Use of N-mixture models for estimating white-tailed deer populations and impacts of predator removal and interspecific competition

by

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Abstract

Predation and competition can have significant effects on population dynamics. Range expansion of coyotes (*Canis latrans*) and the growing number of wild pigs (*Sus scrofa*) can negatively impact white-tailed deer (*Odocoileus virginianus*) populations. Traditional methods for estimating demographics, such as mark-recapture, can be labor intensive and difficult to implement on large scales. N-mixture models rely only on spatially and temporally replicated count data, and can be employed for large-scale monitoring. We evaluated the efficacy of N-mixture models for estimating deer populations, and estimated effects of predator removal and interspecific competition on deer population dynamics using N-mixture models. Time-lapse photography and N-mixture models provided accurate estimates of deer density and may be an effective method for surveying and monitoring deer. Our results indicate that short term coyote removal programs may negatively impact deer populations. Additionally, our data suggest that wild pigs are displacing or excluding deer from pulse food resources.

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ABSTRACT

Automated cameras have become increasingly common for monitoring wildlife populations. However, most analytical methods fail to account for incomplete and variable detection probabilities, which biases density estimates. The goal of this study was to evaluate the accuracy and effectiveness of the repeated point counts (N-mixture) method, which explicitly incorporates detection probability, to monitor white-tailed deer (*Odocoileus virginianus*) by using a known, marked population to collect data and estimate density. Motion-triggered camera surveys were conducted at Auburn University's deer research facility in 2010 and data were standardized at 5-minute intervals to mimic a time-lapse survey. Density estimates were generated using N-mixture models and compared to the known number of marked deer in the population. We compared detection and density estimates generated from a decreasing number of survey days used in analysis and by time periods (DAY, NIGHT, SUNRISE, SUNSET, CREPUSCULAR, ALL TIMES). Detection was significantly less during the day and increased from 0.0087 during a 24-hour survey to 0.0116 during night surveys. Accurate density estimates were generated using 24 hours of data and nighttime only. Accuracy of density estimates increased with increasing number of survey days until day 5, and there was no improvement with additional data. This suggests that, for our system, five-day camera surveys conducted at night were adequate for density estimation and population monitoring. Further, this demonstrates that

N-mixture models with time-lapse photography may be a highly effective method for estimation and monitoring of white-tailed deer populations.

INTRODUCTION

Accurate estimates of population size and structure are essential for wildlife management decisions, particularly decisions regarding harvest. Methods used to estimate population and demographic parameters based on direct counts of white-tailed deer (*Odocoileus virginianus*) have included spotlight counts (McCullough 1982, Fafarman and DeYoung 1986), pellet counts (Eberhardt and Van Etten 1956, Fuller 1991), aerial surveys (Potvin et al. 2002), and thermal imaging surveys (Gill et al. 1997). An assumption with many survey methods is that all animals have equal probability of detection (Krebs 1999) despite the fact that detection is often imperfect and variable between and among species, sites, and years (Pollock et al. 2002, Sollmann et al. 2013). Spotlight counts, for instance, are subjected to variable detection rates (Collier et al. 2007, Collier et al. 2013) and bias associated with sampling along roads (Anderson 2001). Furthermore, many of these methods are labor intensive and limited to certain habitat types (Lancia et al. 1994). Dense vegetation has been shown to affect detection using thermal imaging surveys (Ditchkoff et al. 2005), spotlight counts (Collier et al. 2013), and pellet counts (Langdon 2001).

Automated cameras have been used to monitor wildlife in a variety of habitat types (Jacobson et al. 1997, Koerth et al. 1997, Curtis et al. 2009). One important distinction among automated cameras is related to how the camera is triggered to capture images. Some cameras use an infrared-trigger (IR) to capture images whereas others use time-lapse photography to capture images at regular intervals. IR cameras capture an image when a sensor detects a change in background infrared radiation wavelengths. Both types of surveys face variable detectability due to sex and age of the animal, environmental conditions, and time of day, but variability in sensor detection of an animal present at the station adds additional variability in detection rates among cameras, sites, or dates (Damm et al. 2010). Variation in this IR-sensor detection among cameras may arise from environmental conditions (Bernatas and Nelson 2004, Swann et al. 2004), variable sensitivity or placement of camera sensors (Swann et al. 2004, Damm et al. 2010), or differences in sensor detection of types of species (Damm et al. 2010). The variable detection associated with IR sensors can influence photographic capture rates and confound comparisons between sexes or age classes even in the absence of other factors affecting visitation rates and patterns. Time-lapse photography eliminates this variation but greatly increases the number of images and data storage needs. Large-scale, time-lapse camera surveys can easily result in hundreds of thousands of images, many of which may not contain the targeted species but still need to be evaluated.

Various options are available for design and analysis of camera surveys. Mark-recapture or mark-resight models can be used to analyze camera data containing individuals that are marked or uniquely identifiable (Karanth and Nichols 1998). However, the process of capturing and marking animals often is expensive and time consuming and may not be possible in many situations. Jacobson et al. (1997) developed a survey method for white-tailed deer which utilizes the unique features of branch-antlered bucks (antler configuration and mass, pelage, and body characteristics) to identify individuals. The number of individual branch-antlered bucks and ratios of branch-antlered males to spikes, does, and fawns, are then used to derive population estimates and demographic parameters. This method eliminates the need to commit financial and time resources to capture and mark animals, resulting in significant savings. For example, Jacobson et al. (1997) calculated a cost of $5/ha for a camera density of 1/65 ha, disregarding expenses for labor.

The Jacobson et al. (1997) method provides significant savings over traditional mark-recapture methods. However, the assumption of equal detection between all age classes and sexes is potentially inaccurate and may result in biased estimates (Koerth and Kroll 2000, McCoy et al. 2011, Weckel et al. 2011). Weckel et al. (2011) suggested incorporation of trap success (number of survey days with at least 1 deer photographed/total number of survey days) to adjust the Jacobson et al. (1997) method to account for differences in detection between branch-antlered males, spikes, females, and fawns. This adaptation would also address the potential bias resulting from baited camera sites and different visitation and feeding patterns of males, females, and fawns (Koerth and Kroll 2000, McCoy et al. 2011). However, the amendment proposed by Weckel et al. (2011) does not address variation in detection that exists due to environmental factors or temporal variation in visitation rates.

An alternative to the Jacobson et al. (1997) method is Royle's (2004) N-mixture model. Similar to the Jacobson et al. (1997), the N-mixture model does not require marked individuals, yet accounts for variation in detection. Royle's (2004) N-mixture model incorporates detection probability into the abundance estimate using a mixture of binomial and Poisson distribution models from spatially and temporally replicated counts. Royle's (2004) N-mixture model is a hierarchical model that estimates 2 parameters, detection probability (p) and mean abundance (λ) with spatially and temporally varying covariates. This model assumes that the population is demographically closed, individuals are not counted at more than one site, and all individuals within the sampling unit have some probability of being detected (Royle 2004). Repeated point counts have been utilized in a multitude of avian species including black oystercatchers

(*Haematopus bachmani*; Lyons et al. 2012) and wild turkeys (*Meleagris gallopavo*; Damm 2010). An additional advantage to this method is that individual identification is not required, which may reduce time and effort associated with surveys and facilitate large scale surveys (Lyons et al. 2012).

Our goal for this study was to evaluate the accuracy and effectiveness of Royle's (2004) N-mixture model applied to camera surveys of white-tailed deer. We utilized an enclosed population with a largely known number of marked deer, to compare accuracy of density estimates from camera surveys. Our specific objectives were to 1) evaluate estimation accuracy, 2) determine how detection varied temporally, and 3) determine how changes in camera survey efforts affected accuracy of density estimation for white-tailed deer using Royle's (2004) N-mixture model.

STUDY AREA

Our study focused on Auburn University's deer research facility near Camp Hill, Lee County, Alabama. An eight-foot high-tensile fence enclosed approximately 174 ha within the Piedmont Agricultural Experiment Station. A large creek bisected the property, and vegetation was dominated by hardwood bottomlands and uplands, old pastures, and planted pines. Supplemental feed was available at 3 feeding stations placed throughout the facility as well as several food plots. During the study, the facility contained approximately 100 deer, which descended from the wild deer population within the fence at the time of construction in 2007. At the time of this study, our known population size of marked individuals was 75 deer consisting of 41 males and 34 females. No hunting occurred within the research facility.

METHODS

Auburn University's deer research facility contained a population of white-tailed deer that has been extensively studied during the previous 5 years. Researchers attempted to capture every individual each year and recorded antler and body size and tagged individuals [see Acker (2013) for specific capture and handling techniques]. Individuals were assigned a unique number, freeze branded, and tagged in both ears with cattle ear tags which made identification possible from multiple angles. Capture techniques followed American Society of Mammalogists' guidelines (Sikes et al. 2011) and were in accordance with Auburn University's Institutional Animal Care and Use Committee (2008-1241, 2010-1785).

Camera surveys were conducted in 2010 from September 21- September 27 (survey 1) and October 5- October 11 (survey 2) as part of another research initiative [see Acker (2013)]. Four sites were systematically established for survey 1, and 4 different sites were systematically established for survey 2 with a camera density of approximately 1/44 ha. Specific locations were sought beneath the forest canopy in areas where vegetation would not affect image quality and field of view. Sites were pre-baited 5 days prior to camera deployment with 22 kg of whole corn and were refreshed as needed. Infrared-triggered PixController trail cameras (DigitalEye 7.2, PixController Inc., Export, PA) were set on a 5-minute trigger-delay setting, meaning that no more than one photo could be taken in 5 minutes. Sensitivity, flash brightness, and ISO settings were all standardized. Cameras were set out for 7 days and were placed on steel mounting boards 1.5 m above ground level and aimed downward at a 15° angle (Holtfreter et al. 2008).

All images were processed by a single observer to maintain consistency throughout the study. We identified individual deer by tag number. Only marked deer with readable ear tags were included in the count data because freeze brands were inconsistently legible. We recorded tag number, time, date, and sex for every tagged deer in each picture. We constructed encounter histories as the number of marked individuals per 5-minute time interval for each site, with this interval specified to mimic a time-lapse setting and to standardize time of occasions for all sites. Occasions for which there were no images were given a zero count.

Detection probabilities generated from the N-mixture model (estimated detection) were not reported. Instead we calculated an observed detection (p) for a more direct measure of detection for each date and time as:

$$\frac{n_{it}}{N}$$

where n_{it} was the number of individuals photographed in time t at location i, and N was the total number of marked deer (n = 75). We chose to use this more direct and precise measure of detection as calculated here because it allowed us to calculate detailed, time-specific detection rates without variability and uncertainty of the estimated detection from the N-mixture model. In this paper we focused on evaluating the abundance estimators of the N-mixture model for white-tailed deer. Our precise calculation of detection allowed us to evaluate how detection varied across time (i.e., date, day of the week, time of day) which would not have been possible using the N-mixture model estimator in this study. When calculating observed detection for males and females we divided by the number of each sex (41 males, 34 females). Standard errors were calculated using all date and time specific observed detection probabilities either during each time period or survey day. We compared observed detection between time periods for males and females using a Welch's two sample t-test with significance level set at $\alpha \leq 0.05$.

For analysis of density we used the count of male and female deer in each picture without respect to individual identity. We generated abundance estimates separately for males and females in MATLAB® (The MathWorks, Inc., Natick, Massachusetts) using the maximumlikelihood N-mixture model (Royle 2004) with counts (photos) every 10 minutes. Most camera surveys use a 4- or 5-minute delay setting (Jacobson et al. 1997, Koerth and Kroll 2000, Curtis et al. 2009). However, research has shown that deer spend > 10 minutes feeding when bait is scattered on the ground (Kozicky 1997). Further, a 10-minture trigger delay resulted in equal or greater individual identifications than a 5-minute trigger delay with half the photographs (Acker 2013). To reduce computational time we increased survey occasions to 10 minutes instead of using each image every 5 minutes. Using the 5-minute occasions would have greatly increased computational time with no new information gleaned from the additional photos.

The N-mixture model (Royle 2004) estimates mean abundance (λ). With assumptions made about the area each site represents and the area those animals use, density can be calculated. Mean home range of adult male deer within a high-fence area of 260 ha was 58 ha, and ranged from 24-94 ha (Karns, unpublished data). Deer partitioned the area into quadrants and only ventured outside that area a few times during peak rut (Karns, unpublished data). The deer research facility was slightly smaller (174 ha), and home range size would likely be more constricted. To convert from abundance to density, we assumed that each of the 4 sites represented 43.5 ha (174 total ha/ 4 sites). Then, we multiplied mean abundance (λ) by 4 to account for each site to get density (deer/174 ha), which also represents total population size within the facility.

We reduced camera survey effort for density analysis *post hoc* by utilizing data only from certain time periods of the day and by eliminating number of survey days used to generate density estimates. In general, such a reduction limits the number of picture occasions in a data set and thereby reduces the time required for picture assessment and analysis, but may also affect estimator precision. The time periods we evaluated were DAY (8 hour time period 2 hours after sunrise to 2 hours before sunset), NIGHT (16 hour time period from 2 hours prior to sunset to 2 hours after sunrise), SUNRISE (4 hour time period around sunrise), SUNSET (4 hour time period around sunset), CREPUSCULAR (both sunrise and sunset time periods), and ALL TIMES (24 hours). For the second survey, density estimates were adjusted to account for the number of individuals that visited more than one site, which was a violation of one of the model assumptions of Royle's (2004) N-mixture model. To do this we multiplied density by the percent of individuals that did not visit more than one site. Accuracy of estimates was calculated as the relative deviation from the number of known, marked individuals, and was calculated as $\frac{\hat{N}-N}{N}$, where $\hat{N}$ is the estimated density and N is the true population size.

RESULTS

Of the 75 available marked deer, we observed 34 in survey 1 and 46 in survey 2 (Table 1.1). In survey 1, one deer was observed at more than one site compared to 23 in survey 2. Mean number of deer counted per survey day increased from 69.5 on day 1 to 213 on day 3, and then decreased thereafter. There was no clear trend in detection across survey days (Figure 1.1). However, mean detection probability of females ($\bar{p}$= 0.0101 ± 0.0003) was greater ($P < 0.001$) than that of males ($\bar{p}$ = 0.0075 ± 0.00027). Detection probability of females was greater than detection probability of males during the DAY (female $\bar{p} = 0.0053 \pm 0.00037$, male $\bar{p} = 0.0009 \pm 0.00016$; $P < 0.001$), NIGHT (female $\bar{p} = 0.0124 \pm 0.00042$, male $\bar{p} = 0.0109 \pm 0.00038$; $P = 0.009$), SUNSET (female $\bar{p} = 0.0150 \pm 0.00092$, male $\bar{p} = 0.0101 \pm 0.00075$; $P < 0.001$), and CREPUSCULAR (female $\bar{p} = 0.0138 \pm 0.00062$, male $\bar{p} = 0.0112 \pm 0.00056$; $P = 0.002$) time periods also. Detection decreased following sunrise and increased and peaked following sunset (Figure 1.2). We also found that detection during the DAY time period was less ($P < 0.001$) than all other time periods (Table 1.2).

We did not estimate density for the DAY time period because detection rates were too low. Density estimates for the ALL TIMES and NIGHT time periods provided the most accurate density estimates for the total population. Prior to adjustment for the number of individuals that visited more than one site, abundance estimates for the ALL TIMES and NIGHT time periods from the second survey were 176.8 ± 13.5 and 137.6 ± 13.5, respectively. After adjusting for occurrences of multiple camera visits, female abundance estimates for ALL TIMES (38.3 ± 6.8), NIGHT (32.9 ± 6.7), SUNRISE (168.9 ± 12.3), SUNSET (32.6 ± 8.2), and CREPUSCULAR (40.6 ± 7.9) time periods had an accuracy of 12.6%, 3.2%, 396.8%, 4.1%, and 19.4%, respectively. For males, density estimates for the ALL TIMES (46.7 ± 7.0), NIGHT (39.7 ± 7.1), SUNRISE (18.1 ± 8.3), SUNSET (107.4 ± 42.2), and CREPUSCULAR (90.0 ± 7.1) time periods had an accuracy of 13.9%, 3.2%, 55.9%, 162.0%, and 119.5%, respectively. Using at least 5 survey days resulted in density estimates closest to our true population size for the ALL TIMES and NIGHT time periods, and there was no increase in accuracy with additional days surveyed (Figure 1.3).

DISCUSSION

With the increasing use of automated cameras to survey for white-tailed deer there have been a growing number of studies evaluating the accuracy of these survey methods. Previous studies have compared estimates with other forms of estimation to evaluate accuracy (Jacobson et al. 1997, McKinley et al 2006, Curtis et al. 2009, Weckel et al. 2011). Here we had the unique opportunity to compare our density estimates generated using Royle's (2004) N-mixture model with a known number of marked deer. Our findings suggest that use of N-mixture models can provide accurate density estimates for white-tailed deer. Density estimates from the NIGHT and ALL TIMES time periods were similar to our true population size with fairly small standard errors (coefficient of variation was consistently ~20% or less). Further, density of males and females were accurately estimated for the NIGHT and ALL TIMES time periods so male:female ratio estimates would be representative of the population. Due to the season in which we conducted our camera surveys, we were unable to estimate fawn abundance. In our study area fawns are born in July and August (Gray et al. 2002) and would not be very mobile at the time of the survey. In fact, studies have noted lower fawn:doe ratios during fall surveys than in winter or spring surveys (Jacobson et al. 1997, McCoy et al. 2011), suggesting that information gleaned from fawn:doe ratios during fall surveys in this region may not accurately reflect reality.

It is important to note the fundamental differences in the underlying assumptions of the N-mixture models (Royle 2004) and those of methods which rely on individual identification, such as the Jacobson et al. (1997) method. The Jacobson et al. (1997) method assumes that individual branch-antlered males can be accurately identified, and that there is equal detectability among sexes and age classes. As noted above, the N-mixture model (Royle 2004) estimates mean abundance assuming that all individuals have some probability of being counted, and that individuals will not be counted at more than one site. Making further assumptions about how much area those animals use and what area each site represents we can estimate density. This will be closely tied with camera density, sampling density (effective sampling area), and deer home range size. If camera and sampling density are too high then individuals may be counted at more than one site. This would be an unbiased estimate of the number of animals that use a particular site. However, when extrapolating to the total effective sampling area, density estimates would likely be biased high. Conversely, if camera and sampling density are too low, then some individuals may not be counted and estimates of density and the number of animals that use a particular site may be biased low. The camera and sampling density required to balance these two assumptions would be inversely related to the home range size of the targeted species. Males have a greater home range than females (Vanderhoof and Jacobson 1993, Walter et al. 2011) and would require a lower camera and sampling density to meet the assumptions and accurately estimate density.

Other studies have noted variation in density estimates due to camera density. Jacobson et al. (1997) and McKinley et al. (2006) found that the highest camera density (<1/65 ha) they tested provided more accurate estimates than lower camera densities. This is because the Jacobson et al. (1997) method relies on individual identification, and increasing camera density should increase photographic recapture rates. Increasing camera density increases the probability that all deer will be observed, meeting the criteria that all animals have some probability of being sampled. However, a high camera density can result in individuals being observed at more than one site, which is in violation of one of the N-mixture model assumptions (Royle 2004). This inflates density estimates, as evidenced by our overestimation of density prior to adjustment for individuals that were observed at more than one site during our second survey. If we were surveying an unmarked population we would have been unable to adjust the density estimates. Therefore, ideal camera density for N-mixture models should be low enough that individual deer are unlikely to be counted at more than one site, but high enough to ensure that every individual could be counted on at least one site.

Surveying for a minimum of 5 days resulted in accurate density estimates for the ALL TIMES and NIGHT time periods in this study, suggesting that surveying for 5 days may be sufficient under similar conditions. Jacobson et al. (1997) found that within 10 days they observed >80% of marked deer. Despite our greater camera density, we observed a collective 64% of the total population (marked population) during the two survey periods. Granted, Jacobson et al. (1997) was comparing their photographic recapture rates to the total number of marked deer and not the whole population. McKinley et al. (2006) observed 89% of marked deer at a camera density of 1/41 ha but estimated they only tagged <43% of the female population. The Jacobson et al. (1997) method requires the identification of a minimum number of branch antlered males, so a greater survey period or greater camera density may be necessary to maximize the number of individual deer photographed when using that technique. N-mixture models are not hindered by individual identification, and instead rely upon spatially and temporally replicated count data. Surveys using the N-mixture model (Royle 2004) may not require as many survey days as methods which do require individual identification. Shorter camera surveys that maintain accuracy of estimates can reduce time and therefore cost of examining images, and decrease costs associated with bait, fuel, and labor.

Many studies evaluating camera survey techniques have noted potential bias in different visitation rates among sexes and age classes, and suggest the need to account for this variability in detection (Jacobson et al. 1997, McCoy et al. 2011, Weckel et al. 2011). Jacobson et al. (1997) noted different photographic observation rates between males and females under a range of camera densities. They attributed this to differences in home range size between males and females but failed to account for this difference in the density estimates. We also found a difference between the sexes with male detection probability significantly less than female detection probability. This is contrary to Jacobson et al. (1997) who found that males were photographed more frequently, especially at low camera density (1/259 ha). The difference found by Jacobson et al. (1997) could be due to their lower camera density of 1/65 ha, whereas our camera density was 1/44 ha. Our results are similar to those of Weckel et al. (2011) who noted females were photographed more frequently with a higher camera density (<1/25 ha). Home range size of female deer is approximately half that of males (Vanderhoof and Jacobson 1993, Walter et al. 2011) and a greater camera density would likely result in cameras being placed within a females core area. Further, our study was conducted on a high-fence population with a high population density which may also lead to smaller home ranges (Marchinton and Hirth 1984).

We also observed a significant difference between detection probability during the day and all other time periods which could serve as another potential source of variability in detection that is unaccounted for. It is commonly accepted that detectability is not uniform and may differ between sexes, age classes, individuals, and location (Cutler and Swann 1999, McCoy et al. 2011), however temporal variation is generally not considered. During the day, deer are generally less active (Beier and McCullough 1990) and may be detected less frequently during that time. Further, long term studies may encounter changes in detection probabilities from year to year or season to season. Analyses based on indices or raw counts may result in inaccurate conclusions about population change if a time trend in detection probability exists. Modeling more sources of variation in detection can result in less biased, more accurate estimates of abundance.

We conclude that use of Royle’s (2004) N-mixture model can provide accurate population and demographic estimates for white-tailed deer if the survey design does not violate model assumptions. We found that surveying for 5 nights returned highly accurate estimates of male and female deer abundance in our study area. Our study was conducted on a high-fence population, and in a wild population it may take longer than 5 nights to obtain enough captures to accurately estimate abundance because population density may be less than in this closed, high-fence area. Our results may also be influenced by the manipulation of a motion-trigger delay setting to mimic a time-lapse setting. Variability exists in the sensitivity of motion sensors (Damm et al. 2010) and deer that were present at the site may have not been photographed. However, our estimates of accuracy would likely be conservative if this occurred. Regardless, our results indicate that time-lapse camera surveys using N-mixture model analysis has high potential for use in monitoring white-tailed deer populations.

MANAGEMENT IMPLICATIONS

We suggest that the repeated counts approach (Royle 2004) for estimating deer density and demographics could be widely adopted for monitoring deer populations and informing harvest management decisions. Our results can be used to better plan future camera surveys and monitoring programs for white-tailed deer in an economically efficient way and help to reduce survey effort. For example, in our study area shortening camera survey lengths to 5 days would decrease costs associated with fuel, bait, and labor, while also reducing the number of pictures to examine. Additionally, surveying only at night could further reduce effort without reducing estimation precision. We found that abundance estimates using only night time data provided comparable estimates to surveying for 24 hours, which would result in a 50% decrease in the number of photographs using a time-lapse setting.

Other considerations when designing a survey are camera density and sampling density (effective sampling area). Ideal camera and sampling density will differ among survey techniques. For the Jacobson et al. (1997) method or even Mark-Recapture it is important to place cameras close enough to either maximize number of unique individuals photographed or to increase recapture rates. For N-mixture models (Royle 2004), camera and sampling density need to balance the model assumptions of every individual having some probability of being detected, and of individuals not being photographed at more than one site. Lower camera and sampling densities could result in sex biased estimates favoring males (Jacobson et al. 1997), depending on home range size. If the sampling density is much larger or smaller than the home range size of the animal, the effective sampling area must be adjusted to convert from site-specific abundance to density. Otherwise, estimates of density would be biased. Studies of free-ranging deer should evaluate the relationship between home range size and density estimates from repeated point counts surveys.

Our study comparing known numbers of marked deer to abundance estimates from N-mixture models indicate that repeated counts of unmarked deer using time-lapse photography is potentially a highly effective and efficient way to survey white-tailed deer. Although the code is available for Program R (The R Foundation for Statistical Computing, 2009; Royle and Dorazio 2008) the repeated counts method still requires the knowledge of computer code and software. Further, hierarchical models are technically cumbersome while the Jacobson et al. (1997) method is perceived to be a useful tool for managers because it does not require advanced quantitative analyses. However, the Jacobson et al. (1997) approach does not address sources of potentially significant estimation bias (spatial, temporal, gender and age detection biases). We contend that although an analysis is more familiar and technically easier, potentially biased estimates that do not account for the complexities of detection variability could lead managers to incorrect inference and flawed decisions.

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TABLES AND FIGURES

Table 1.1. True population size of marked deer (N) and number of male, female, and total deer identified from two camera surveys of a fenced white-tailed deer population at Auburn University's deer research facility located near Camp Hill, Alabama from September and October of 2010.

	Survey 1	Survey 2	Collective	N^a
Male	19	24	26	41
Female	15	22	22	34
Total	34	46	48	75

[a] Total number of marked deer.

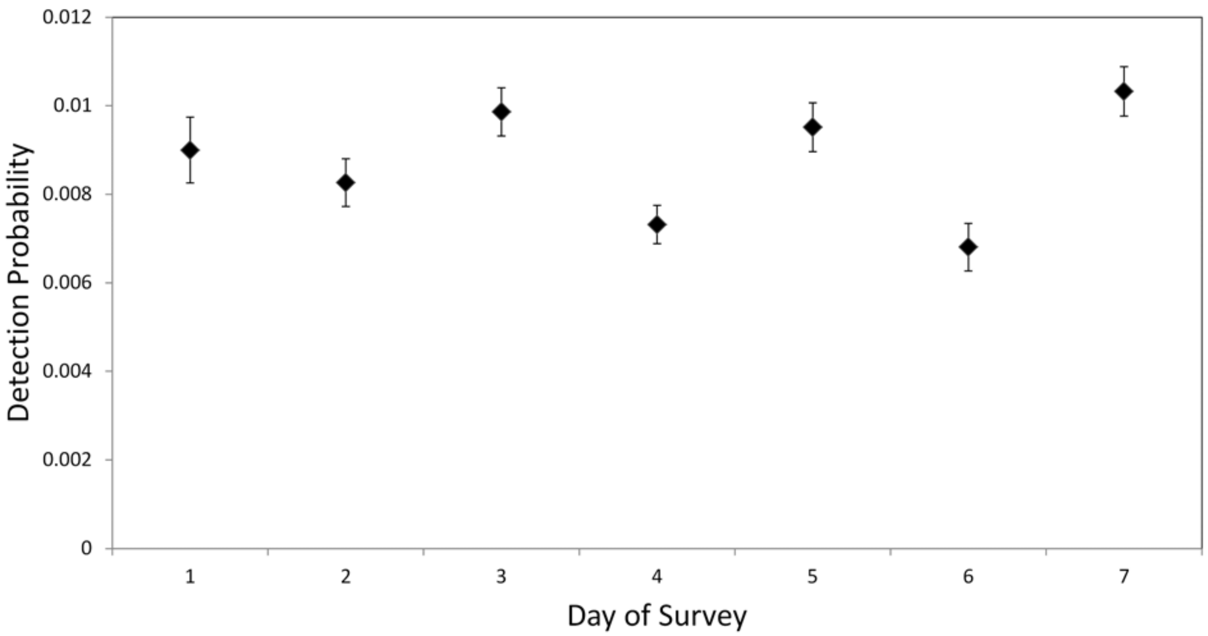

Figure 1.1. Detection probability for a fenced population of white-tailed deer by survey day at Auburn University's deer research facility located near Camp Hill, Alabama during September and October of 2010.

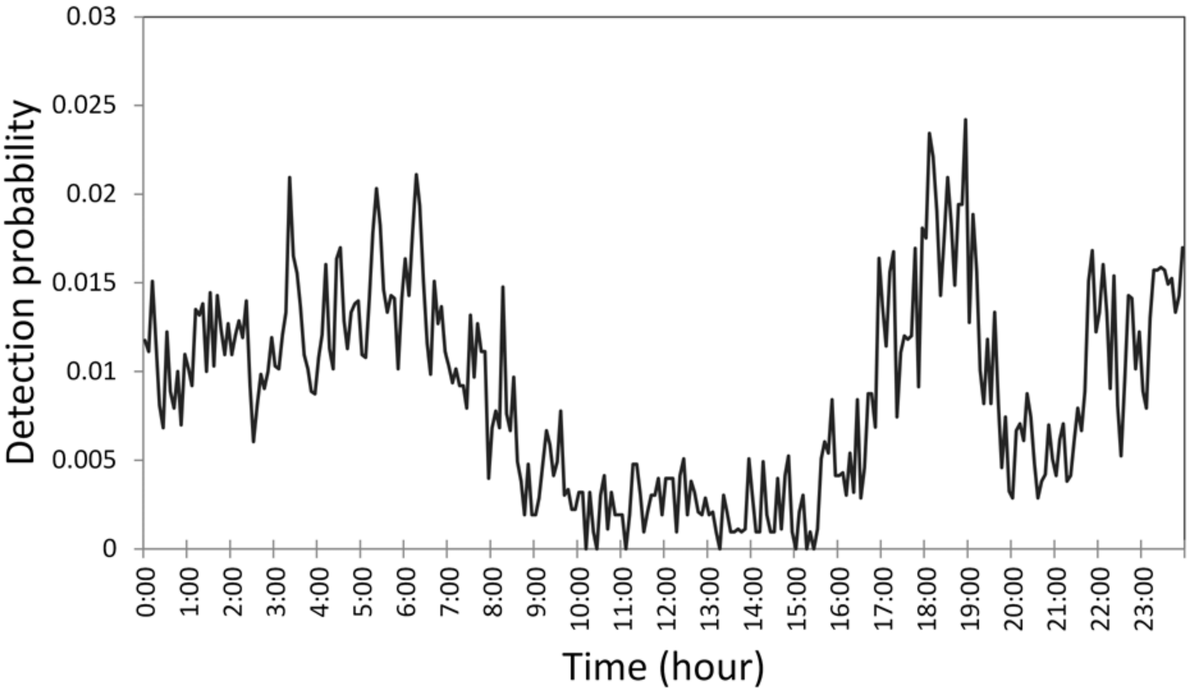

Figure 1.2. Detection rate for a fenced population of white-tailed deer by time of day at Auburn University's deer research facility located near Camp Hill, Alabama from September and October of 2010.

Table 1.2. Detection rate and density estimates by time period, DAY (2 hours after sunrise to 2 hours before sunset), NIGHT (2 hours before sunset to 2 hours after sunrise), SUNRISE (2 hours before and after sunrise), SUNSET (2 hours before and after sunset), CREPUSCULAR (2 hours before and after both sunrise and sunset), and ALL TIMES (24 hours) of a fenced white-tailed deer population at Auburn University's deer research facility located near Camp Hill, Alabama from September and October of 2010. The true population size of marked deer was 75.

Time period	Mean detection probability	SE	Mean density estimate	SE
DAY	0.0029	0.00019	N/A[a]	N/A[a]
NIGHT	0.0116	0.00029	72.6	13.8
SUNRISE	0.0124	0.00059	187.0	20.5
SUNSET	0.0123	0.00062	140.0	50.5
CREPESCULAR	0.0124	0.00043	130.7	15.1
ALL TIMES	0.0087	0.00021	77.4	13.8

[a] These values were inestimable due to low detection rate.

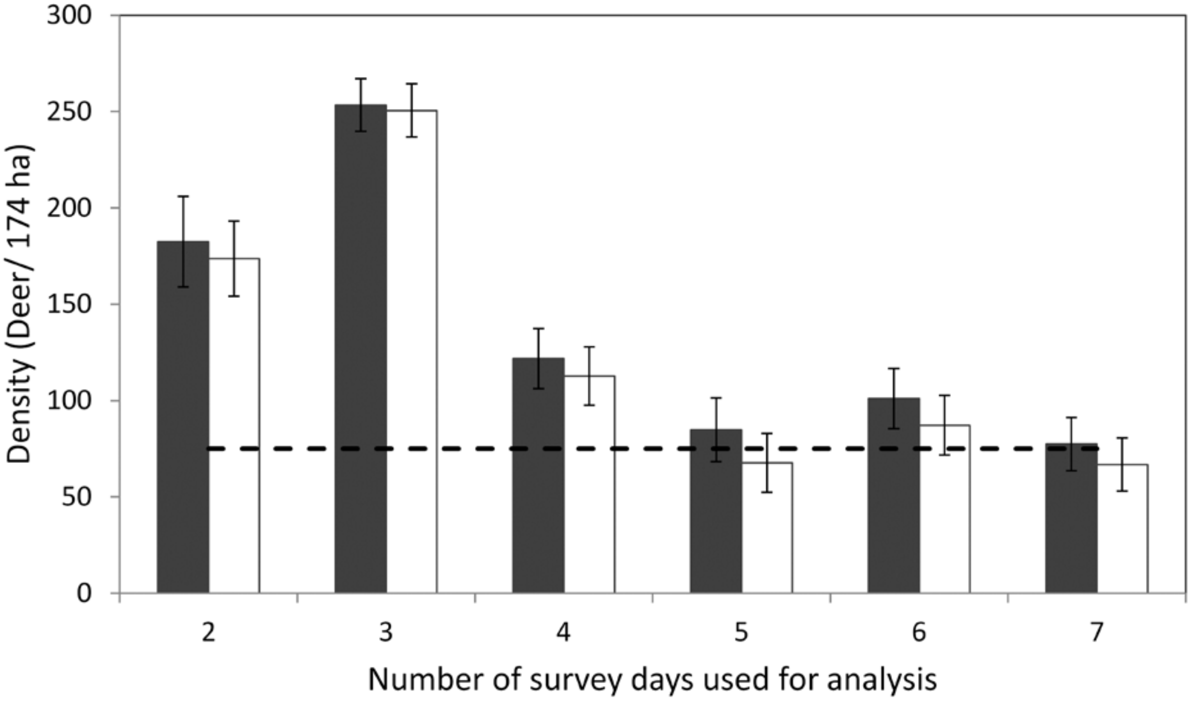

Figure 1.3. Density estimates for a marked, known population of fenced white-tailed deer by number of survey days used for analysis using repeated point counts for two different time periods, Night (2 hours before sunset to 2 hours after sunrise; open bars) and All Times (24 hours; solid bars) at Auburn University's deer research facility located near Camp Hill, Alabama from September and October of 2010. True density of the marked population is denoted by the black dashed line.

Chapter 2:

Impacts of predator removal and interspecific competition on white-tailed deer population dynamics

ABSTRACT

Predation and interspecific competition can have significant effects on population dynamics and influence management decisions. Expansion of coyotes (*Canis latrans*) into the Southeast has altered the predator community, and many studies have shown that coyote predation on white-tailed deer (*Odocoileus virginianus*) fawns can reduce recruitment. Predator removal temporarily increases fawn recruitment, however the long term effects of coyote removal on population dynamics are still unclear. Additionally, wild pigs (*Sus scrofa*), which have recently expanded in range and numbers, are thought to displace or exclude deer from pulse food resources. Understanding the impacts of coyote removal and wild pig presence and abundance on deer population dynamics will give insight on how changing community structure affects an important native game species, and will be imperative for future management of white-tailed deer. We estimated white-tailed deer population size and structure at Fort Rucker, Alabama, and evaluated the effects of coyote removal, wild pigs, change in harvest regulations, and habitat type on these parameters using N-mixture models for open populations in UNMARKED. We conducted time-lapse camera surveys in the spring and fall of 2011-2012 and spring of 2013 to collect count data of does, bucks, and fawns. Fort Rucker biologists removed coyotes since spring 2011. Coyote removal increased site-specific fawn abundance. However, the increase in fawn abundance did not result in a significant increase in the adult population.

Additionally, our data suggest that wild pigs displace or exclude deer from pulse food resources, and support the hypothesis that wild pigs compete with deer.

INTRODUCTION

As species ranges expand and contract in response to anthropomorphic environmental alterations (e.g., climate change, exotic species introductions) ecological community structure can become highly altered. There are a variety of species in the southeastern United States that have been extirpated (e.g., red wolves [*Canis rufus*], Nowak 2002; cougars [*Puma concolor*], Lindzey 1987), and a variety of others that have been introduced and/or expanded their range (e.g., red imported fire ants [*Solenopsis invictaI*], Deyrup et al. 2000; coyotes [*Canis latrans*], Parker 1995) to exploit vacated niches within the remaining communities. New predators may impact prey populations differently than their extirpated predecessors (Salo et al. 2010), and new competitors could alter native species behavior and population dynamics (Gurnell et al. 2004). This could have ramifications for management strategies in either conservation or harvest contexts. Management of a species often relies on or requires a thorough understanding of population dynamics, or temporal changes in population size and structure. For management to affect population size, it must influence either gains (i.e., reproduction or immigration) or losses to the population (i.e., mortality or emigration). Processes such as predation and interspecific competition can have potentially significant effects on population dynamics, and would demand knowledge at the community level to fully explain a population of interest. Coyotes, wild pigs (*Sus scrofa*), and white-tailed deer (*Odocoileus virginianus*) in the southeastern US provide opportunities to study the emerging dynamics between relatively new predators, competitors, and a native, intensively managed and highly important game species.

White-tailed deer have been extensively studied due to their economic importance, and many factors driving deer population dynamics have already been determined and quantified. However, the recent expansion of coyotes into the southeastern United States (Parker 1995) has altered the predator community, and their impact on deer population dynamics is still uncertain. Coyotes were once restricted to the Great Plains region, but with the extirpation of apex predators and the clearing of land for agriculture coyotes now inhabit the entire continental United States (Parker 1995). Coyotes will likely impact prey populations differently than the extirpated gray wolf (*Canis lupus*) in the north or the red wolf in the south and east, which coyotes have theoretically replaced in the ecological communities in this region (Ballard et al. 1999). Generally, introduced predators have greater impacts on prey populations than do native predators (Salo et al. 2007, Salo et al. 2010). Although not a major threat to mature deer, coyotes have been shown to heavily prey upon fawns (Saalfeld and Ditchkoff 2007, VanGilder et al. 2009, Kilgo et al. 2012, Jackson and Ditchkoff 2013, McCoy et al. 2013), and food habit studies have reported that deer occur most frequently in coyotes' diet during the fawning period in the Southeast (Wooding 1984, Ballard et al. 2001, Schrecengost et al. 2008) and also during the winter in deer and coyotes' northern ranges (Patterson et al. 1998). Additionally, low fawn survival has been noted in several areas across the Southeast (Saalfeld and Ditchkoff 2007, Kilgo et al. 2012, Jackson and Ditchkoff 2013, McCoy et al. 2013) and other reaches of coyote and deer distribution (Cook et al. 1971, Bartush and Lewis 1981, Long et al. 1998), primarily attributed to coyote predation. Some deer populations might benefit from this new predator, but with a shift towards Quality Deer Management (QDM) promoting high female harvests and lower population levels than under traditional management (Miller and Marchinton 1995), coyotes may have the potential to significantly impact deer populations.

Coyote removal is an option for managers and private landowners to negate effects of coyote predation on fawn recruitment. Predator control programs have had mixed results, and certain factors may lead to removal having more of an effect on prey populations. To be effective, Ballard et al. (2001) suggested that 1) predator control be used when deer populations are well below carrying capacity of the habitat, 2) predation is a limiting factor, 3) predator populations be substantially reduced (reduced by roughly 70%), 4) removal occurs prior to fawning, and 5) the study area be relatively small (<1000 km^2). Predator removal studies conducted when deer populations are below carrying capacity have resulted in increases in fawn:doe ratios (Beasom 1974, Bartush and Lewis 1981, Stout 1982). Conversely, deer herds that were at or near carrying capacity experienced little to no increase in recruitment following predator removal (Bartmann et al. 1992). Studies conducted on small scales have shown that predator removal can increase fawn survival and recruitment when predation is limiting and a majority of the coyote population is removed (Ballard et al. 2001). Although some studies have found substantial increases to white-tailed deer fawn recruitment in the season following coyote removal (156% increase in fawn recruitment, Beasom 1974; 154%, Stout 1982; 153%, VanGilder et al. 2009; 115%, Howze et al. 2009), more information is needed on the effects of successive years of coyote removal on deer population dynamics.

The impetus for most predator removal programs is to reduce human-wildlife conflicts, minimize loss of livestock, and increase or maintain game species populations (Parker 1995). Coyotes will likely not be completely eradicated, and removal programs may play an important role for deer management in the future. Following removal, coyotes can quickly recolonize removal areas, and open-area removals typically contend with immigration of predators from neighboring areas (Korpimäki et al. 2002). For example, a predator removal study found that track counts dropped to near zero in an experimental area until removal efforts ceased, then gradually increased thereafter until reaching control area levels within five months (Beasom 1974). Areas which aren’t fenced often require continuous predator removal (Holt et al. 2008, Salo et al. 2010). Maintaining removal efforts to increase deer abundance and hunter harvest opportunities can be costly to implement, especially on larger scales. Hurley et al. (2011) found that coyote removal increased fawn survival 15% and determined that in ten years 65 additional yearling males would be produced, costing $1,581 per deer using an average annual cost of coyote removal at $10,276. If trophy management is the objective, then an estimated 6 additional 4-year-old males in ten years would cost $17,127 per deer over ten years (Hurley et al. 2011). A better understanding of the effects of coyote removal on population growth rate could enable managers to strategically plan long-term removal efforts to maximize cost effectiveness.

Although it is easy to perceive the link between predation and prey population dynamics, the relationship between interspecific competition and population dynamics may be more abstruse. Competition can be defined as one organism negatively impacting another by controlling access to (e.g. reduced access to high quality resources, Wauters et al. 2001) or consuming a limited resource (Keddy 1989). This can adversely affect population dynamics such as reproduction, survival, or recruitment of immigrants. Potential exists for wild pigs to compete with deer due to dietary overlap (Wood and Roark 1980, Taylor and Hellgren 1997). Wild pigs are an introduced species in North America, and are expanding in range and numbers. Their success can be attributed to intentional introductions and stocking for meat and commercial hunting (Long 2003), a high fecundity rate (Dzieciolowski et al. 1992, Taylor et al. 1998), high dietary plasticity (Genov 1981, Taylor and Hellgren 1997, Baubet et al. 2004), low predator abundances (Ickes 2001, Massei and Genov 2004), and their tolerance to a wide range of environmental conditions as evidenced by their wide native distribution in Europe and Asia (Baskin and Danell 2003).

Few studies have detailed the impacts of wild pigs on white-tailed deer populations, however anecdotal observations indicate that pigs displace or exclude deer from pulse food resources (Tolleson et al. 1995, Taylor and Hellgren 1997). The displacement of deer by wild pigs might result from some negative effect of wild pigs on deer populations, or it may be apparent and result from changes in detectability in deer survey data. Wild pigs can potentially lower detection probability of deer at baited sites or food resources which can have implications for camera surveys geared at estimating abundance. Tolleson et al. (1995) also stated that wild pigs are an important competitor with deer, and that deer will avoid foraging in areas utilized by wild pigs. This competition has potential to impact population parameters. Studies of the effects of wild pigs on deer are needed to accurately estimate deer population parameters. Understanding white-tailed deer population dynamics given the changes in community structure will be imperative for future management decisions.

Estimates of white-tailed deer population size, age structure, and sex ratios and impacts of coyote removal and wild pigs on these parameters will give insight on how altered community structure affects an important native game species, and will be imperative for future management of white-tailed deer. Traditionally, these parameters would be estimated using mark-recapture methods, and potentially require multiple studies to determine population parameters and how they are affected by coyote removal and wild pigs. Mark-recapture is labor intensive and can be costly to implement on large scales. Dail and Madsen (2011) proposed a hierarchical model which can estimate population parameters and covariate effects on those parameters using only spatially and temporally replicated count data. N-mixture models can accurately estimate white-tailed deer density using count data from camera surveys for a single season (Keever, unpublished data). Expanding this to an open population allows inference to be made regarding impacts of coyote removal and wild pigs on population parameters in current and subsequent years. In this study, we use the Dail-Madsen (2011) model to identify and estimate factors that influence white-tailed deer population dynamics. Specifically, we estimated density, age and sex structure, recruitment, and apparent survival using time-lapse camera surveys and N-mixture models (Royle 2004) for open populations (Dail and Madsen 2011). Through covariate analyses we determined the effects of coyote removal on fawn abundance and investigated a time-lag effect of coyote removal. We also estimated the impact of wild pigs, habitat characteristics, and change in harvest regulations on deer population parameters.

STUDY AREA

This study was conducted at Fort Rucker in southeastern Alabama (Dale and Coffee counties) located near Enterprise, Alabama. Fort Rucker was a U.S. Army installation where helicopter pilots were trained for the Army Aviation branch and the U.S. Air Force. The facility was 255 km^2 but the upper third (57 km^2) was an impact area and off limits to access. A 2.4-m-tall chain linked fence topped with barbed wire partially encased the facility while still allowing movement of animals. Fort Rucker was located in the Lower Coastal Plains physiographic region and had fragile deep sands derived from marine and fluvial sediments (Mitchell 2008). The plant community was primarily pine (*Pinus* spp.; typically located in upland areas) and mixed pine-hardwood forests (usually found on lower slopes and alluvial bottoms) dominated by: loblolly pine (*Pinus taeda*), shortleaf pine (*P. echinata*), longleaf pine (*P. palustris*), slash pine (*P. elliottii*), sweetgum (*Liquidambar styraciflua*), yellow-poplar (*Liriodendron tulipifera*), southern red oak (*Quercus falcata*), laurel oak (*Q. laurifolia*), and persimmon (*Diospyros virginiana*), among others. Hardwood stands consisted of various species of hickory (*Carya* spp.), oak (*Quercus* spp.), and magnolia (*Magnolia* spp.) and were found primarily in alluvial valleys (Mount and Diamond 1992). Wildlife food plots were dispersed throughout the installation with various crops planted to supplement natural food sources as well as wildlife openings which were maintained by mowing. The main water source was Lake Tholocco with various creeks throughout the facility.

Management practices on the post included prescribed burns which began in the 1980s but increased in intensity and frequency with around 45 km^2 burned annually. Additionally, thinning and herbicides were used to maintain desired species composition. Predator control in the form of coyote removal began in spring of 2011. Efforts were concentrated before the fawning period, however, coyote trapping continued opportunistically throughout the course of this study. Wild pig trapping also occurred throughout the installation. All land resources were managed in compliance with Federal, State, and local regulations while operating for the good of the U.S. Army.

Archery and firearm hunting were permitted on Fort Rucker with exception of the impact area. In the 1980s Fort Rucker showed signs of poor white-tailed deer herd condition (e.g., body weights, parasite counts, etc.). This suggested that the population was above the carrying capacity of the habitat, and managers increased antlerless harvest to decrease the population. Herd conditions improved but deer densities fell below preferred levels. Fort Rucker biologists decreased antlerless harvest in 1995, however, the population never rebounded and harvest rates were considered too low. Recently, harvest of white-tailed deer was below 100 deer on the entire facility. For the 2011-2012 hunting season, 59 deer were harvested including 18 does and 41 bucks. Following the 2011-2012 hunting season harvest of does was prohibited, and only 22 antlered deer were reported harvested in the 2012-2013 season. The low harvest rates were thought to be a result of greater coyote predation on fawns. A study conducted at Fort Rucker from 2009 to 2010 found fawn survival to six months to be 0.26 (95% CI = 0.10 – 0.68) with a probability of mortality due to coyote predation of 0.65 (95% CI = 0.14 – 0.86; Jackson and Ditchkoff 2013).

METHODS

We conducted time-lapse camera surveys from 22 February-2 March 2011 (primary period 1), 26 September-4 October 2011 (primary period 2), 21 February-1 March 2012 (primary period 3), 24 September-5 October 2012 (primary period 4), and 19 February-27 February 2013 (primary period 5). Twenty-six sites were established 2.41 km apart based on a grid design throughout the base excluding the impact area (Figure 2.1). For each primary period we randomly selected 20 sites to survey using a random number generator. Fort Rucker biologists located site centroids with handheld GPS units. Near the centroid, we placed cameras in locations with signs of deer activity or suitable habitat to maximize capture probability. To decrease bias in camera placement, locations were first sought within a 91-m buffer of the centroid, then within a 183-m and 274-m buffer as needed. Cameras were placed on trees approximately 1.5 m above the ground and oriented either north or south. Any vegetation obstructing the camera’s view of the bait was cleared. Each site was pre-baited one week prior to the survey with 11 kg of corn 4 m away from the cameras. Sites were refreshed with corn after 3 to 4 days and re-baited with 11 kg of corn when cameras were deployed. We used Reconyx PC-85 game cameras (RECONYX, Inc., Holmen, Wisconsin) set on a 4-minute time-lapse setting.

Cameras were set out for a minimum of 7 days, and sites were refreshed with corn after 3 days. Sites were visited a total of 5 times each primary period: 1) prebait, 2) refresh bait and trim vegetation, 3) deploy cameras, refresh bait, and trim vegetation, 4) refresh bait and trim vegetation, and 5) retrieve cameras.

Deer were counted in each image, and were classified as bucks, does, fawns, or unknowns. A deer was classified as an unknown when the deer's position in the image made determining sex and/or age impossible (e.g., the head was outside the frame of the image). All images were processed by a single observer to maintain consistent classification. Due to computational limitations and the large amount of images generated from the 4-minute time-lapse setting, sampling occasions were condensed to times of peak activity (Keever, unpublished data). In spring surveys, images from 15:36 to 8:12 were used, and in fall surveys, images from 16:36 to 8:24 were used, representing 2 hours before mean sunset time till 2 hours after mean sunrise time. Although most camera surveys for deer use a 4- or 5-minute delay setting (Jacobson et al. 1997, Koerth and Kroll 2000, Curtis et al. 2009) we used images captured every 12 minutes for analyses. Kozicky (1997) reported that deer spend more than 10 minutes feeding at scattered bait piles, and Acker (2013) reported that a 10-minute trigger delay resulted in equivocal individual identifications as a 5-minute trigger delay setting.

Population abundance, covariate effects, and standard errors were estimated using the program R (The R Foundation for Statistical Computing, 2013, version 3.0.2) UNMARKED package (Fiske and Chandler 2011) for N-mixture models of open populations (Dail and Madsen 2011). The Dail-Madsen model (Dail and Madsen 2011) was a generalized form of the Royle (2004) repeated counts N-mixture model, allowing for a robust design where the closure assumption must only be met within a primary period. In our paper we use the symbols and parameter nomenclature used by Fiske and Chandler (2011). Initial abundance (λ) was modeled using a Poisson distribution, $N_{it} \sim Poisson(\lambda)$ where N_{it} was the number of individuals at site i in primary period t. In subsequent years, abundance was the result of mortality, recruitment, and movements, such that

$$N_{it+1} = G_{it} + S_{it}$$

The number recruited to the population (G_{it}) followed $G_{it} \sim Poisson(\gamma_{it})$, and the number that survived and did not emigrate (S_{it}) was modeled as $S_{it} \sim Binomial(N_{it-1}, \omega_{it})$. The detection process was modeled as $y_{ijt} \sim Binomial(N_{it}, p_{ijt})$, where y_{ijt} is the observed count and p_{ijt} at site i in sampling occasion j and primary period t. The four parameters estimated by the model were initial abundance (λ_i), apparent survival probability (ω_{it}), recruitment rate (γ_{it}), and detection probability (p_{ijt}). Since individuals were unmarked it was not possible to differentiate between emigration and death or immigration and recruitment. Therefore, recruitment rate (γ_{it}) was the rate at which individuals were gained at a site, and apparent survival probability (ω_{it}) was one minus the probability of losing an individual at a site. We used the auto-regressive model for does and bucks where recruitment rate (γ_{it}) was modeled as $G_{it} \sim Poisson(\gamma_{it} \times N_{it-1})$ and impacted the latent parameter G_{it}. Fawns were modeled using the trend dynamic in which $N_{it} \sim Poisson(N_{it-1} \times \gamma_{it})$, where γ_{it} was the finite rate of increase and directly affected abundance, and the latent parameters S_{it} and G_{it} were not included. A Poisson distribution was used for initial abundance (λ_i) in buck, doe, and fawn models. The model also required a specified K value, which is an integer defining the upper bound for integration of the likelihood. A low K value could bias parameter estimates, and a high K value would increase computational time. We used the null model (constant model for all parameters) to determine a K value which produced stable parameter estimates. A K value of 200 was used for the doe and buck models, and a K value of 100 was used for the fawn models.

Each of the four estimated parameters can be modelled as a function of covariates (Fiske and Chandler 2011). Covariates used for detection (p) were amount of precipitation (rain), time of day (time), frequency of wild pig site visitation (pHog), and season. Hourly precipitation amounts were obtained from the National Oceanic and Atmospheric Association. Each site and occasion within an hour had the same value for rain. Time was a quartic function ($\text{time}+\text{time}^2+\text{time}^3+\text{time}^4$) to account for the crepuscular behavior of deer and variation in temporal visitation rates of deer (Keever, unpublished data). PHog was the number of images with wild pigs per hour and was site specific. We included this covariate to account for the effect of temporal separation or behavioral exclusion of deer from bait sites on detection. Season was a binary number with spring as the reference group. Landscape classifications provided by Fort Rucker were used as covariates for initial abundance (λ). The percentage of developed lands (Dev), hardwoods (Hrdwd), mixed pine-hardwood forests (Mixed), and pines (Pine) were determined in a 340 ha area around each survey point using ArcGIS (ESRI, Inc., Redlands, CA). This area represented the approximate mean home range size of bucks (Appendix A). Covariates for recruitment (γ) included coyote removal (Coy), a time-lag effect of coyote removal (Lag), and the number of individual wild pigs identified that used a specific site (Hog). The Lag covariate was a binary number where 1 represented coyote removal occurred at the site the year before and 0 was no coyote removal the year before. The Hog covariate was intended to serve as an index of hog abundance or density, and was included here to assess the impact of hog abundance/density on deer population demographics. Coyote removal by Fort Rucker biologists began in spring 2011 and occurred at random sites throughout the study. Only sites where coyotes were removed prior to or during the fawning period were counted as having coyote removal. We modeled apparent survival (ω) using variables for harvest separately for males (HarM) and females (HarF). We standardized all continuous covariate data by subtracting the mean and dividing by the standard deviation.

We compared models using AIC corrected for small sample size (AICc), with the number of survey occasions as the sample size, and model probability (w) (Burnham and Anderson 2002). Due to the large number of covariates and potential candidate models, we used a hierarchical or sequential process to run models similar to Franklin et al. (2004) or McGowan et al. (2011). We first compared all detection (p) models for does, bucks, and fawns using the average initial abundance ($\lambda(.)$) and recruitment ($\gamma(.)$) models, and for does and bucks the average apparent survival ($\omega(.)$) model. Detection models were run first because it could impact the biological parameters (initial abundance, recruitment, apparent survival) that we were most interested in. Then, the best detection models (cumulative AICc weight (w) of > 90) were used to compare abundance (λ) models with the average recruitment ($\gamma(.)$) and apparent survival ($\omega(.)$) models. Initial abundance models were run next because the other parameters (recruitment and apparent survival) are transitions from the initial abundance to determine abundance in the next time step. For fawns, the best models were then compared to recruitment (γ) models for final model selection. In does and bucks, the best models from the abundance (λ) selection process were compared first to apparent survival (ω) models, then recruitment (γ) models, and this order was arbitrary.

All estimates of covariate effects were estimated using model averaging due to uncertainty in model selection (Burnham and Anderson 2002). Covariate effects were reported as odds ratios or the estimates of effects on the unstandardized scale (β values). Site-specific abundance estimates were generated using the built in empirical Bayes method in UNMARKED (Fiske and Chandler 2011). The posterior probability distributions for each season and site were weighted by model probability (w) for the top models (ΔAICc < 2). We then created mean probability distributions of abundance for each season by taking the arithmetic mean of site-specific probability distributions. To convert from abundance to density, we divided mean abundance by an effective sampled area (ESA) using Bayes nets in Netica (Norsys Software Corp., 2012, version 5.09) (Appendix B). We adjusted for estimated home range size because sampling density was low relative to home range size, and estimates of density and the number of animals that use a particular site would be biased low. We searched the literature for home range estimates of free-ranging deer in the Southeast and surrounding states (Appendix A). Each sampling unit represented an area of 5.83 km^2, which was larger than the average home range size of deer (Appendix A). We used the compilation of estimates of home range size to create a home range size probability distribution for bucks, and a home range size probability distribution for does and fawns to account for uncertainty in home range size. We used the first 95% of the probability of density for bucks, does, and fawns to eliminate the effects that the tails of the probability distributions had on estimated density.

RESULTS

We had 1 camera fail during primary period 1, 3 cameras fail during primary period 4, and 2 cameras fail during primary period 5. A total of 279,052 images were produced and processed during the 5 primary periods. Deer were present in 6,998 (2.5%) of those images. Bucks were observed in images more frequently (53.2% of images with deer) than any other classification, followed by does (34.9% of images with deer), unknowns (16.3% of images with deer), and fawns (8.4% of images with deer; Table 2.1). We had a count of 1,176 unknown deer (14.0 % of total count). After reducing camera survey occasions to every 12 minutes at night, we had total of 62,432 survey occasions. There was no coyote removal prior to spring 2011 (primary period 1). For fall 2011 (primary period 2) and spring 2012 (primary period 3) there were 8 sites where coyote removal occurred, which resulted in the removal of 17 coyotes from camera sites. For fall 2012 and spring 2013 there were 9 sites where coyotes were removed, and 4 of those sites had coyotes removed the year prior. There were 14 coyotes removed for fall 2012 and spring 2013 from camera sites. We identified a total of 11 wild pigs at 2 of 19 sites in spring 2011, 21 wild pigs at 9 of 20 sites in fall 2011, 15 wild pigs at 6 of 20 sites in spring 2012, 46 wild pigs at 5 of 16 sites in fall 2012, and 54 wild pigs at 10 of 18 sites in spring 2013.

The top buck detection (p) model estimated detection based on amount of precipitation, frequency of wild pig site visitation, time of day, and season ($w = 0.62$; Table 2.2). However, there was some uncertainty in model selection, and 2 other models were deemed competitive. All other top models included time of day and season as covariates for detection. We found that bucks were 1.74 times as likely (1.44-2.12; 95% C.L.) to be detected in the spring than the fall. Also, we noted a negative relationship between detection probability and amount of precipitation (-1.04 ± 0.81; β ± SE) and frequency of wild pig site visitation (-0.21 ± 0.16; β ± SE). Additionally, we found a quartic relationship between detection and time of day (Figure 2.2). The top detection (p) model for does included frequency of wild pig site visitation and time of day, however there was considerable model uncertainty (top model $w = 0.36$) and the top 4 models were supported as competing models for doe detection probability ($w \geq 0.15$; Table 2.3). The top four models all had frequency of wild pig site visitation and time as covariates for detection. We did not find an effect of season on doe detection probability. We found a negative effect of rain (-0.55 ± 0.05; β ± SE) and frequency of wild pig site visitation (-0.38 ± 0.17; β ± SE) on doe detection probability. We also noted a quartic relationship between detection probability of does and time of day. For fawns, the top detection (p) model included the amount of precipitation, frequency of wild pig visitation, time of day, and season as covariates of detection probability ($w = 0.69$; Table 2.4). Only one other model was competitive, and it included frequency of wild pig visitation, time of day, and season ($w = 0.29$). Notably, all models that included the effect of season were ranked higher than models without the effect of season. We found that fawns were 13.06 times as likely (6.14-27.77; 95% C.L.) to be detected in the spring than in the fall. We also found a negative effect of frequency of wild pig site visitation (-1.99 ± 0.96; β ± SE) and precipitation (-2.10 ± 2.09; β ± SE) on fawn detection. Similarly to does and bucks, we found a quartic relationship between detection probability of fawns and time of day.

There were a total of 48 initial abundance models for bucks, and the top 10 were selected for the next model selection step based on the criteria of a cumulative $w \geq 0.90$. The top model ($w = 0.27$) included number of wild pigs, % hardwood, % mixed pine-hardwood, and % pine as covariates for initial abundance, and precipitation, frequency of wild pig visitation, time of day, and season for detection (Table 2.5). We found a positive relationship between initial abundance and % developed lands and % pines (Figure 2.3). We found a negative relationship between initial abundance of bucks and % hardwoods, % mixed pine-hardwoods, and the number of wild pigs identified using a site (Figure 2.4). The top initial abundance model for does estimated abundance based on % developed land and % pines, and detection based on the amount of precipitation, frequency of wild pig visitation, time of day, and season ($w = 0.28$). However, there was a great deal of uncertainty in model selection and 16 models were selected as competitive (Table 2.6). We found a positive relationship between initial doe abundance and % pines (Figure 2.5). We found a negative relationship between initial abundance of does and % hardwoods, % mixed pine-hardwoods, and number of wild pigs. We found no effect of % developed lands on initial doe abundance. The top model for fawn abundance included number of wild pigs, % hardwood, % mixed pine-hardwood, and % pine as covariates for initial abundance, and precipitation, frequency of wild pig visitation, time of day, and season as covariates for detection ($w = 0.22$; Table 2.7). Due to uncertainty in model selection, 6 models were selected for the next step in the hierarchical process. We found a positive relationship between initial fawn abundance and % developed lands and % pines (Figure 2.6). We found a negative relationship between initial fawn abundance and % hardwoods, % mixed pine-hardwoods, and the number of wild pigs identified using a site.

The top apparent survival probability model ($w = 0.30$) for bucks included the constant model for apparent survival, number of wild pigs, % hardwood, % mixed pine-hardwood, and % pine as covariates for initial abundance, and the amount of precipitation, frequency of wild pig visitation, time of day, and season for detection probability (Table 2.8). In fact, all models which included the constant for apparent survival were better than models which included the harvest covariate. Since there was some uncertainty in model selection, 7 models were selected for the next step in the hierarchical model selection process. The top apparent survival model for does included the constant model for apparent survival, % developed lands and % pine for initial abundance, and amount of precipitation, frequency of wild pig visitation, time of day, and season for detection probability ($w = 0.31$; Table 2.9). There was some uncertainty in model selection and 10 models were selected. All of those models included the constant model for apparent survival probability and % pine for initial abundance.

The top overall model for bucks estimated initial abundance as a function of the number of wild pigs, % hardwoods, % mixed pine-hardwoods, and % pine, and detection probability was modeled with amount of precipitation, frequency of wild pig visitation, time of day, and season with no covariates for recruitment or apparent survival ($w = 0.15$; Table 2.10). We found no effect of wild pigs (0.02 ± 0.03; β ± SE) or a time lag effect of coyote removal (0.04 ± 0.03; β ± SE) on buck recruitment rate. The top model for does included % pine and % developed lands as covariates for initial abundance, amount of precipitation, frequency of wild pig visitation, time of day, and season as covariates for detection, and no covariates for recruitment or apparent survival ($w = 0.11$; Table 2.11). We found no effect of coyote removal the year prior (0.08 ± 0.16; β ± SE) or wild pigs (0.05 ± 0.07; β ± SE) on doe recruitment rate. The top recruitment model for fawns included the effect of coyote removal and a time lag effect of coyote removal to estimate recruitment rate, the number of wild pigs, % hardwood, % mixed pine-hardwood, and % pine for initial abundance, and detection based on the amount of precipitation, frequency of wild pig visitation, time of day, and season ($w = 0.10$; Table 2.12). The next two best approximating models estimated recruitment as a function of coyote removal ($w = 0.07$ and $w = 0.06$, respectively). We found a positive relationship between coyote removal and the finite rate of increase of fawns (0.32 ± 0.30; β ± SE), however we also observed a negative effect of coyote removal the previous year (-0.26 ± 0.41; β ± SE) on the predicted finite rate of increase (Figure 2.7). We did not observe any effect of the number of wild pigs on the finite rate of increase of fawns (-0.003 ± 0.02; β ± SE).

Density estimates of bucks, does, and fawns decreased until spring 2012 (Table 2.13). Mean fawn:doe estimates were 0.80 in spring 2011, 0.79 in fall 2011, 0.69 in spring 2012, 0.72 in fall 2012, and 0.67 in spring 2013. Sites that never had coyote removal had 0.37 fawns per doe. Sites that had coyote removal only in the current year (no time lag effect) had 0.86 fawns per doe. Sites that had coyote removal the year before but not in the current year (lag effect) had fawn:doe ratio of 0.38. Sites that had 2 consecutive years of coyote removal (coyote and lag effect) had 0.77 fawns per doe. Mean buck:doe ratios during the study period were 1:1.41 in spring 2011, 1:1.45 in fall 2011, 1:1.52 in spring 2012, 1:1.54 in fall 2012, and 1:1.64 in spring 2013. There was a slight decrease in total density each spring (Figure 2.8). However, there were large standard errors and little change in density over the course of the study.

DISCUSSION

Understanding the factors that influence white-tailed deer population dynamics is important for making informed management decisions. Gains and losses to the population can be affected by community level processes such as predation and interspecific competition. Typically, estimating demographics and impacts of predation and competition requires years of intensive data collection, and is therefore primarily limited to relatively small spatial scales (Williams et al. 2002). The model proposed by Dail and Madsen (2011) extended N-mixture models (Royle 2004) to open populations to estimate demographic parameters from spatially and temporally replicated count data. We used this model to estimate density, age and sex ratios, and the impacts of predator removal and wild pigs on these parameters. Our estimates of density were low, however still within the range of recorded density estimates in the southeast (3-98 deer/km^2, Kie et al. 1983, DeYoung 1985, Keyser et al. 2005, Kilgo et al. 2010, Donohue et al. 2013). Sex ratios were fairly balanced (1:1.5 bucks per doe), and within the range of estimates under normal hunting scenarios (1:1 to 1:3.5 bucks per doe; Keyser et al. 2006). Fawn:doe ratios were greater than prior estimates of fawn:doe ratios at Fort Rucker (0.28 fawns per doe; Jackson and Ditchkoff 2013). Jackson and Ditchkoff (2013) did not account for differences in detection probability, and their study was prior to any coyote removal on the installation. Our estimates of fawn:doe ratios without any coyote removal were similar to those reported by Kilgo et al. (2010) following coyote establishment (0.41 fawns per doe), and with coyote removal our estimates were similar to pre coyote establishment fawn:doe ratios (0.80; Kilgo et al. 2010). Howze et al. (2009) reported fawn:doe ratios of 0.97 on coyote removal sites and 0.45 on non-removal zones. Similarly, Beasom (1974) reported 0.82 fawns per doe when coyotes were removed and 0.32 on the control area.

An issue with estimating density is accounting for the space that an animal uses and uncertainty in home rage or animal space use. Sampling density (site spacing) may over- or under-represent the area that the targeted species utilizes, and would result in biased estimates of density when converting from site abundance. Spatial capture-recapture models (Royle and Young 2008, Royle et al. 2009) use the number and location of individual activity centers to estimate density, however these models require individuals to be uniquely identifiable. Chandler and Royle (2013) developed a spatially-explicit model for unmarked populations to estimate density. This model capitalizes on the spatial structure of count data from close proximity sites to make inferences about spatial distribution and population size (Chandler and Royle 2013). However, that method requires high sampling density which would prove costly and difficult for large study areas. Instead, to convert from abundance to density we divided abundance estimates by an ESA. There are many ways to determine the ESA and different methods can produce very different density estimates (Parmenter et al. 2003, Soisalo and Cavalcanti 2006, Foster and Harmsen 2012). The ESA ultimately adjusts for the discrepancy between sampling density (site spacing) and home range size when extrapolating density to the entire study area. Sites were spaced to meet the model assumption that deer were not counted at more than once site. Our sampling density was 1 site per 5.83 km^2, whereas the mean home range of females based on a literature search was only 1.38 km^2, and for males was 3.23 km^2. It is well established that males tend to have a greater home range than females (Vanderhoof and Jacobson 1993, Walter et al. 2011), and also that density can affect home range size (Smith 1970, Bertrand et al. 1996, Kilpatrick et al. 2001). Additionally, it has been posited that bait sites can shift or alter home ranges of deer (Van Brackle et al. 1995). Although studies have found shifts in deer core use areas due to baiting, those studies noted no effect on total home range size (Kilpatrick and Stober 2002, Cooper et al. 2006), suggesting that our use of bait would not impact the assumed size of the area an animal uses. By creating a probability distribution of home range and using that rather than a single estimate of home range size to convert to density, we accounted for variability and also uncertainty in home range size and animal space use. In the end our density estimates represent the probable density given uncertainty in abundance estimates and home range size.

Camera surveys conducted in the fall can underrepresent fawn abundance and recruitment (McCoy et al. 2011), particularly in populations in the Southeast where fawns are born during late summer (Causey 1990, Gray et al. 2002). Our estimates of fawn density and fawn:doe ratios were consistent for fall and spring surveys because detection probability was incorporated into the estimation process. We did note, however, that season greatly influenced detection probability of bucks and fawns. Detection probability of fawns and bucks was greater in the spring than in the fall. The fact that fawns were more likely to be detected in the spring was not unexpected because in southern Alabama fawns are born in late summer (Gray et al. 2002) and would not be very mobile at the time of the fall survey. Spring surveys took place in late February, which was near the end of the breeding season in southeastern Alabama (Causey 1990). During the rut bucks reduce feeding effort (Geist 1982), and may be more likely to visit bait sites following the rut to feed, which could explain the greater detection probability of bucks in the spring. Although some studies raised concern with variation in use of bait by sex or age class biasing estimates of population size (Jacobson et al. 1997, McCoy et al. 2011), the incorporation of detection probability into the estimation process should have accounted for this. Additionally, we noted that an increase in precipitation greatly decreased detection probability for bucks, does, and fawns.

When two co-occurring species utilize the same food or habitat resources, competition for limited resources can occur (Begon et al. 2005). Our data indicate that wild pigs displace or exclude deer from pulse food resources, and support the hypothesis that wild pigs are a competitor with deer. Although we did not observe an effect of wild pigs on recruitment, we found that the number of wild pigs negatively affected the initial distribution of deer (initial abundance). The more wild pigs at a site, the lower the initial deer abundance or density were at that site. This could be the result of direct interference competition, and wild pigs could be excluding deer from food resources. Also, there is potential for competition between these species to be indirect, e.g. through exploitation of food resources. The diet of wild pigs is primarily comprised of plant material (e.g., roots, bulbs, tubers, stems, leaves, and hard and soft mast; Ditchkoff and Mayer 2009), and slightly overlaps with deer diet (Wood and Roark 1980, Taylor and Hellgren 1997). Population dynamics of large herbivores are typically driven by competition for limiting food resources (Sinclair 1989). The most adverse effects of competition are reduced reproductive output and survival (Begon et al. 2005), but reduced immigration and changes in habitat use can also result from competition (Gurnell et al. 2001, Gurnell et al. 2004).

Our data also indicate that detection probability of deer decreased with increasing frequency of wild pig site visitation. Spatial and temporal avoidance or resource partitioning is a common behavioral mechanism to cope with competition and allow coexistence (Palomares and Caro 1999, Dhondt 2012). Our findings suggest that deer avoid wild pigs and may be spatially and temporally partitioning resources, as would be expected if wild pigs excluded deer from pulse food resources. This form of interference competition typically results from either agonistic interactions or exclusion from a territory or resource (Begon et al. 1996). Wild pigs display agonistic behaviors with other pigs when resources are limiting and defendable (Schnebel and Griswold 1983; Sparklin et al. 2009), however, it is unknown whether agonistic interactions occur between wild pigs and deer.

It is possible that we did not observe an effect of wild pigs on deer recruitment because deer population density was low at the site and food was not limiting. Deer density at the study site was on the low end of the range for other areas in the Southeast (3-98 deer/km^2, Kie et al. 1983, DeYoung 1985, Keyser et al. 2005, Kilgo et al. 2010, Donohue et al. 2013), and food may not be limiting reproduction. Deer population density can greatly impact health and body mass (Shea et al. 1992, Keyser et al. 2005) which can affect reproductive output (McCullough 1979, Kie and White 1985). Resource partitioning could also explain the lack of effect of wild pigs on deer recruitment. Spatial or temporal resource partitioning reduces overlap of resource use and allows coexistence of competitors (Schoener 1974). Spatial segregation and partitioning of resources is important for closely related bird species occupying the same habitat (Robinson and Terborgh 1995, Wiens 2012). At greater population densities when resources are limiting, spatial and temporal separation may not be as effective at mitigating the negative repercussions of competition to population dynamics. More intensive studies at greater deer densities would better elucidate the interspecific competition between pigs and deer.

Similar to previous studies (Beasom 1974, Stout 1982, Howze et al. 2009, VanGilder et al. 2009), we found that coyote removal increased fawn recruitment rates. Removal of coyotes increased the finite rate of increase of fawns meaning there was greater fawn abundance following removal relative to the year prior. If coyote removal occurred the year before and not in the current year we observed decreased fawn abundance relative to the year prior. However, coyote removal would have resulted in more fawns the year before (during the year of coyote removal) so there would be a net gain in fawns produced relative to if there was never any coyote removal. For example, based on our estimated finite rate of increase, if we start with 100 fawns and don't have coyote removal for 2 years we would end up with 67 fawns ($100 \times 0.822 \times 0.822$). If we had coyote removal in the first year and not the second, then we would end up with 77 fawns ($100 \times 1.156 \times 0.669$). If we removed coyotes in the second year but not the first, then we would end up with 95 fawns ($100 \times 0.822 \times 1.156$). If we had 2 years of coyote removal, then we would end up with 104 fawns ($100 \times 1.156 \times 0.898$). After removal, coyotes quickly recolonize areas (Beasom 1974, Mosnier et al. 2008) and move in from neighboring lands (Korpimäki et al. 2002). Coyotes actively defend territories and exhibit significant home range fidelity (Kitchen et al. 2000). However, yearlings and non-breeding adults tend to disperse (Gese et al. 1996). When coyotes are removed from an area, one or more coyotes may move in and occupy a vacant territory prior to the next fawning season (Beasom 1974, Connolly 1995), and could result in elevated predation and reduced recruitment of fawns the following year.

With two consecutive years of coyote removal at a site we observed a lower finite rate of increase compared to a site with no coyote removal the year prior. Returning to the previous example, if we start with 100 fawns and we remove coyotes for 2 years we end up with 104 fawns. Although we had an increase of 4 fawns, the rate at which fawn abundance is changing is decreasing. If we remove coyotes 3 years in a row we could get 93 fawns ($100 \times 1.156 \times 0.898 \times 0.898$), assuming there is no difference in the finite rate of increase for 3 consecutive years of coyote removal relative to 2. Reduction in coyote density can result in increased reproductive output (Andelt 1987, 1996), which would result in more coyotes and an increased energetic demand for the mated pair during pup rearing. Female coyotes expend an additional 142% over field metabolic rate for an average litter size during lactation, and even during pup dependence males expend an additional 46.8% and females an additional 53.3% over field metabolic rate to supply pups with food (Laundré and Hernández 2003). Pup rearing occurs from June to September (Chamberlain and Leopold 2001, Schrecengost et al. 2008), concurrent with the fawning season (Causey 1990, Gray et al. 2002). Deer represent a greater source of nutrients than other dietary items and would likely be favored during this time when deer fawns are most vulnerable and coyote nutrient demands are at their peak. Despite two successive years of coyote removal the increased energetic burden of pup rearing could result in increased predation on fawns. Till and Knowlton (1983) demonstrated that depredation of lambs was driven by coyote pup rearing, and upon removal of coyote pups coyote predation on sheep ceased. Additionally, increased nutrient requirements of coyotes may result in increased movements and coyote movement (based on per-hour rate) was found to be greater during the fawning period (Turner et al. 2011). Increased movements during fawning would bring coyotes into contact with vulnerable fawns more frequently, and could explain the decrease in the finite rate of increase of fawns following 2 years of coyote removal.

We found no effect of coyote removal on buck or doe recruitment the following year, which suggests that the documented increase in fawn abundance did not translate to the adult population. Many predator removal programs fail to see effects on population future size (Holt et al. 2008). Predator removals which are ineffective at obtaining desired prey population increases tend to be conducted on open-areas (Salo et al. 2010). Fort Rucker is only partially fenced, and animals can move freely onto or off the installation. After removal, coyotes can move in from neighboring lands (Korpimäki et al. 2002). Additionally, Fort Rucker is a large installation and coyotes are removed throughout the installation whereas coyote removal is most effective on a smaller scale (Ballard et al. 2001). Our density estimates are for the entire installation, and do not represent density at sites with coyote removal compared to sites without coyote removal which could be why coyote removal on density at the scale of the entire installation. Concentrating removal efforts to a small area of the base and removing more of the predator population for successive years could result in increases to prey population size, theoretically, if predation were additive (Ballard et al. 2001). Although Hurley et al. (2011) noted that coyote removal successfully decreased depredation of mule deer fawns, there was no effect on fawn ratios or mule deer abundance in Idaho, suggesting that mortality was compensatory (Ballard et al. 2001). Coyote predation in the Southeast may be additive due to mild winters and abundant food resources for deer. It is generally assumed that the effects of predation on ecological communities are more pronounced in mild environments (Callaway et al. 2002). An alternative explanation for a lack of population size response to coyote removal is that deer in our study population were limited by food resources. However, this was unlikely due to the low population density and good condition of deer (Spiller, unpublished data). We did note an increase in doe abundance following antlered deer only hunting season, suggesting that reducing harvest may be more efficient at increasing deer populations than coyote removal.

Predation and interspecific competition can have substantial impacts on population dynamics under the right conditions. In this study we used non-invasive methods to evaluate the effects of both predation and interspecific competition on a valued game species, white-tailed deer. Although our data demonstrate that interspecific competition with wild pigs is likely occurring, at the very least as behavioral exclusion over pulse resources, the impacts to deer demographics are limited, probably due to existing low deer population density. However, we can conclude that pigs affect deer detection probabilities. Not accounting for the effects of pigs on deer detection and subsequent demographics could result in underestimating deer abundance and impact harvest and other management strategies (e.g., lethal coyote control) for deer populations. Furthermore, we did not directly manipulate the hog population to observe and estimate deer response but rather passively studied associations between existing hog densities and deer demographics which may have reduced our capacity to detect a demographic interaction. Low deer population density may render the population more vulnerable to the limiting or regulating effects of coyote predation. Our results suggest that contrary to previously published data describing the effects of coyote removal on deer populations (Beasom 1974, Stout 1982, VanGilder et al. 2009, Howze et al. 2009), short term coyote control efforts may actually have a negative impact on deer populations. Management of white-tailed deer may need to include successive years of coyote removal coupled with a reduction in doe harvest to increase low density herds. Although this study took place in the Southeast, these findings can provide insights for areas outside this region regarding the effects of coyote predation and interspecific competition on white-tailed deer population dynamics and help guide management decisions.

Intensive data collection, such as capture recapture or manipulative experiments excluding wild pigs and removing coyotes, may further reveal the complex species interactions shaping deer herds in the altered communities of the Southeast.

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TABLES AND FIGURES

Table 2.1. Uncorrected counts of deer separated into sex and age classes from 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

	Buck	Doe	Fawn	Unknown	Total
Count	3829	2715	656	1176	8376
Number of images with deer[a]	3723	2443	588	1139	6998
Percent of sites deer were counted[b]	100%	100%	92.3%	100%	100%

[a] A total of 279,052 images were produced during the 5 surveys

[b] n=26

Table 2.2. Comparison of detection (p) models for buck abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown.

Model	AICc	ΔAICc	K	Lik	w
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	9737.67	0	9	1.00	0.62
λ(.)γ(.)ω(.)p(rain+time+season)	9740.23	2.56	10	0.28	0.17
λ(.)γ(.)ω(.)p(pHog+time+season)	9740.30	2.64	10	0.27	0.17
λ(.)γ(.)ω(.)p(time+season)	9742.90	5.24	11	0.07	0.05
λ(.)γ(.)ω(.)p(rain+pHog+time)	9766.98	29.32	8	0	0
λ(.)γ(.)ω(.)p(pHog+time)	9768.28	30.62	9	0	0
λ(.)γ(.)ω(.)p(rain+time)	9775.35	37.68	9	0	0
λ(.)γ(.)ω(.)p(time)	9776.54	38.88	10	0	0
λ(.)γ(.)ω(.)p(rain+season)	9940.36	202.69	5	0	0
λ(.)γ(.)ω(.)p(season)	9941.11	203.44	6	0	0
λ(.)γ(.)ω(.)p(rain+pHog+season)	9942.07	204.40	6	0	0
λ(.)γ(.)ω(.)p(pHog+season)	9942.81	205.14	7	0	0
λ(.)γ(.)ω(.)p(pHog)	9965.16	227.49	4	0	0
λ(.)γ(.)ω(.)p(.)	9965.37	227.70	5	0	0
λ(.)γ(.)ω(.)p(rain+pHog)	9965.39	227.73	5	0	0
λ(.)γ(.)ω(.)p(rain)	9965.63	227.97	6	0	0

Table 2.3. Comparison of detection (p) models for doe abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown.

Model	AICc	ΔAICc	K	Lik	w
λ(.)γ(.)ω(.)p(pHog+time)	7657.45	0	9	1.00	0.36
λ(.)γ(.)ω(.)p(rain+pHog+time)	7658.04	0.58	10	0.75	0.27
λ(.)γ(.)ω(.)p(pHog+time+season)	7658.76	1.31	10	0.52	0.19
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	7659.18	1.73	11	0.42	0.15
λ(.)γ(.)ω(.)p(time)	7663.77	6.32	8	0.04	0.02
λ(.)γ(.)ω(.)p(rain+time)	7664.50	7.04	9	0.03	0.01
λ(.)γ(.)ω(.)p(time+season)	7664.67	7.22	9	0.03	0.01
λ(.)γ(.)ω(.)p(rain+time+season)	7665.21	7.76	10	0.02	0.01
λ(.)γ(.)ω(.)p(pHog)	7728.88	71.43	5	0	0
λ(.)γ(.)ω(.)p(rain+pHog)	7730	72.55	6	0	0
λ(.)γ(.)ω(.)p(pHog+season)	7730.34	72.89	6	0	0
λ(.)γ(.)ω(.)p(rain+pHog+season)	7731.35	73.90	7	0	0
λ(.)γ(.)ω(.)p(.)	7731.57	74.12	4	0	0
λ(.)γ(.)ω(.)p(season)	7732.74	75.29	5	0	0
λ(.)γ(.)ω(.)p(rain)	7732.76	75.31	5	0	0
λ(.)γ(.)ω(.)p(rain+season)	7733.80	76.35	6	0	0

Table 2.4. Comparison of detection (p) models for fawn abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown.

Model	AICc	ΔAICc	K	Lik	w
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	2218.91	0	10	1.00	0.69
λ(.)γ(.)ω(.)p(pHog+time+season)	2220.65	1.75	9	0.42	0.29
λ(.)γ(.)ω(.)p(rain+time+season)	2227.16	8.25	9	0.02	0.01
λ(.)γ(.)ω(.)p(time+season)	2228.91	10	8	0.01	0
λ(.)γ(.)ω(.)p(rain+pHog+season)	2238.58	19.67	6	0	0
λ(.)γ(.)ω(.)p(pHog+season)	2239.95	21.04	5	0	0
λ(.)γ(.)ω(.)p(rain+season)	2243.96	25.05	5	0	0
λ(.)γ(.)ω(.)p(season)	2245.34	26.44	4	0	0
λ(.)γ(.)ω(.)p(rain+pHog+time)	2289.38	70.47	9	0	0
λ(.)γ(.)ω(.)p(pHog+time)	2289.83	70.93	8	0	0
λ(.)γ(.)ω(.)p(rain+pHog)	2310.74	91.83	5	0	0
λ(.)γ(.)ω(.)p(pHog)	2310.81	91.90	4	0	0
λ(.)γ(.)ω(.)p(rain+time)	2316.00	97.09	8	0	0
λ(.)γ(.)ω(.)p(time)	2316.27	97.36	7	0	0
λ(.)γ(.)ω(.)p(.)	2331.68	112.78	3	0	0
λ(.)γ(.)ω(.)p(rain)	2331.75	112.84	4	0	0

Table 2.5. Comparison of initial abundance (λ) models for buck abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p) models were used for initial abundance (λ) model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9726.80	0	15	1.00	0.27
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9727.90	1.09	16	0.58	0.16
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+time+season)	9728.46	1.65	14	0.44	0.12
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	9729.26	2.46	13	0.29	0.08
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	9729.28	2.47	14	0.29	0.08
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+time+season)	9729.41	2.61	15	0.27	0.07
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	9730.36	3.56	15	0.17	0.05
λ(Dev+Hog)γ(.)ω(.)p(rain+time+season)	9731.00	4.19	12	0.12	0.03
λ(Hog)γ(.)ω(.)p(rain+pHog+time+season)	9731.78	4.98	12	0.08	0.02
λ(Dev+Hog)γ(.)ω(.)p(pHog+time+season)	9731.81	5.00	12	0.08	0.02
λ(Hog+Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	9732.30	5.50	13	0.06	0.02

λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9732.53	5.72	13	0.06	0.02
λ(Hog+Mixed)γ(.)ω(.)p(rain+pHog+time+season)	9733.31	6.51	13	0.04	0.01
λ(Hog)γ(.)ω(.)p(rain+time+season)	9733.88	7.08	11	0.03	0.01
λ(Hog+Hrdwd)γ(.)ω(.)p(rain+time+season)	9734.28	7.47	12	0.02	0.01
λ(Hog)γ(.)ω(.)p(pHog+time+season)	9734.38	7.57	11	0.02	0.01
λ(Hog+Pine)γ(.)ω(.)p(rain+time+season)	9734.63	7.83	12	0.02	0.01
λ(Hog+Hrdwd)γ(.)ω(.)p(pHog+time+season)	9734.90	8.09	12	0.02	0
λ(Hog+Pine)γ(.)ω(.)p(pHog+time+season)	9735.11	8.31	12	0.02	0
λ(Hog+Mixed)γ(.)ω(.)p(rain+time+season)	9735.39	8.59	12	0.01	0
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9735.55	8.75	13	0.01	0
λ(Hog+Mixed)γ(.)ω(.)p(pHog+time+season)	9735.90	9.10	12	0.01	0
λ(Pine)γ(.)ω(.)p(rain+pHog+time+season)	9737.49	10.69	12	0	0
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	9737.67	10.86	11	0	0
λ(Dev+Pine)γ(.)ω(.)p(rain+time+season)	9738.10	11.29	12	0	0
λ(Dev+Pine)γ(.)ω(.)p(pHog+time+season)	9738.10	11.30	12	0	0
λ(Dev)γ(.)ω(.)p(rain+pHog+time+season)	9738.13	11.33	12	0	0

λ(Mixed)γ(.)ω(.)p(rain+pHog+time+season)	9738.98	12.18	12	0	0
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9739.02	12.22	15	0	0
λ(Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	9739.31	12.51	12	0	0
λ(Dev+Mixed)γ(.)ω(.)p(rain+pHog+time+season)	9739.86	13.06	13	0	0
λ(Dev+Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	9740.08	13.28	13	0	0
λ(Pine)γ(.)ω(.)p(pHog+time+season)	9740.11	13.31	11	0	0
λ(Pine)γ(.)ω(.)p(rain+time+season)	9740.12	13.32	11	0	0
λ(.)γ(.)ω(.)p(rain+time+season)	9740.23	13.43	10	0	0
λ(.)γ(.)ω(.)p(pHog+time+season)	9740.30	13.50	10	0	0
λ(Dev)γ(.)ω(.)p(rain+time+season)	9740.61	13.81	11	0	0
λ(Dev)γ(.)ω(.)p(pHog+time+season)	9740.74	13.94	11	0	0
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	9741.57	14.77	14	0	0
λ(Mixed)γ(.)ω(.)p(rain+time+season)	9741.57	14.77	11	0	0
λ(Mixed)γ(.)ω(.)p(pHog+time+season)	9741.60	14.80	11	0	0
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+time+season)	9741.65	14.85	14	0	0
λ(Hrdwd)γ(.)ω(.)p(rain+time+season)	9741.88	15.08	11	0	0

λ(Hrdwd)γ(.)ω(.)p(pHog+time+season)	9741.95	15.14	11	0	0
λ(Dev+Mixed)γ(.)ω(.)p(rain+time+season)	9742.36	15.56	12	0	0
λ(Dev+Mixed)γ(.)ω(.)p(pHog+time+season)	9742.46	15.66	12	0	0
λ(Dev+Hrdwd)γ(.)ω(.)p(rain+time+season)	9742.57	15.76	12	0	0
λ(Dev+Hrdwd)γ(.)ω(.)p(pHog+time+season)	9742.69	15.89	12	0	0

Table 2.6. Comparison of initial abundance (λ) models for doe abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p) models were used for initial abundance (λ) model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7451.47	0	13	1.00	0.28
λ(Pine)γ(.)ω(.)p(rain+pHog+time+season)	7452.56	1.10	12	0.58	0.16
λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.00	2.54	13	0.28	0.08
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.00	2.54	15	0.28	0.08
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.02	2.55	16	0.28	0.08
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time)	7454.57	3.11	12	0.21	0.06
λ(Pine)γ(.)ω(.)p(rain+pHog+time)	7456.06	4.59	11	0.10	0.03
λ(Dev+Pine)γ(.)ω(.)p(pHog+time+season)	7456.27	4.81	12	0.09	0.03
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7456.98	5.51	15	0.06	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7457.02	5.56	14	0.06	0.02
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	7457.10	5.64	11	0.06	0.02

λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7457.28	5.82	15	0.05	0.02
λ(Pine)γ(.)ω(.)p(pHog+time+season)	7457.41	5.95	11	0.05	0.01
λ(Hog)γ(.)ω(.)p(rain+pHog+time+season)	7457.44	5.97	12	0.05	0.01
λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time)	7457.51	6.04	12	0.05	0.01
λ(Mixed)γ(.)ω(.)p(rain+pHog+time+season)	7458.33	6.86	12	0.03	0.01
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	7458.66	7.19	13	0.03	0.01
λ(Dev+Pine)γ(.)ω(.)p(pHog+time)	7458.66	7.20	11	0.03	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	7458.78	7.31	15	0.03	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	7458.80	7.33	14	0.03	0.01
λ(Hog+Pine)γ(.)ω(.)p(pHog+time+season)	7458.84	7.37	12	0.03	0.01
λ(Hog+Mixed)γ(.)ω(.)p(rain+pHog+time+season)	7458.86	7.39	13	0.02	0.01
λ(Dev)γ(.)ω(.)p(rain+pHog+time+season)	7458.87	7.41	12	0.02	0.01
λ(Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	7458.93	7.46	12	0.02	0.01
λ(Hog+Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	7459.39	7.92	13	0.02	0.01
λ(Pine)γ(.)ω(.)p(pHog+time)	7460.17	8.70	10	0.01	0
λ(Dev+Mixed)γ(.)ω(.)p(rain+pHog+time+season)	7460.28	8.81	13	0.01	0

λ(Dev+Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	7460.53	9.06	13	0.01	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7460.66	9.19	14	0.01	0
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time)	7461.03	9.56	14	0.01	0
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time)	7461.11	9.64	13	0.01	0
λ(.)γ(.)ω(.)p(rain+pHog+time)	7461.46	9.99	10	0.01	0
λ(Hog+Pine)γ(.)ω(.)p(pHog+time)	7461.60	10.13	11	0.01	0
λ(Hog)γ(.)ω(.)p(rain+pHog+time)	7461.72	10.25	11	0.01	0
λ(.)γ(.)ω(.)p(pHog+time+season)	7462.02	10.56	10	0.01	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	7462.10	10.64	14	0	0
λ(Hog)γ(.)ω(.)p(pHog+time+season)	7462.33	10.86	11	0	0
λ(Mixed)γ(.)ω(.)p(rain+pHog+time)	7462.60	11.13	11	0	0
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time)	7462.86	11.40	12	0	0
λ(Hog+Mixed)γ(.)ω(.)p(rain+pHog+time)	7463.07	11.60	12	0	0
λ(Dev)γ(.)ω(.)p(rain+pHog+time)	7463.20	11.73	11	0	0
λ(Mixed)γ(.)ω(.)p(pHog+time+season)	7463.23	11.76	11	0	0
λ(Hrdwd)γ(.)ω(.)p(rain+pHog+time)	7463.28	11.81	11	0	0

λ(Dev+Hog)γ(.)ω(.)p(pHog+time+season)	7463.53	12.07	12	0	0
λ(Hog+Hrdwd)γ(.)ω(.)p(rain+pHog+time)	7463.67	12.20	12	0	0
λ(Hog+Mixed)γ(.)ω(.)p(pHog+time+season)	7463.73	12.27	12	0	0
λ(Dev)γ(.)ω(.)p(pHog+time+season)	7463.79	12.32	11	0	0
λ(Hrdwd)γ(.)ω(.)p(pHog+time+season)	7463.84	12.37	11	0	0
λ(Hog+Hrdwd)γ(.)ω(.)p(pHog+time+season)	7464.27	12.81	12	0	0
λ(Dev+Mixed)γ(.)ω(.)p(rain+pHog+time)	7464.54	13.07	12	0	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time)	7464.75	13.28	13	0	0
λ(Dev+Hrdwd)γ(.)ω(.)p(rain+pHog+time)	7464.84	13.37	12	0	0
λ(Dev+Mixed)γ(.)ω(.)p(pHog+time+season)	7465.18	13.71	12	0	0
λ(Dev+Hrdwd)γ(.)ω(.)p(pHog+time+season)	7465.43	13.97	12	0	0
λ(.)γ(.)ω(.)p(pHog+time)	7465.58	14.12	9	0	0
λ(Hog)γ(.)ω(.)p(pHog+time)	7465.81	14.35	10	0	0
λ(Mixed)γ(.)ω(.)p(pHog+time)	7466.71	15.24	10	0	0
λ(Dev+Hog)γ(.)ω(.)p(pHog+time)	7466.95	15.48	11	0	0
λ(Hog+Mixed)γ(.)ω(.)p(pHog+time)	7467.15	15.69	11	0	0

λ(Dev)γ(.)ω(.)p(pHog+time)	7467.32	15.86	10	0	0
λ(Hrdwd)γ(.)ω(.)p(pHog+time)	7467.40	15.93	10	0	0
λ(Hog+Hrdwd)γ(.)ω(.)p(pHog+time)	7467.76	16.30	11	0	0
λ(Dev+Mixed)γ(.)ω(.)p(pHog+time)	7468.65	17.18	11	0	0
λ(Dev+Hrdwd)γ(.)ω(.)p(pHog+time)	7468.95	17.48	11	0	0

Table 2.7. Comparison of initial abundance (λ) models for fawn abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (*w*) are shown. Only the best detection (*p*) models were used for initial abundance (λ) model comparisons.

Model	AICc	ΔAICc	K	Lik	*w*
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2192.50	0	14	1.00	0.22
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2192.61	0.10	14	0.95	0.21
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	2193.42	0.92	12	0.63	0.14
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	2193.72	1.22	13	0.54	0.12
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	2193.77	1.26	13	0.53	0.12
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2194.41	1.91	12	0.38	0.08
λ(Dev+Hog)γ(.)ω(.)p(pHog+time+season)	2194.80	2.29	11	0.32	0.07
λ(Dev+Pine)γ(.)ω(.)p(pHog+time+season)	2195.68	3.17	11	0.20	0.04
λ(Dev+Mixed)γ(.)ω(.)p(rain+pHog+time+season)	2200.36	7.86	12	0.02	0
λ(Dev+Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	2201.00	8.50	12	0.01	0
λ(Dev+Mixed)γ(.)ω(.)p(pHog+time+season)	2201.75	9.24	11	0.01	0

λ(Dev+Hrdwd)γ(.)ω(.)p(pHog+time+season)	2202.39	9.89	11	0.01	0
λ(Dev)γ(.)ω(.)p(rain+pHog+time+season)	2203.25	10.74	11	0	0
λ(Dev)γ(.)ω(.)p(pHog+time+season)	2204.74	12.24	10	0	0
λ(Hog+Mixed)γ(.)ω(.)p(rain+pHog+time+season)	2206.12	13.61	12	0	0
λ(Hog+Mixed)γ(.)ω(.)p(pHog+time+season)	2207.62	15.12	11	0	0
λ(Mixed)γ(.)ω(.)p(rain+pHog+time+season)	2209.68	17.18	11	0	0
λ(Mixed)γ(.)ω(.)p(pHog+time+season)	2211.22	18.72	10	0	0
λ(Hog)γ(.)ω(.)p(rain+pHog+time+season)	2214.81	22.31	11	0	0
λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2216.51	24.00	12	0	0
λ(Hog)γ(.)ω(.)p(pHog+time+season)	2216.51	24.01	10	0	0
λ(Hog+Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	2216.81	24.30	12	0	0
λ(Hog+Pine)γ(.)ω(.)p(pHog+time+season)	2218.19	25.69	11	0	0
λ(Hog+Hrdwd)γ(.)ω(.)p(pHog+time+season)	2218.50	26.00	11	0	0
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	2218.91	26.40	10	0	0
λ(Pine)γ(.)ω(.)p(rain+pHog+time+season)	2220.31	27.80	11	0	0
λ(.)γ(.)ω(.)p(pHog+time+season)	2220.65	28.15	9	0	0

λ(Hrdwd)γ(.)ω(.)p(rain+pHog+time+season)	2220.70	28.20	11	0	0
λ(Pine)γ(.)ω(.)p(pHog+time+season)	2222.04	29.53	10	0	0
λ(Hrdwd)γ(.)ω(.)p(pHog+time+season)	2222.44	29.94	10	0	0
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	35447.83	33255.32	14	0	0
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	35449.83	33257.33	15	0	0

Table 2.8. Comparison of apparent survival probability (ω) models for buck abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p) and initial abundance (λ) models were used for apparent survival probability (ω) model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9726.82	0	15	1.00	0.30
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9727.89	1.07	16	0.58	0.17
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+time+season)	9728.46	1.64	14	0.44	0.13
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	9729.26	2.44	13	0.29	0.09
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	9729.28	2.46	14	0.29	0.09
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9729.41	2.59	15	0.27	0.08
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9730.36	3.54	15	0.17	0.05
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	9731.00	4.18	12	0.12	0.04
λ(Hog)γ(.)ω(.)p(rain+pHog+time+season)	9731.78	4.96	12	0.08	0.03
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	9731.81	4.98	12	0.08	0.02
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarM)p(rain+pHog+time+season)	26746.45	17019.63	16	0	0

λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarM)p(rain+pHog+time+season)	26747.06	17020.24	17	0	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarM)p(rain+pHog+time+season)	26747.81	17020.99	15	0	0
λ(Dev+Hog)γ(.)ω(HarM)p(rain+pHog+time+season)	26748.27	17021.45	13	0	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarM)p(rain+pHog+time+season)	26748.40	17021.58	16	0	0
λ(Dev+Hog)γ(.)ω(HarM)p(rain+pHog+time+season)	26748.84	17022.02	14	0	0
λ(Hog)γ(.)ω(HarM)p(rain+pHog+time+season)	26751.97	17025.15	13	0	0
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarM)p(rain+pHog+time+season)	26753.85	17027.03	16	0	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarM)p(rain+pHog+time+season)	26754.00	17027.18	15	0	0
λ(Dev+Hog)γ(.)ω(HarM)p(rain+pHog+time+season)	26754.57	17027.75	13	0	0

Table 2.9. Comparison of apparent survival probability (ω) models for doe abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p) and initial abundance (λ) models were used for apparent survival probability (ω) model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7451.47	0	13	1.00	0.31
λ(Pine)γ(.)ω(.)p(rain+pHog+time+season)	7452.57	1.10	12	0.58	0.18
λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.01	2.54	13	0.28	0.09
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.01	2.54	15	0.28	0.09
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.03	2.56	16	0.28	0.09
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time)	7454.58	3.10	12	0.21	0.07
λ(Pine)γ(.)ω(.)p(rain+pHog+time)	7456.06	4.59	11	0.10	0.03
λ(Dev+Pine)γ(.)ω(.)p(pHog+time+season)	7456.27	4.80	12	0.09	0.03
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7456.98	5.51	15	0.06	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7457.03	5.56	14	0.06	0.02
λ(.)γ(.)ω(.)p(rain+pHog+time+season)	7457.10	5.63	11	0.06	0.02

λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7457.29	5.82	15	0.05	0.02
λ(Pine)γ(.)ω(.)p(pHog+time+season)	7457.41	5.94	11	0.05	0.02
λ(Hog)γ(.)ω(.)p(rain+pHog+time+season)	7457.44	5.97	12	0.05	0.02
λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time)	7457.51	6.04	12	0.05	0.02
λ(Mixed)γ(.)ω(.)p(rain+pHog+time+season)	7458.33	6.86	12	0.03	0.01
λ(Pine)γ(.)ω(HarF)p(rain+pHog+time)	26662.15	19210.68	12	0	0
λ(Dev+Pine)γ(.)ω(HarF)p(rain+pHog+time)	26663.81	19212.34	13	0	0
λ(Pine)γ(.)ω(HarF)p(rain+pHog+time+season)	26664.03	19212.55	13	0	0
λ(Hog+Pine)γ(.)ω(HarF)p(rain+pHog+time)	26664.15	19212.68	13	0	0
λ(Dev+Pine)γ(.)ω(HarF)p(rain+pHog+time+season)	26665.68	19214.21	14	0	0
λ(Hog+Pine)γ(.)ω(HarF)p(rain+pHog+time+season)	26666.03	19214.56	14	0	0
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(HarF)p(rain+pHog+time)	26667.26	19215.79	15	0	0
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(HarF)p(rain+pHog+time+season)	26669.08	19217.61	16	0	0
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarF)p(rain+pHog+time)	26669.26	19217.79	16	0	0
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarF)p(rain+pHog+time+season)	26669.41	19217.93	16	0	0
λ(Pine)γ(.)ω(HarF)p(pHog+time+season)	26670.75	19219.28	12	0	0

λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(HarF)p(rain+pHog+time+season)	26671.08	19219.61	17	0	0
λ(Dev+Pine)γ(.)ω(HarF)p(pHog+time+season)	26672.39	19220.92	13	0	0
λ(.)γ(.)ω(HarF)p(rain+pHog+time+season)	26676.74	19225.27	12	0	0
λ(Mixed)γ(.)ω(HarF)p(rain+pHog+time+season)	26678.52	19227.05	13	0	0
λ(Hog)γ(.)ω(HarF)p(rain+pHog+time+season)	26678.74	19227.27	13	0	0

Table 2.10. Comparison of recruitment rate (γ), apparent survival probability (ω), initial abundance (λ), and detection probability (p) models for buck abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p), initial abundance (λ), and apparent survival probability (ω) models were used for model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9726.80	0	15	1	0.15
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	9727.91	1.11	16	0.57	0.09
λ(Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	9728.19	1.38	16	0.50	0.08
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+time+season)	9728.46	1.65	14	0.44	0.07
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	9728.54	1.73	16	0.42	0.06
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	9729.26	2.46	17	0.29	0.05
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	9729.26	2.46	13	0.29	0.05
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	9729.28	2.48	14	0.29	0.04
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+time+season)	9729.41	2.61	15	0.27	0.04
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	9729.62	2.82	17	0.24	0.04

λ(Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+time+season)	9729.65	2.85	15	0.24	0.04
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	9730	3.20	17	0.20	0.03
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+time+season)	9730.22	3.42	15	0.18	0.03
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	9730.38	3.58	15	0.17	0.03
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+time+season)	9730.59	3.79	16	0.15	0.02
λ(Dev+Hog)γ(Hog)ω(.)p(rain+pHog+time+season)	9730.66	3.85	14	0.15	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(pHog+time+season)	9730.74	3.94	15	0.14	0.02
λ(Dev+Hog)γ(Lag)ω(.)p(rain+pHog+time+season)	9730.97	4.17	14	0.12	0.02
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	9731.06	4.26	18	0.12	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(pHog+time+season)	9731.08	4.28	15	0.12	0.02
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+time+season)	9731.16	4.36	16	0.11	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+time+season)	9731.51	4.71	16	0.09	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(pHog+time+season)	9731.82	5.02	16	0.08	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(pHog+time+season)	9732.11	5.31	16	0.07	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+time+season)	9732.44	5.63	17	0.06	0.01
λ(Dev+Hog)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	9732.45	5.65	15	0.06	0.01

λ(Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(pHog+time+season)	9732.61	5.81	16	0.05	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(pHog+time+season)	9733.65	6.85	17	0.03	0

Table 2.11. Comparison of recruitment rate (γ), apparent survival probability (ω), initial abundance (λ), and detection probability (p) models for doe abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p), initial abundance (λ), and apparent survival probability (ω) models were used for model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7451.47	0	13	1.00	0.11
λ(Dev+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	7451.59	0.11	14	0.94	0.10
λ(Pine)γ(.)ω(.)p(rain+pHog+time+season)	7452.57	1.10	12	0.58	0.06
λ(Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	7452.78	1.31	13	0.52	0.06
λ(Dev+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	7452.82	1.35	15	0.51	0.06
λ(Dev+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	7452.95	1.47	14	0.48	0.05
λ(Hog+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.01	2.54	13	0.28	0.03
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.01	2.54	15	0.28	0.03
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	7454.03	2.56	16	0.28	0.03
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	7454.05	2.58	17	0.28	0.03

λ(Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	7454.08	2.61	14	0.27	0.03
λ(Dev+Pine)γ(Hog)ω(.)p(rain+pHog+time)	7454.09	2.62	13	0.27	0.03
λ(Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	7454.09	2.62	13	0.27	0.03
λ(Dev+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	7454.13	2.66	16	0.26	0.03
λ(Hog+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	7454.18	2.71	14	0.26	0.03
λ(Dev+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time)	7454.56	3.09	14	0.21	0.02
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time)	7454.58	3.11	12	0.21	0.02
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	7455.19	3.72	18	0.16	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	7455.32	3.85	17	0.15	0.02
λ(Dev+Pine)γ(Lag)ω(.)p(rain+pHog+time)	7455.38	3.91	13	0.14	0.02
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	7455.43	3.96	17	0.14	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	7455.44	3.97	16	0.14	0.02
λ(Hog+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	7455.47	4.00	15	0.14	0.02
λ(Hog+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	7455.52	4.05	14	0.13	0.01
λ(Pine)γ(Hog)ω(.)p(rain+pHog+time)	7455.66	4.19	12	0.12	0.01
λ(Pine)γ(.)ω(.)p(rain+pHog+time)	7456.06	4.59	11	0.10	0.01

λ(Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time)	7456.19	4.72	13	0.09	0.01
λ(Dev+Pine)γ(.)ω(.)p(pHog+time+season)	7456.28	4.80	12	0.09	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time)	7456.37	4.90	16	0.09	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time)	7456.56	5.09	15	0.08	0.01
λ(Dev+Pine)γ(Hog)ω(.)p(pHog+time+season)	7456.57	5.10	13	0.08	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time)	7456.74	5.27	17	0.07	0.01
λ(Pine)γ(Lag)ω(.)p(rain+pHog+time)	7456.91	5.44	12	0.07	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time)	7456.98	5.51	16	0.06	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7456.98	5.51	15	0.06	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time)	7457.03	5.56	14	0.06	0.01
λ(Dev+Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time)	7457.70	6.23	16	0.04	0
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time)	7457.79	6.32	15	0.04	0
λ(Dev+Pine)γ(Lag)ω(.)p(pHog+time+season)	7457.93	6.46	13	0.04	0
λ(Dev+Pine)γ(Lag+Hog)ω(.)p(pHog+time+season)	7458.05	6.58	14	0.04	0

Table 2.12. Comparison of recruitment rate (γ), initial abundance (λ), and detection probability (p) models for fawn abundance estimation using 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama. For each model, AIC corrected for small sample size, relative difference in AICc, number of estimable parameters (K), model likelihood (Lik), and model probability (w) are shown. Only the best detection (p), and initial abundance (λ) models were used for model comparisons.

Model	AICc	ΔAICc	K	Lik	w
λ(Hog+Hrdwd+Mixed+Pine)γ(Coy+Lag)ω(.)p(rain+pHog+time+season)	2191.34	0	16	1.00	0.10
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy)ω(.)p(rain+pHog+time+season)	2191.90	0.56	15	0.76	0.07
λ(Hog+Hrdwd+Mixed+Pine)γ(Coy)ω(.)p(rain+pHog+time+season)	2192.19	0.85	15	0.65	0.06
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2192.50	1.16	14	0.56	0.05
λ(Hog+Hrdwd+Mixed+Pine)γ(Coy+Lag)ω(.)p(pHog+time+season)	2192.54	1.20	15	0.55	0.05
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2192.61	1.27	14	0.53	0.05
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy)ω(.)p(pHog+time+season)	2193.10	1.76	14	0.41	0.04
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy+Lag)ω(.)p(rain+pHog+time+season)	2193.13	1.79	16	0.41	0.04
λ(Hog+Hrdwd+Mixed+Pine)γ(Coy+Lag+Hog)ω(.)p(rain+pHog+time+season)	2193.30	1.96	17	0.37	0.04
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	2193.45	2.11	15	0.35	0.03

λ(Hog+Hrdwd+Mixed+Pine)γ(Coy)ω(.)p(pHog+time+season)	2193.55	2.21	14	0.33	0.03
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy+Hog)ω(.)p(rain+pHog+time+season)	2193.59	2.25	16	0.32	0.03
λ(Dev+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	2193.72	2.38	13	0.30	0.03
λ(Hog+Hrdwd+Mixed+Pine)γ(.)ω(.)p(pHog+time+season)	2193.77	2.43	13	0.30	0.03
λ(Hog+Hrdwd+Mixed+Pine)γ(Coy+Hog)ω(.)p(rain+pHog+time+season)	2194.08	2.74	16	0.25	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy+Lag)ω(.)p(pHog+time+season)	2194.25	2.91	15	0.23	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	2194.42	3.08	15	0.21	0.02
λ(Dev+Pine)γ(.)ω(.)p(rain+pHog+time+season)	2194.41	3.07	12	0.22	0.02
λ(Dev+Pine)γ(Coy)ω(.)p(rain+pHog+time+season)	2194.44	3.10	13	0.21	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Coy+Lag+Hog)ω(.)p(pHog+time+season)	2194.50	3.16	16	0.21	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	2194.58	3.24	15	0.20	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	2194.61	3.27	15	0.20	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(pHog+time+season)	2194.61	3.27	14	0.19	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy+Hog)ω(.)p(pHog+time+season)	2194.78	3.44	15	0.18	0.02
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy+Lag+Hog)ω(.)p(rain+pHog+time+season)	2194.90	3.56	17	0.17	0.02
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	2195.19	3.85	16	0.15	0.01

λ(Hog+Hrdwd+Mixed+Pine)γ(Coy+Hog)ω(.)p(pHog+time+season)	2195.44	4.10	15	0.13	0.01
λ(Dev+Pine)γ(Coy+Lag)ω(.)p(rain+pHog+time+season)	2195.55	4.21	14	0.12	0.01
λ(Hog+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(pHog+time+season)	2195.69	4.35	14	0.11	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(Hog)ω(.)p(pHog+time+season)	2195.70	4.36	14	0.11	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag)ω(.)p(pHog+time+season)	2195.72	4.38	14	0.11	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(Coy+Lag+Hog)ω(.)p(pHog+time+season)	2196.00	4.66	16	0.10	0.01
λ(Dev+Pine)γ(Coy+Hog)ω(.)p(rain+pHog+time+season)	2196.11	4.77	14	0.09	0.01
λ(Dev+Pine)γ(Lag)ω(.)p(rain+pHog+time+season)	2196.39	5.05	13	0.08	0.01
λ(Hog+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(pHog+time+season)	2196.40	5.06	15	0.08	0.01
λ(Dev+Pine)γ(Hog)ω(.)p(rain+pHog+time+season)	2196.41	5.07	13	0.08	0.01
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	2196.58	5.24	16	0.07	0.01
λ(Dev+Pine)γ(Coy+Lag+Hog)ω(.)p(rain+pHog+time+season)	2197.30	5.96	15	0.05	0
λ(Dev+Hrdwd+Mixed+Pine)γ(Lag+Hog)ω(.)p(pHog+time+season)	2197.70	6.36	15	0.04	0
λ(Dev+Pine)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	2198.38	7.04	14	0.03	0
λ(Dev+Hog)γ(.)ω(.)p(pHog+time+season)	35441.83	33250.49	11	0	0
λ(Dev+Hog)γ(.)ω(.)p(rain+pHog+time+season)	35443.83	33252.49	12	0	0

λ(Dev+Hog)γ(Hog)ω(.)p(pHog+time+season)	35443.83	33252.49	12	0	0
λ(Dev+Hog)γ(Lag)ω(.)p(pHog+time+season)	35443.83	33252.49	12	0	0
λ(Dev+Hog)γ(Coy)ω(.)p(pHog+time+season)	35443.83	33252.49	12	0	0
λ(Dev+Hog)γ(Hog)ω(.)p(rain+pHog+time+season)	35445.83	33254.49	13	0	0
λ(Dev+Hog)γ(Lag)ω(.)p(rain+pHog+time+season)	35445.83	33254.49	13	0	0
λ(Dev+Hog)γ(Coy)ω(.)p(rain+pHog+time+season)	35445.83	33254.49	13	0	0
λ(Dev+Hog)γ(Lag+Hog)ω(.)p(pHog+time+season)	35445.83	33254.49	13	0	0
λ(Dev+Hog)γ(Coy+Lag)ω(.)p(pHog+time+season)	35445.83	33254.49	13	0	0
λ(Dev+Hog)γ(Coy+Hog)ω(.)p(pHog+time+season)	35445.83	33254.49	13	0	0
λ(Dev+Hog)γ(Lag+Hog)ω(.)p(rain+pHog+time+season)	35447.83	33256.49	14	0	0
λ(Dev+Hog)γ(Coy+Lag)ω(.)p(rain+pHog+time+season)	35447.83	33256.49	14	0	0
λ(Dev+Hog)γ(Coy+Hog)ω(.)p(rain+pHog+time+season)	35447.83	33256.49	14	0	0
λ(Dev+Hog)γ(Coy+Lag+Hog)ω(.)p(pHog+time+season)	35447.83	33256.49	14	0	0
λ(Dev+Hog)γ(Coy+Lag+Hog)ω(.)p(rain+pHog+time+season)	35449.83	33258.49	15	0	0

Table 2.13. Density estimates for bucks, does, and fawns ($\bar{x}$) and standard deviation (SD) for spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

	Spring 2011		Fall 2011		Spring 2012		Fall 2012		Spring 2013	
	$\bar{x}$	SD	$\bar{x}$	SD	$\bar{x}$	SD	$\bar{x}$	SD	$\bar{x}$	SD
Bucks	1.8	2.4	1.53	2.4	1.29	2.1	1.42	2.2	1.45	2.2
Does	2.55	3.0	2.22	2.9	1.96	2.5	2.18	2.9	2.39	3.1
Fawns	2.05	2.8	1.76	2.6	1.36	2.2	1.58	2.5	1.61	2.4

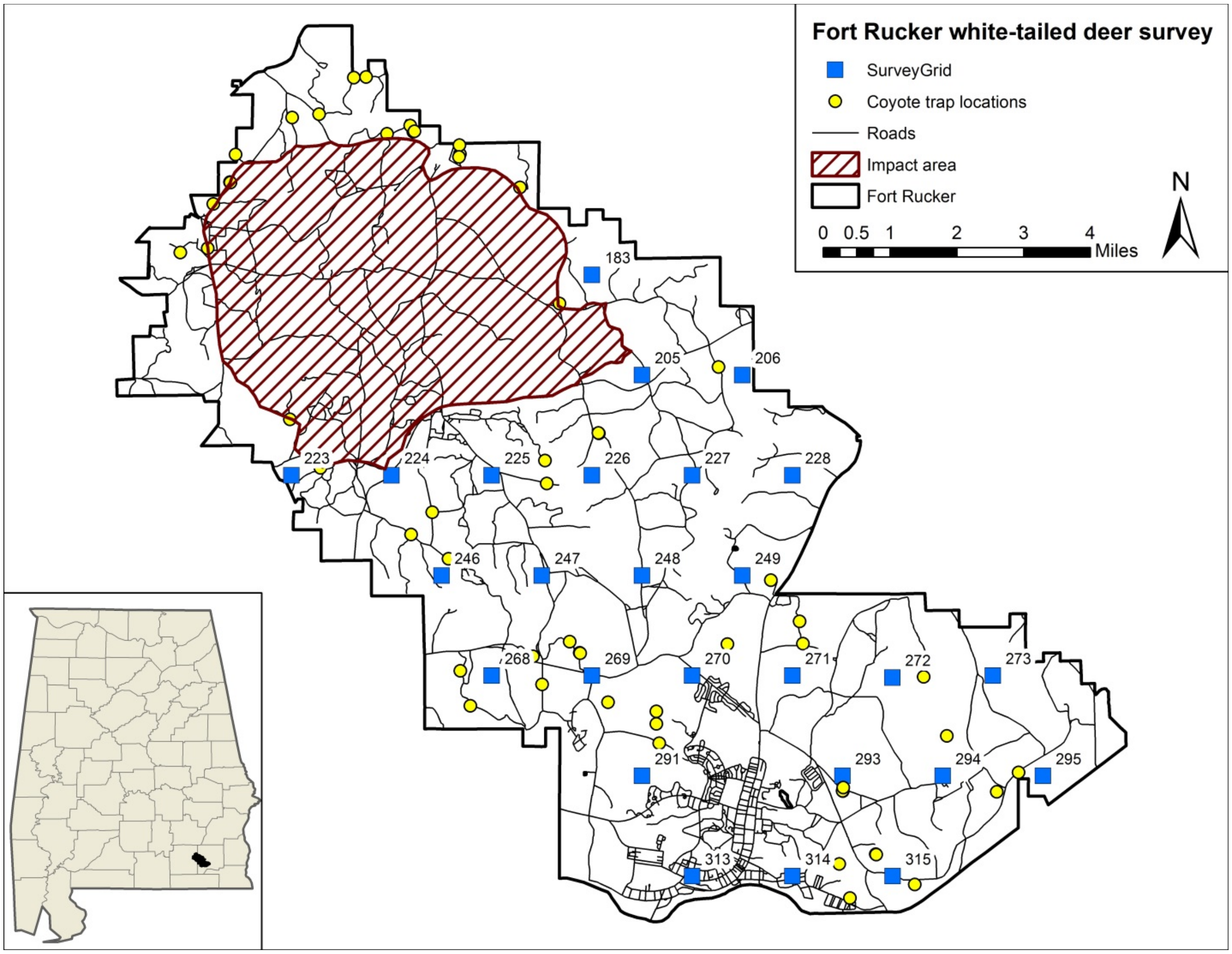

Figure 2.1. Map of the study area and survey grid at Fort Rucker located in southeastern Alabama for 5 time-lapse camera surveys conducted spring and fall of 2011-2012 and spring of 2013.

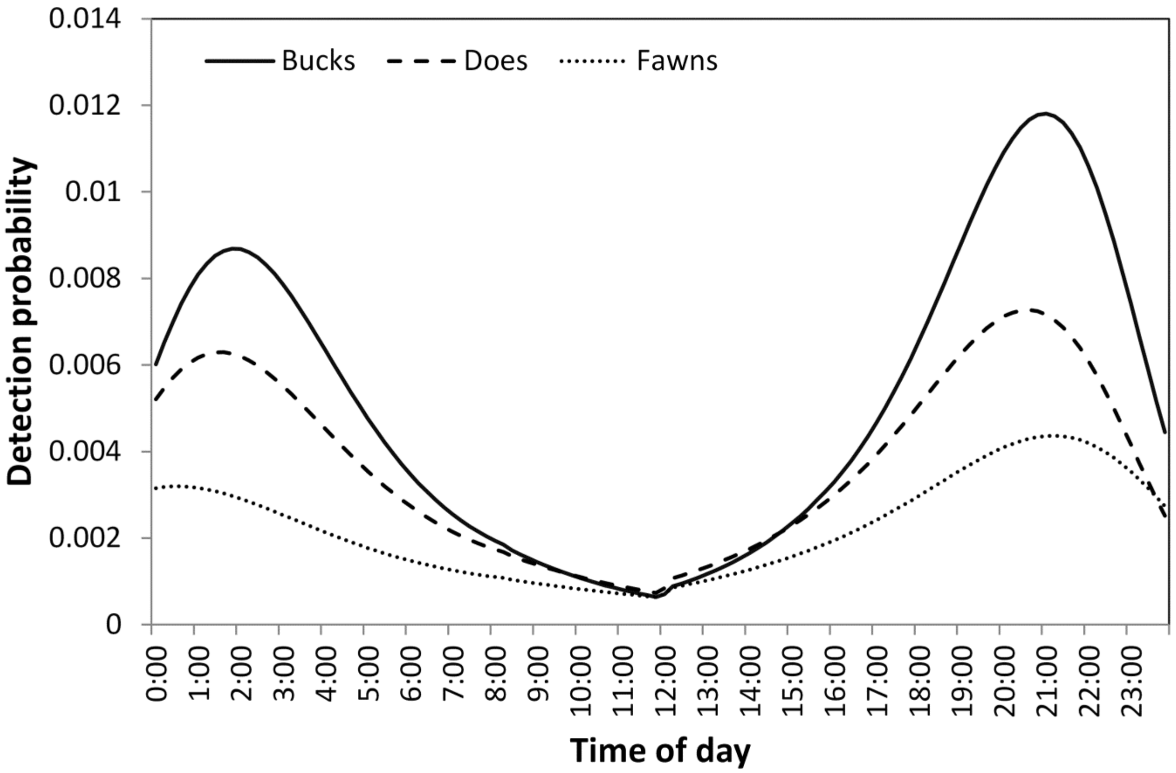

Figure 2.2. Relationship between time of day and detection probability (p) for buck, doe, and fawn abundance estimation using time-lapse camera surveys conducted in spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

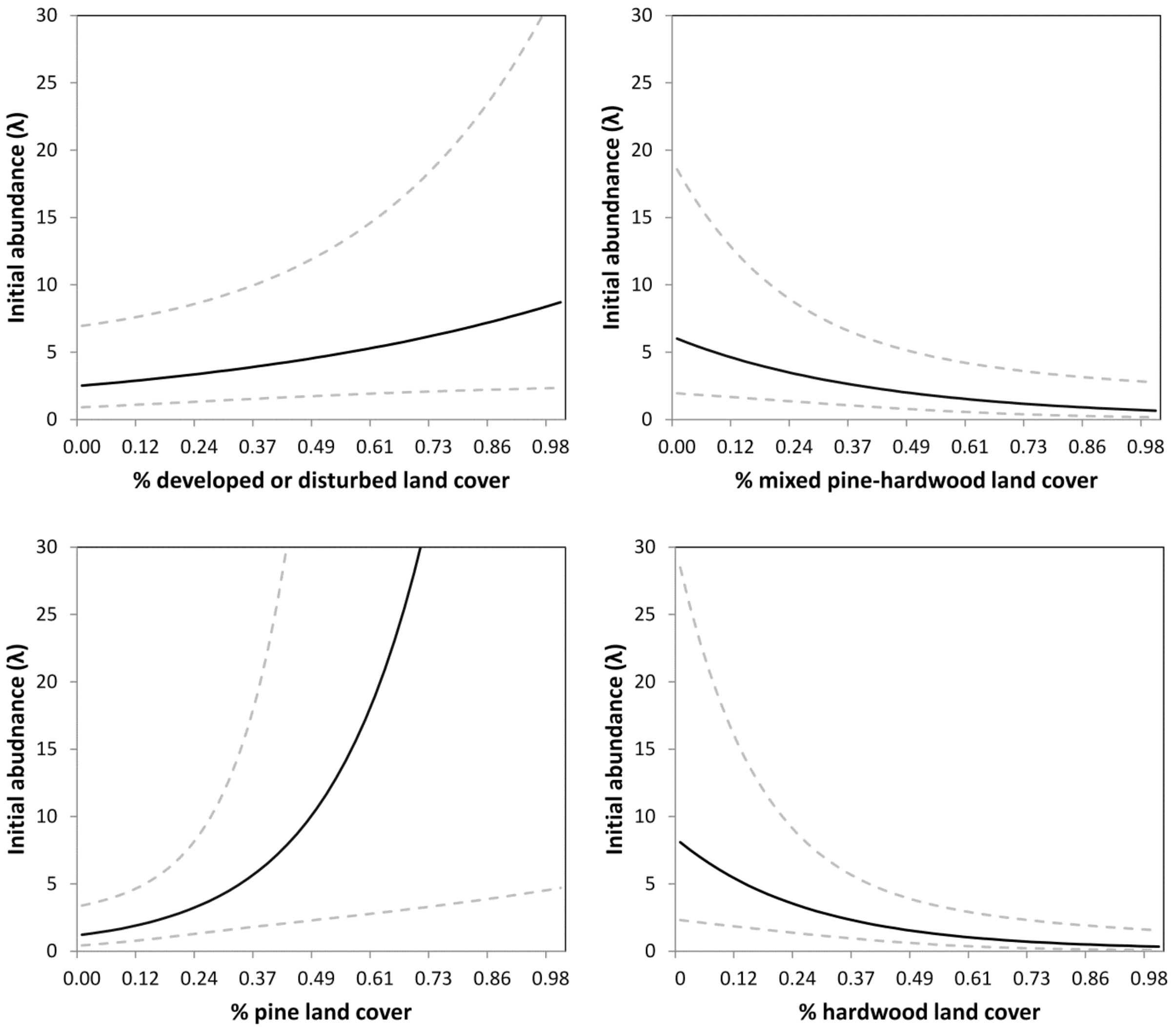

Figure 2.3. Modeled covariate effects of percent land cover (solid black line) with upper and lower confidence limits (dashed grey line) on initial abundance (λ) for buck abundance estimation using time-lapse camera surveys conducted in spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

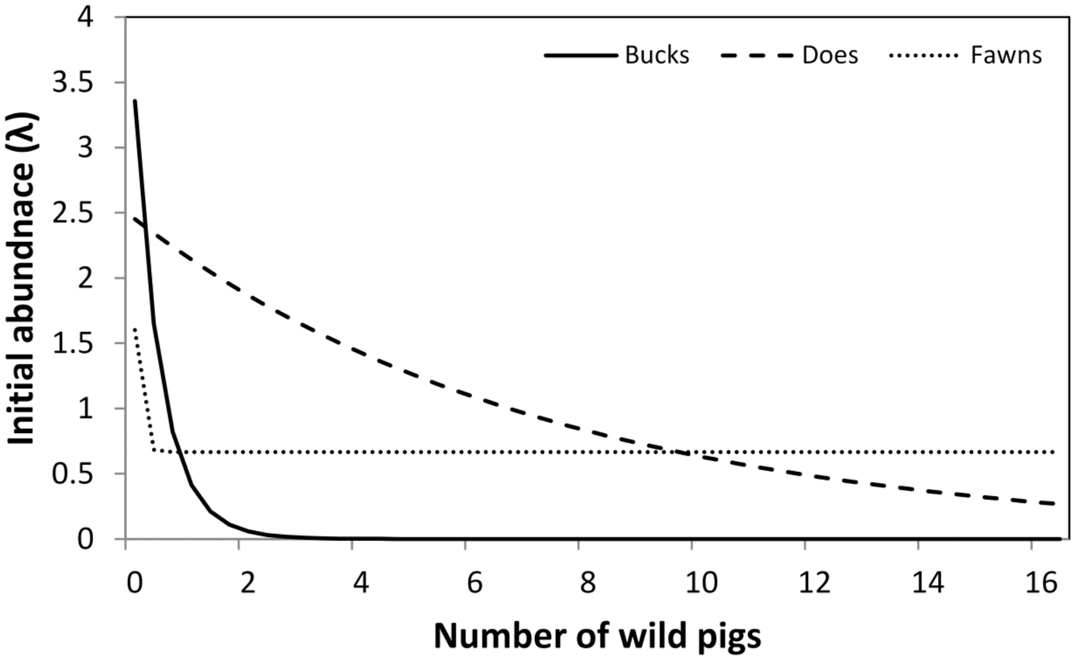

Figure 2.4. Relationship between the number of wild pigs and initial abundance (λ) for buck, doe, and fawn abundance estimation using time-lapse camera surveys conducted in spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

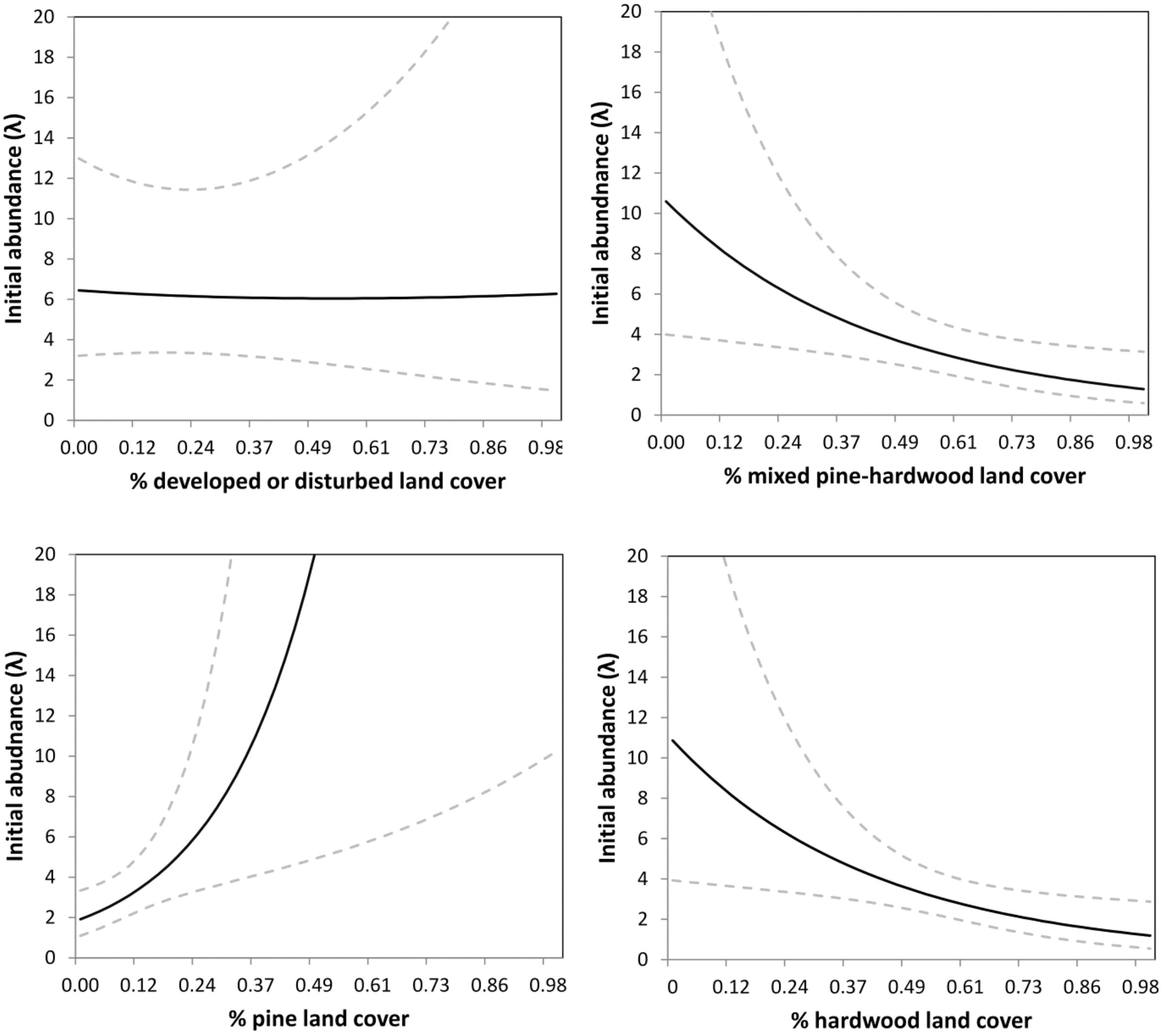

Figure 2.5. Modeled covariate effects of percent land cover (solid black line) with upper and lower confidence limits (dashed grey line) on initial abundance (λ) for doe abundance estimation using time-lapse camera surveys conducted in spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

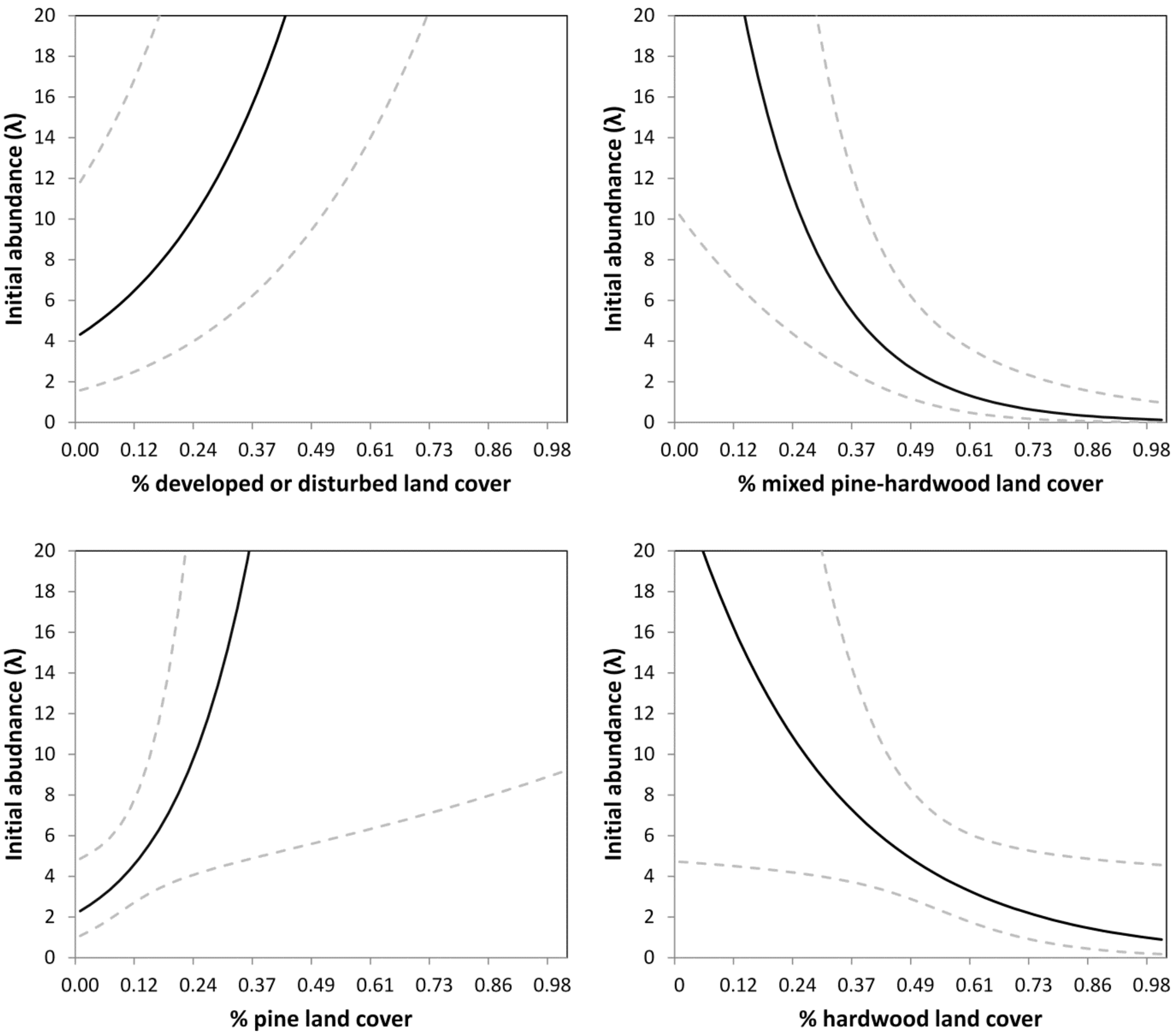

Figure 2.6. Modeled covariate effects of percent land cover (solid black line) with upper and lower confidence limits (dashed grey line) on initial abundance (λ) for fawn abundance estimation using time-lapse camera surveys conducted in spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

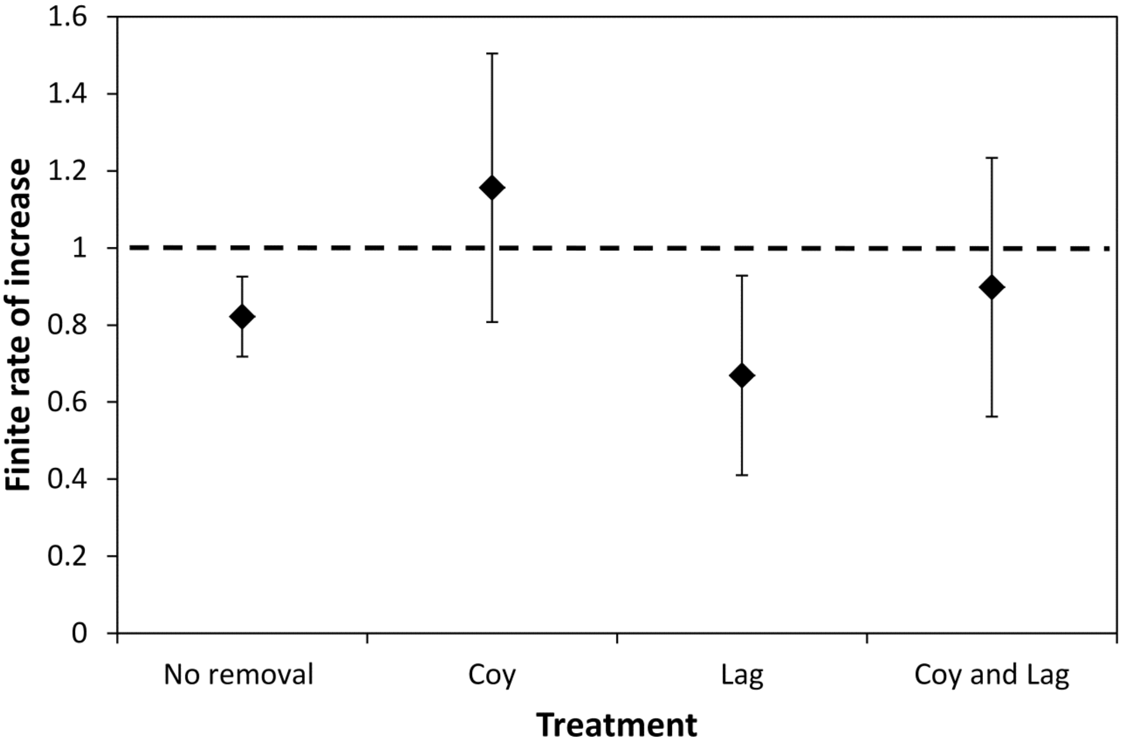

Figure 2.7. The finite rate of increase of white-tailed deer fawns under different coyote removal treatments at Fort Rucker, Alabama. No removal represented sites that never had coyote removal, Coy was sites that had coyote removal in the current year but not last year, Lag was sites that had coyote removal last year but not in the current year, and Coy and Lag was sites that had 2 consecutive years of coyote removal.

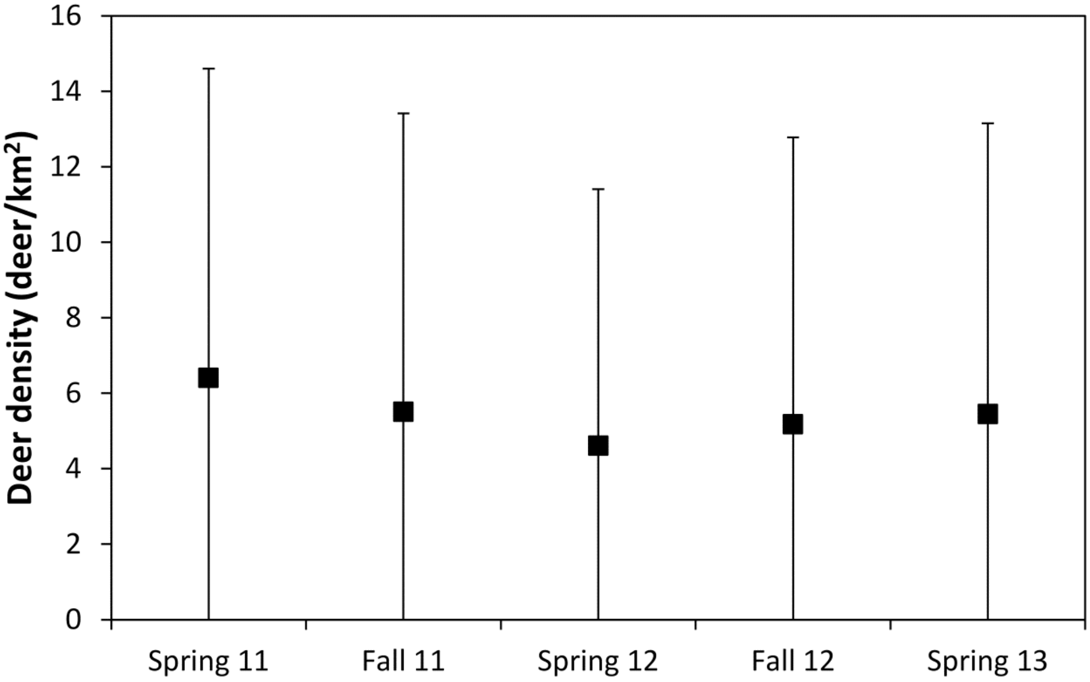

Figure 2.8. Density (deer/km^2) of white-tailed deer and standard deviation for spring and fall of 2011-2012 and spring of 2013 at Fort Rucker, Alabama.

Appendix A. Home range probability distribution.

Literature compilation of 20 sources of white-tailed deer home ranges focusing on southeastern states and corresponding references used to create the home range probability distribution for bucks and does. Reported values of home range size were then fit to a Weibull distribution using EasyFit (Mathwave Technologies, 2014, version 5.5). The Anderson-Darling goodness of fit statistic for the Weibull distribution for bucks was 0.45 and for does was 0.39, and the Weibull distribution was ranked in the top 5 distributions for both bucks and does.

Table A.1. Studies reporting home range size (km^2) of buck and doe white-tailed deer. The location, time of study, and whether or not supplemental feed was available is also reported.

Source	Bucks	Does	Time of study	Location	Supplemental feed
Brunjes et al. 2009		1.47	Spring	Texas	No
Brunjes et al. 2009		4.32	Spring	Texas	No
Brunjes et al. 2009		0.92	Summer	Texas	No
Brunjes et al. 2009		2.08	Summer	Texas	No
Brunjes et al. 2009		2.25	Year Long	Texas	No
Brunjes et al. 2009		1.77	Year long	Texas	No
Campell et al. 2004	2.27	0.82	Fall	West Virginia	No
Campell et al. 2004	0.98	0.79	Summer	West Virginia	No
Campell et al. 2004	0.64	0.91	Winter	West Virginia	No
Clements et al. 2011	3.98		Jan-May	Iowa	No
Clements et al. 2011	2.66		Jun-Sep	Iowa	No
Clements et al. 2011	4.65		Sep-Dec	Iowa	No
Hölzenbein and Schwede 1989		0.25	Dec	Virginia	

Hölzenbein and Schwede 1989		0.50	Oct-Dec	Virginia	
Hölzenbein and Schwede 1989		0.39	Sep-Oct	Virginia	
Hölzenbein and Marchinton 1992	0.63		Fall	Virginia	
Hölzenbein and Marchinton 1992	1.07		Summer	Virginia	
Ivey and Causey 1981		0.63	Nov-March	Alabama	No
Kilgo et al. 1998		0.22	Jan-Sep	Florida	No
Kilgo et al. 1998		0.26	Sep-Jan	Florida	No
Labisky and Fritzen 1998		0.23	Aug-Sep	Florida	No
Labisky and Fritzen 1998		0.31	Sep-Oct	Florida	No
Labisky and Fritzen 1998		0.32	Oct-Dec	Florida	No
Land et al. 1993	4.72	1.94	Year long	Florida	No
Land et al. 1993	10.49		Year long	Florida	No
Nixon et al. 1991	3.23	0.85	Summer	Illinois	No
Rhoads et al. 2010		1.92	Year long	Pennsylvania	No
Root et al. 1988	7.27	1.92	November	Missouri	
Root et al. 1988	7.14	2.85	November	Missouri	

Root et al. 1988	5.98	3.00	November	Missouri	
Root et al. 1988		2.36	November	Missouri	
Root et al. 1988		2.02	November	Missouri	
Root et al. 1988		2.00	November	Missouri	
Sargent and Labisky 1995	3.50		Apr-June	Florida	No
Sargent and Labisky 1995	1.50		Apr-June	Florida	No
Sargent and Labisky 1995	7.00		Apr-Mar	Florida	No
Sargent and Labisky 1995	2.90		Apr-Mar	Florida	No
Sargent and Labisky 1995	2.60		Jan-Mar	Florida	No
Sargent and Labisky 1995	0.60		Jan-Mar	Florida	No
Sargent and Labisky 1995	3.90		July-Sep	Florida	No
Sargent and Labisky 1995	2.40		July-Sep	Florida	No
Sargent and Labisky 1995	4.20		Oct-Dec	Florida	No
Sargent and Labisky 1995	1.00		Oct-Dec	Florida	No
Smith 1970	6.23	2.45		Florida	
Storm et al. 2007		0.53	Sumer	Illinois	No

Storm et al. 2007		0.90	Winter	Illinois	No
Thayer et al. 2009	2.31		Feb-May	Louisiana	Yes
Thayer et al. 2009	1.53		Feb-May	Louisiana	Yes
Thayer et al. 2009	0.86		June-Sep	Louisiana	Yes
Thayer et al. 2009	0.70		June-Sep	Louisiana	Yes
Thayer et al. 2009	1.18		Oct-Feb	Louisiana	Yes
Thayer et al. 2009	1.47		Year long	Louisiana	Yes
Thayer et al. 2009	1.08		Year long	Louisiana	Yes
Vanderhoof and Jacobson 1993	6.66	3.17	Dec-May	Mississippi	No
Vanderhoof and Jacobson 1993	4.18	2.02	June-Nov	Mississippi	No
Vanderhoof and Jacobson 1993	6.91	3.43	Year long	Mississippi	No
Walter et al. 2009		0.99	Year long	Illinois	No
Walter et al. 2009		1.34	Year long	Michigan	No
Walter et al. 2009		1.20	Year long	Nebraska	No
Walter et al. 2009		1.47	Year long	Wisconsin	No
Walter et al. 2011	3.50	0.95	Year long	Missouri	No

Webb et al. 2009		0.38	Birth	Oklahoma	No
Webb et al. 2009	4.01	1.22	Spring	Oklahoma	No
Webb et al. 2009	3.15	0.83	Year long	Oklahoma	No

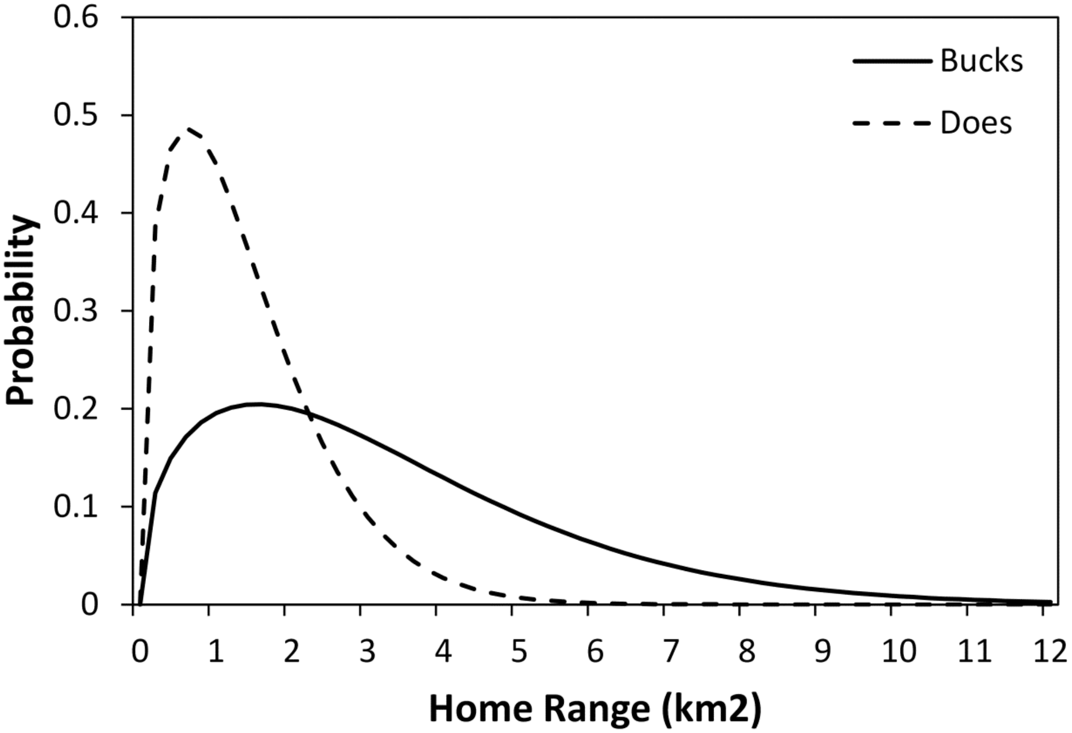

Figure A.1. Probability of home range size (km^2) for bucks and does.

Brunjes, K. J., W. B. Ballard, M. H. Humphrey, F. Harwell, N. E. McIntyre, P. R. Krausman, and M. C. Wallace. 2009. Home ranges of sympatric mule deer and white-tailed deer in Texas. Southwestern Naturalist 54:253-260.

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Thayer, J. W., M. J. Chamberlain, and S. Durham. 2009. Space use and survival of male white-tailed deer in a bottomland hardwood forest of south-central Louisiana. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 63:1-6.

Vanderhoof, R. E., and H. A. Jacobson. 1993. Food plots and deer home range movements in the southern Coastal Plain. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 47:33-42.

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N. E. Mathews, C. K. Nielsen, E. M. Schauber, T. R. Van Deelen, and S. R. Winterstein. 2009. Regional assessment on influence of landscape configuration and connectivity on range size of white-tailed deer. Landscape Ecology 24:1405-1420.

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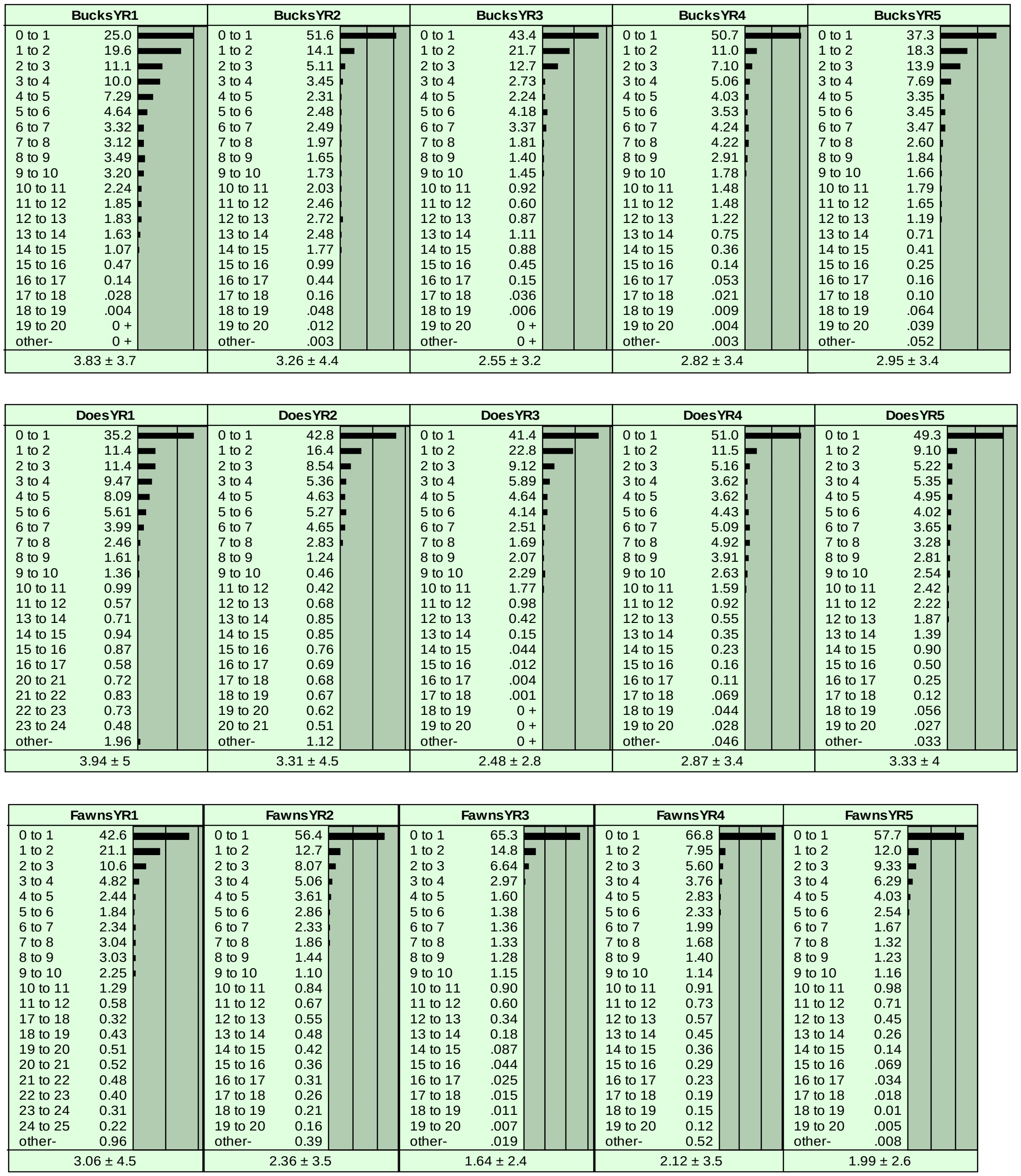
Appendix B. Netica model to estimate deer abundance and density



BucksYR1		BucksYR2		BucksYR3		BucksYR4		BucksYR5	
0 to 1	25.0	0 to 1	51.6	0 to 1	43.4	0 to 1	50.7	0 to 1	37.3
1 to 2	19.6	1 to 2	14.1	1 to 2	21.7	1 to 2	11.0	1 to 2	18.3
2 to 3	11.1	2 to 3	5.11	2 to 3	12.7	2 to 3	7.10	2 to 3	13.9
3 to 4	10.0	3 to 4	3.45	3 to 4	2.73	3 to 4	5.06	3 to 4	7.69
4 to 5	7.29	4 to 5	2.31	4 to 5	2.24	4 to 5	4.03	4 to 5	3.35
5 to 6	4.64	5 to 6	2.48	5 to 6	4.18	5 to 6	3.53	5 to 6	3.45
6 to 7	3.32	6 to 7	2.49	6 to 7	3.37	6 to 7	4.24	6 to 7	3.47
7 to 8	3.12	7 to 8	1.97	7 to 8	1.81	7 to 8	4.22	7 to 8	2.60
8 to 9	3.49	8 to 9	1.65	8 to 9	1.40	8 to 9	2.91	8 to 9	1.84
9 to 10	3.20	9 to 10	1.73	9 to 10	1.45	9 to 10	1.78	9 to 10	1.66
10 to 11	2.24	10 to 11	2.03	10 to 11	0.92	10 to 11	1.48	10 to 11	1.79
11 to 12	1.85	11 to 12	2.46	11 to 12	0.60	11 to 12	1.48	11 to 12	1.65
12 to 13	1.83	12 to 13	2.72	12 to 13	0.87	12 to 13	1.22	12 to 13	1.19
13 to 14	1.63	13 to 14	2.48	13 to 14	1.11	13 to 14	0.75	13 to 14	0.71
14 to 15	1.07	14 to 15	1.77	14 to 15	0.88	14 to 15	0.36	14 to 15	0.41
15 to 16	0.47	15 to 16	0.99	15 to 16	0.45	15 to 16	0.14	15 to 16	0.25
16 to 17	0.14	16 to 17	0.44	16 to 17	0.15	16 to 17	.053	16 to 17	0.16
17 to 18	.028	17 to 18	0.16	17 to 18	.036	17 to 18	.021	17 to 18	0.10
18 to 19	.004	18 to 19	.048	18 to 19	.006	18 to 19	.009	18 to 19	.064
19 to 20	0 +	19 to 20	.012	19 to 20	0 +	19 to 20	.004	19 to 20	.039
other-	0 +	other-	.003	other-	0 +	other-	.003	other-	.052
3.83 ± 3.7		3.26 ± 4.4		2.55 ± 3.2		2.82 ± 3.4		2.95 ± 3.4	

DoesYR1		DoesYR2		DoesYR3		DoesYR4		DoesYR5	
0 to 1	35.2	0 to 1	42.8	0 to 1	41.4	0 to 1	51.0	0 to 1	49.3
1 to 2	11.4	1 to 2	16.4	1 to 2	22.8	1 to 2	11.5	1 to 2	9.10
2 to 3	11.4	2 to 3	8.54	2 to 3	9.12	2 to 3	5.16	2 to 3	5.22
3 to 4	9.47	3 to 4	5.36	3 to 4	5.89	3 to 4	3.62	3 to 4	5.35
4 to 5	8.09	4 to 5	4.63	4 to 5	4.64	4 to 5	3.62	4 to 5	4.95
5 to 6	5.61	5 to 6	5.27	5 to 6	4.14	5 to 6	4.43	5 to 6	4.02
6 to 7	3.99	6 to 7	4.65	6 to 7	2.51	6 to 7	5.09	6 to 7	3.65
7 to 8	2.46	7 to 8	2.83	7 to 8	1.69	7 to 8	4.92	7 to 8	3.28
8 to 9	1.61	8 to 9	1.24	8 to 9	2.07	8 to 9	3.91	8 to 9	2.81
9 to 10	1.36	9 to 10	0.46	9 to 10	2.29	9 to 10	2.63	9 to 10	2.54
10 to 11	0.99	11 to 12	0.42	10 to 11	1.77	10 to 11	1.59	10 to 11	2.42
11 to 12	0.57	12 to 13	0.68	11 to 12	0.98	11 to 12	0.92	11 to 12	2.22
13 to 14	0.71	13 to 14	0.85	12 to 13	0.42	12 to 13	0.55	12 to 13	1.87
14 to 15	0.94	14 to 15	0.85	13 to 14	0.15	13 to 14	0.35	13 to 14	1.39
15 to 16	0.87	15 to 16	0.76	14 to 15	.044	14 to 15	0.23	14 to 15	0.90
16 to 17	0.58	16 to 17	0.69	15 to 16	.012	15 to 16	0.16	15 to 16	0.50
20 to 21	0.72	17 to 18	0.68	16 to 17	.004	16 to 17	0.11	16 to 17	0.25
21 to 22	0.83	18 to 19	0.67	17 to 18	.001	17 to 18	.069	17 to 18	0.12
22 to 23	0.73	19 to 20	0.62	18 to 19	0 +	18 to 19	.044	18 to 19	.056
23 to 24	0.48	20 to 21	0.51	19 to 20	0 +	19 to 20	.028	19 to 20	.027
other-	1.96	other-	1.12	other-	0 +	other-	.046	other-	.033
3.94 ± 5		3.31 ± 4.5		2.48 ± 2.8		2.87 ± 3.4		3.33 ± 4	

FawnsYR1		FawnsYR2		FawnsYR3		FawnsYR4		FawnsYR5	
0 to 1	42.6	0 to 1	56.4	0 to 1	65.3	0 to 1	66.8	0 to 1	57.7
1 to 2	21.1	1 to 2	12.7	1 to 2	14.8	1 to 2	7.95	1 to 2	12.0
2 to 3	10.6	2 to 3	8.07	2 to 3	6.64	2 to 3	5.60	2 to 3	9.33
3 to 4	4.82	3 to 4	5.06	3 to 4	2.97	3 to 4	3.76	3 to 4	6.29
4 to 5	2.44	4 to 5	3.61	4 to 5	1.60	4 to 5	2.83	4 to 5	4.03
5 to 6	1.84	5 to 6	2.86	5 to 6	1.38	5 to 6	2.33	5 to 6	2.54
6 to 7	2.34	6 to 7	2.33	6 to 7	1.36	6 to 7	1.99	6 to 7	1.67
7 to 8	3.04	7 to 8	1.86	7 to 8	1.33	7 to 8	1.68	7 to 8	1.32
8 to 9	3.03	8 to 9	1.44	8 to 9	1.28	8 to 9	1.40	8 to 9	1.23
9 to 10	2.25	9 to 10	1.10	9 to 10	1.15	9 to 10	1.14	9 to 10	1.16
10 to 11	1.29	10 to 11	0.84	10 to 11	0.90	10 to 11	0.91	10 to 11	0.98
11 to 12	0.58	11 to 12	0.67	11 to 12	0.60	11 to 12	0.73	11 to 12	0.71
17 to 18	0.32	12 to 13	0.55	12 to 13	0.34	12 to 13	0.57	12 to 13	0.45
18 to 19	0.43	13 to 14	0.48	13 to 14	0.18	13 to 14	0.45	13 to 14	0.26
19 to 20	0.51	14 to 15	0.42	14 to 15	.087	14 to 15	0.36	14 to 15	0.14
20 to 21	0.52	15 to 16	0.36	15 to 16	.044	15 to 16	0.29	15 to 16	.069
21 to 22	0.48	16 to 17	0.31	16 to 17	.025	16 to 17	0.23	16 to 17	.034
22 to 23	0.40	17 to 18	0.26	17 to 18	.015	17 to 18	0.19	17 to 18	.018
23 to 24	0.31	18 to 19	0.21	18 to 19	.011	18 to 19	0.15	18 to 19	0.01
24 to 25	0.22	19 to 20	0.16	19 to 20	.007	19 to 20	0.12	19 to 20	.005
other-	0.96	other-	0.39	other-	.019	other-	0.52	other-	.008
3.06 ± 4.5		2.36 ± 3.5		1.64 ± 2.4		2.12 ± 3.5		1.99 ± 2.6	

Figure B.1. Mean probability distribution of abundance in spring and fall of 2011-2012 and spring of 2013 for bucks, does, and fawns at Fort Rucker, Alabama.

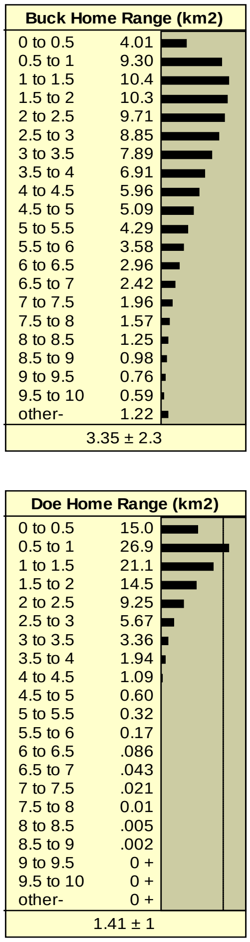
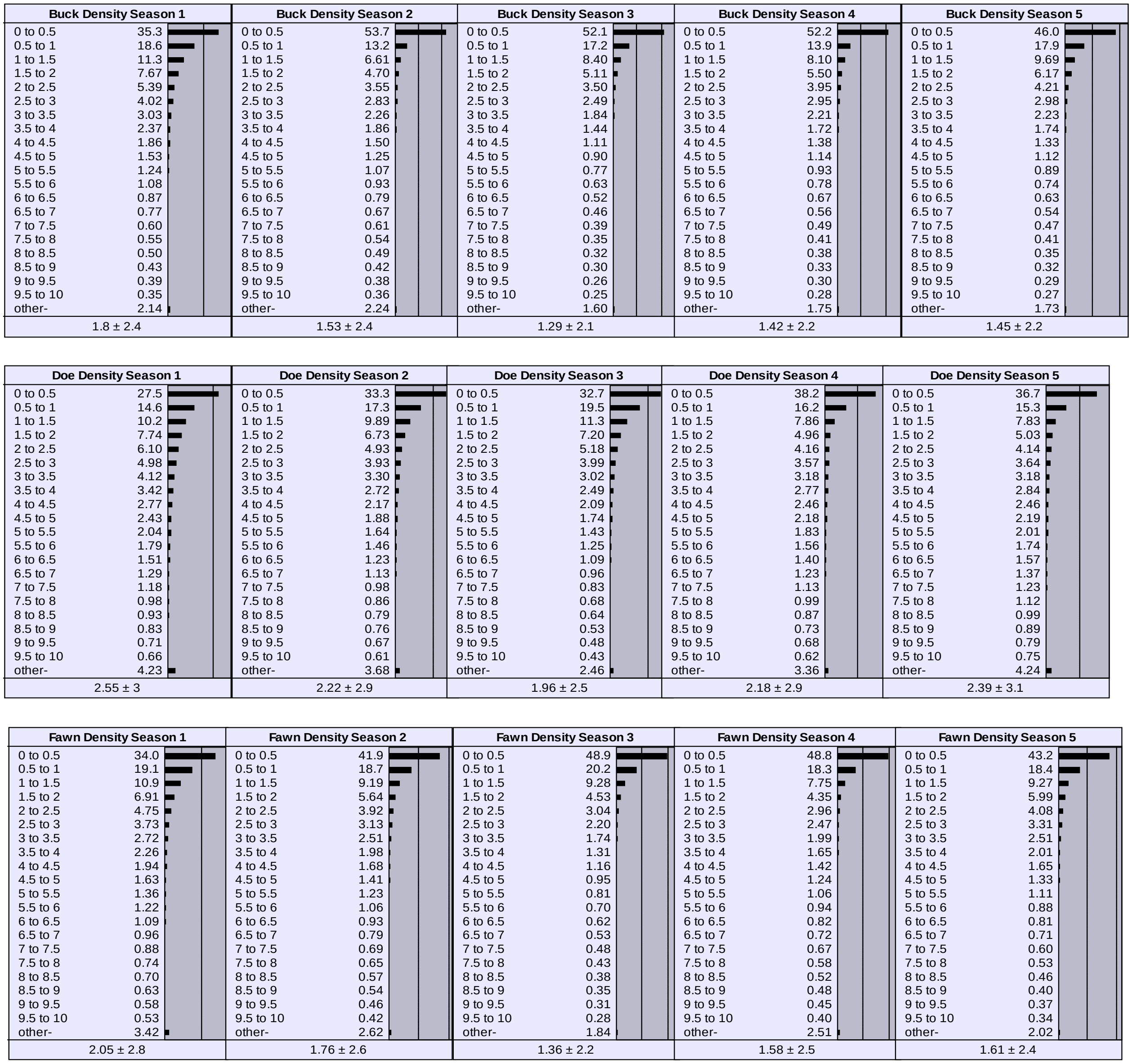


Figure B.2. Probability distribution of home range size for bucks and does based on a literature search used in a model to estimate density at Fort Rucker, Alabama.



	Buck Density Season 1	Buck Density Season 2	Buck Density Season 3	Buck Density Season 4	Buck Density Season 5
0 to 0.5	35.3	53.7	52.1	52.2	46.0
0.5 to 1	18.6	13.2	17.2	13.9	17.9
1 to 1.5	11.3	6.61	8.40	8.10	9.69
1.5 to 2	7.67	4.70	5.11	5.50	6.17
2 to 2.5	5.39	3.55	3.50	3.95	4.21
2.5 to 3	4.02	2.83	2.49	2.95	2.98
3 to 3.5	3.03	2.26	1.84	2.21	2.23
3.5 to 4	2.37	1.86	1.44	1.72	1.74
4 to 4.5	1.86	1.50	1.11	1.38	1.33
4.5 to 5	1.53	1.25	0.90	1.14	1.12
5 to 5.5	1.24	1.07	0.77	0.93	0.89
5.5 to 6	1.08	0.93	0.63	0.78	0.74
6 to 6.5	0.87	0.79	0.52	0.67	0.63
6.5 to 7	0.77	0.67	0.46	0.56	0.54
7 to 7.5	0.60	0.61	0.39	0.49	0.47
7.5 to 8	0.55	0.54	0.35	0.41	0.41
8 to 8.5	0.50	0.49	0.32	0.38	0.35
8.5 to 9	0.43	0.42	0.30	0.33	0.32
9 to 9.5	0.39	0.38	0.26	0.30	0.29
9.5 to 10	0.35	0.36	0.25	0.28	0.27
other-	2.14	2.24	1.60	1.75	1.73
	1.8 ± 2.4	1.53 ± 2.4	1.29 ± 2.1	1.42 ± 2.2	1.45 ± 2.2

	Doe Density Season 1	Doe Density Season 2	Doe Density Season 3	Doe Density Season 4	Doe Density Season 5
0 to 0.5	27.5	33.3	32.7	38.2	36.7
0.5 to 1	14.6	17.3	19.5	16.2	15.3
1 to 1.5	10.2	9.89	11.3	7.86	7.83
1.5 to 2	7.74	6.73	7.20	4.96	5.03
2 to 2.5	6.10	4.93	5.18	4.16	4.14
2.5 to 3	4.98	3.93	3.99	3.57	3.64
3 to 3.5	4.12	3.30	3.02	3.18	3.18
3.5 to 4	3.42	2.72	2.49	2.77	2.84
4 to 4.5	2.77	2.17	2.09	2.46	2.46
4.5 to 5	2.43	1.88	1.74	2.18	2.19
5 to 5.5	2.04	1.64	1.43	1.83	2.01
5.5 to 6	1.79	1.46	1.25	1.56	1.74
6 to 6.5	1.51	1.23	1.09	1.40	1.57
6.5 to 7	1.29	1.13	0.96	1.23	1.37
7 to 7.5	1.18	0.98	0.83	1.13	1.23
7.5 to 8	0.98	0.86	0.68	0.99	1.12
8 to 8.5	0.93	0.79	0.64	0.87	0.99
8.5 to 9	0.83	0.76	0.53	0.73	0.89
9 to 9.5	0.71	0.67	0.48	0.68	0.79
9.5 to 10	0.66	0.61	0.43	0.62	0.75
other-	4.23	3.68	2.46	3.36	4.24
	2.55 ± 3	2.22 ± 2.9	1.96 ± 2.5	2.18 ± 2.9	2.39 ± 3.1

	Fawn Density Season 1	Fawn Density Season 2	Fawn Density Season 3	Fawn Density Season 4	Fawn Density Season 5
0 to 0.5	34.0	41.9	48.9	48.8	43.2
0.5 to 1	19.1	18.7	20.2	18.3	18.4
1 to 1.5	10.9	9.19	9.28	7.75	9.27
1.5 to 2	6.91	5.64	4.53	4.35	5.99
2 to 2.5	4.75	3.92	3.04	2.96	4.08
2.5 to 3	3.73	3.13	2.20	2.47	3.31
3 to 3.5	2.72	2.51	1.74	1.99	2.51
3.5 to 4	2.26	1.98	1.31	1.65	2.01
4 to 4.5	1.94	1.68	1.16	1.42	1.65
4.5 to 5	1.63	1.41	0.95	1.24	1.33
5 to 5.5	1.36	1.23	0.81	1.06	1.11
5.5 to 6	1.22	1.06	0.70	0.94	0.88
6 to 6.5	1.09	0.93	0.62	0.82	0.81
6.5 to 7	0.96	0.79	0.53	0.72	0.71
7 to 7.5	0.88	0.69	0.48	0.67	0.60
7.5 to 8	0.74	0.65	0.43	0.58	0.53
8 to 8.5	0.70	0.57	0.38	0.52	0.46
8.5 to 9	0.63	0.54	0.35	0.48	0.40
9 to 9.5	0.58	0.46	0.31	0.45	0.37
9.5 to 10	0.53	0.42	0.28	0.40	0.34
other-	3.42	2.62	1.84	2.51	2.02
	2.05 ± 2.8	1.76 ± 2.6	1.36 ± 2.2	1.58 ± 2.5	1.61 ± 2.4

Figure B.3. Probability distribution of density in spring and fall of 2011-2012 and spring of 2013 for bucks, does, and fawns at Fort Rucker, Alabama.