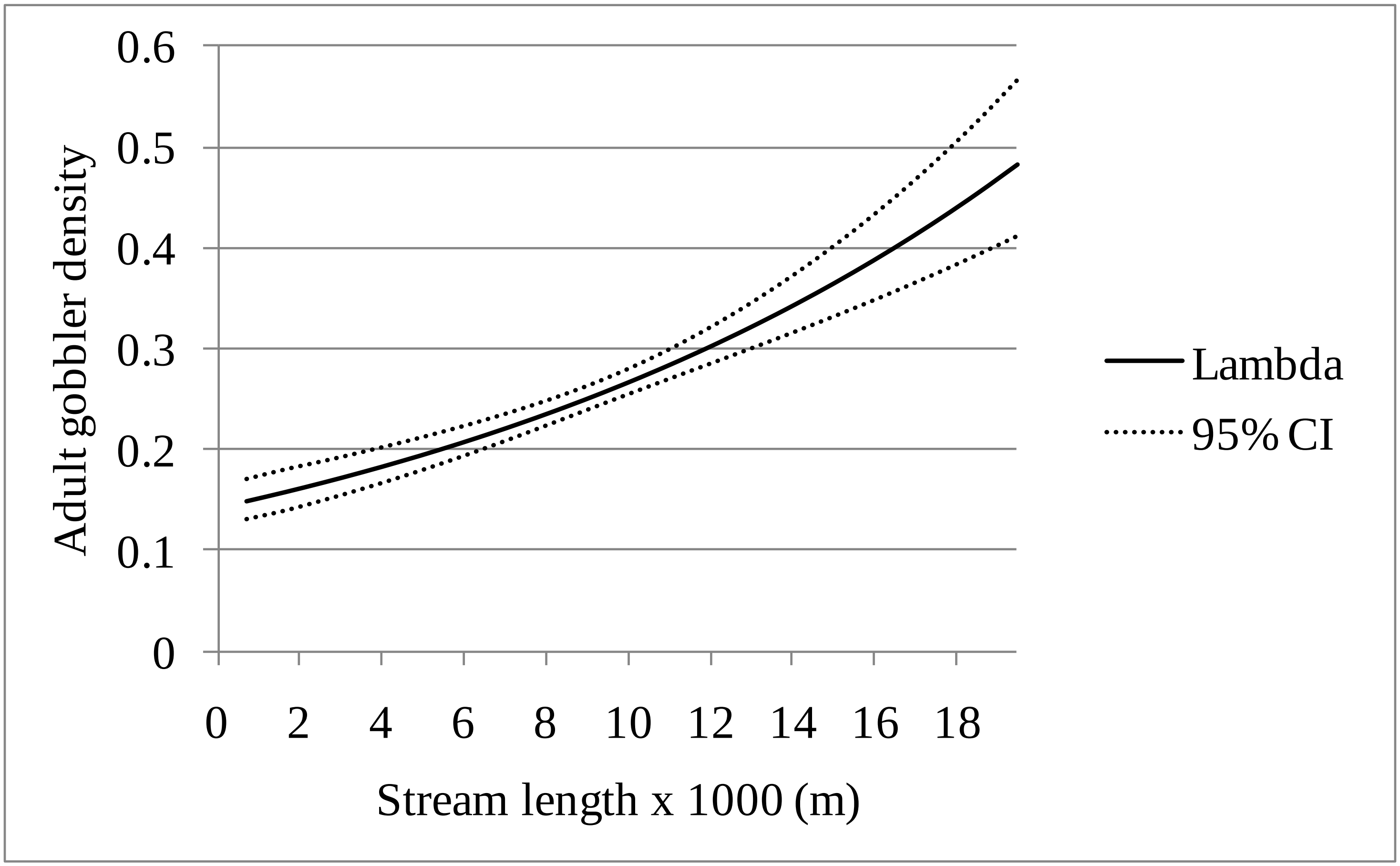
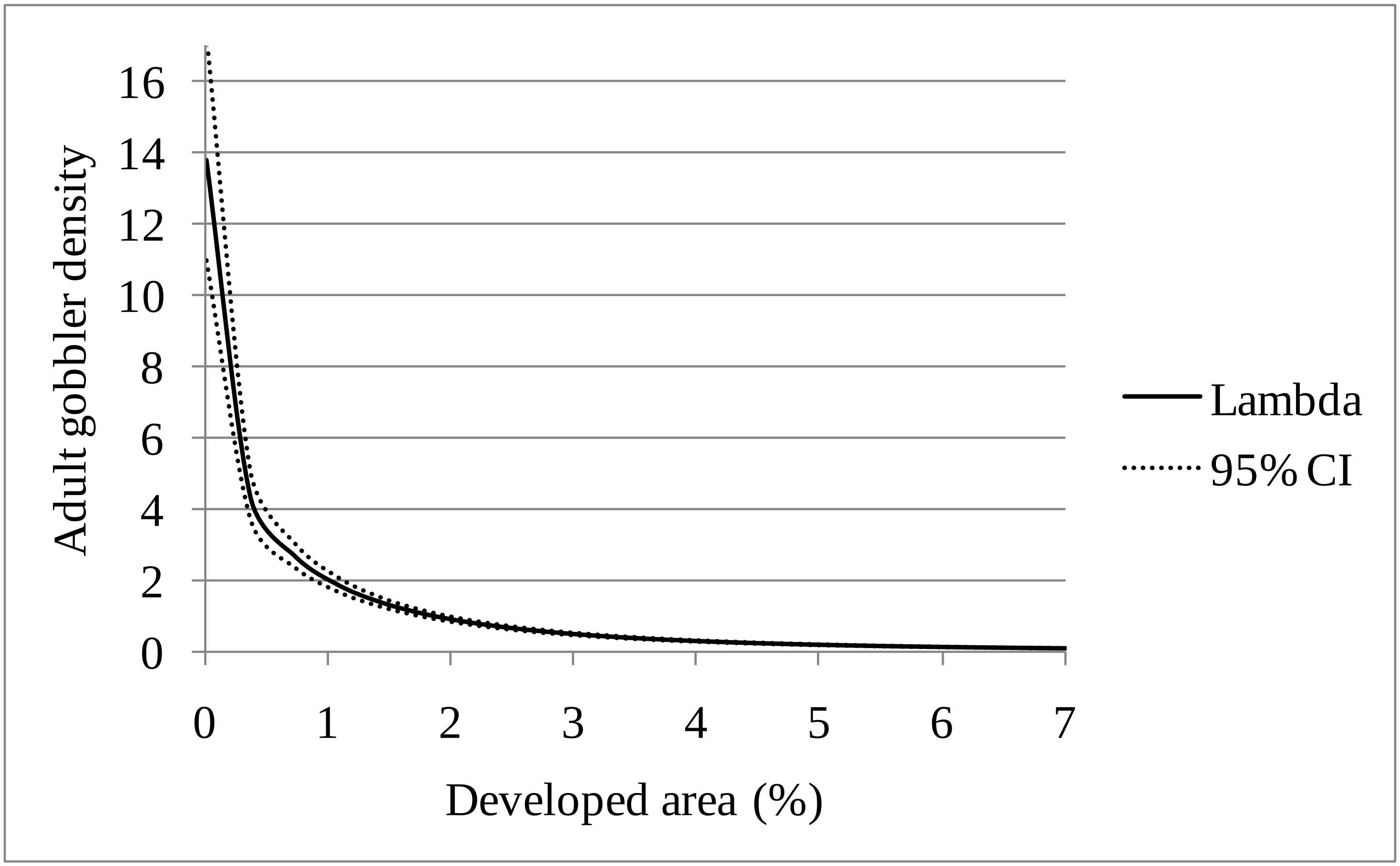


Figure 3.16. Relationship of wild turkey adult gobbler density to percentage of developed area within a 100ha and 1000ha circular surrounding time-lapse cameras in southwest Alabama, summer 2008.



CHAPTER IV: CONCLUSION

Precise and accurate estimates of demographics such as age structure, productivity, and density are necessary for determining habitat and harvest management strategies for wildlife populations. The importance of incorporating detection rates into these demographic estimates cannot be overstated, as failure to include detection can lead to underestimated parameters.

We established the necessity for modeling camera detection when using PIR sensors in population demographic estimation, as variation in the odds of detection for our cameras was rampant. Assuming detection is modeled and surveyed areas are representative, we found automated cameras show great promise for estimating large-scale population demographics precisely and accurately. In addition, after cost associated with initial purchase of equipment, automated camera surveys can easily and inexpensively be repeated across space and time.

We successfully developed and tested a method for estimating wild turkey (*Meleagris gallopavo*) population size and structure in Alabama at a relatively large scale using time lapse cameras. Quality large scale spatial habitat data seems crucial to adequately modeling wild turkey distribution across the landscape. Prior to implementing this method as a monitoring tool, modeling of hypotheses should be improved for fitting wild turkey count data, and additional density hypotheses should be explored to explain extra variation in counts. While some flaws became apparent throughout this research, our estimates of density were comparable to those found in previous literature from the southeast, leading us to believe the method showed promise for estimating unbiased, precise wild turkey densities.