Spatial Variability in Abundance, Detectability and Survival of White-Tailed Deer Across a Heterogeneous Landscape of Fear

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# Table of Contents

**Introduction** ........................................................................................................................................................................ 1

Literature Cited ............................................................................................................................................................................. 2

**Spatial and Temporal Variations in White-Tailed Deer Abundance and Detectability Across a Heterogeneous Landscape of Fear** ........................................................................................................................................................................ 4

Abstract ..................................................................................................................................................................................... 5

Introduction ................................................................................................................................................................................ 6

Study Area ................................................................................................................................................................................. 8

Methods .................................................................................................................................................................................... 10

  Study Design ....................................................................................................................................................................... 10
  N-mixture Models .............................................................................................................................................................. 12
  Activity Analysis ................................................................................................................................................................. 14

Results .................................................................................................................................................................................... 14

Discussion ................................................................................................................................................................................. 18

Management Implications .................................................................................................................................................... 23

Literature Cited ........................................................................................................................................................................ 23

Tables .................................................................................................................................................................................... 27

Figures .................................................................................................................................................................................... 33

**Fawn Survival in the Exurban, Heterogeneous, Predator Rich Landscape of North-Western Connecticut** ........................................................................................................................................................................ 42

Abstract .................................................................................................................................................................................. 43
Introduction ................................................................................................................. 44
Study Area .................................................................................................................. 46
Methods ....................................................................................................................... 46
  Capture and Monitoring ......................................................................................... 46
  Landscape and Weather Variables .......................................................................... 48
  Analysis ..................................................................................................................... 49
Results .......................................................................................................................... 50
  Cause-Specific Mortality ......................................................................................... 51
  Survival Analysis ...................................................................................................... 51
Discussion .................................................................................................................... 53
  Cause-specific mortality .......................................................................................... 53
  Landscape Scale ...................................................................................................... 54
  Habitat covariates .................................................................................................... 55
  Biological covariates ................................................................................................ 57
  Management Implications ....................................................................................... 58

Literature Cited .......................................................................................................... 59
Tables ............................................................................................................................. 62
Figures .......................................................................................................................... 65

Accounting for Bias in White-tailed Deer Aerial Surveys Through the Calibration of a
Sightability Model in Connecticut .................................................................................. 71

Abstract ....................................................................................................................... 72
Introduction .................................................................................................................. 72
Methods ....................................................................................................................... 74
Sightability Model ....................................................................................................... 75
Results ............................................................................................................................................. 76

Sightability Models ......................................................................................................................... 76
Population Estimates ....................................................................................................................... 77
Discussion ......................................................................................................................................... 77

Literature Cited ............................................................................................................................... 78
Tables .............................................................................................................................................. 80

Figures ............................................................................................................................................ 81
Introduction

Spatial heterogeneity is a topic of growing interest in the study of ecological systems (Massé and Côté 2012). Heterogeneity by definition refers to the complexity or variability of an ecological property of interest across both space and time (Li and Reynolds 1995) and is therefore dependent on the scale of observation (Gustafson 1998). Across human-dominated landscapes forest habitat is under conversion to agricultural and or urbanized areas, creating spatial heterogeneity in natural habitats (Bonnot et al. 2013). This spatial heterogeneity in natural habitats influences resource availability and predation risk across the landscape.

Predator-prey interactions result in both direct and indirect effects on prey species, influencing demographics and population dynamics (Bonnot et al. 2013). Predation risk is heterogenous due to is structuring across both space and time at multiple scales (Tolon et al. 2009). Prey that can perceive this risk can modify their behavior or modify space use in order to avoid predation risk (Tolon et al. 2009). This idea of heterogeneity in predation risk is commonly referred to as a dynamic ‘landscape of fear, transforming based on predator populations and variations in land cover types that affect the spatial distribution of both prey resources and predator populations (Atuo and O’Connell 2017).

For a wide range of species, the majority of mortality is anthropogenic, most notably through hunter harvest (Tolon et al. 2009). Hunting like traditional predation varies both across space (lands open and closed to hunting) and time (seasons and hunter daily activity) and can subsequently shape the landscape of fear. With over 13 million participants, human hunters outnumber wolves and cougars 165 to 1 further supporting the idea that human hunters may be acting as ecological predators influencing prey both directly and indirectly (Kays et al. 2017).
Across the eastern United States white-tailed deer populations are generally considered overabundant, with negative effects on forest ecosystems, human health and native biota (Foster et al. 2002, McShea 2012). White-tailed deer are habitat generalists and occur across both agricultural, forested and human dominated landscapes alike. Hunting is the primary source of population control and is generally considered the greatest source of mortality on adult deer, while fawns are primarily affected by traditional predators (bobcats, bears and coyotes).

Behavior and or space use modifications to hunting risk may affect harvest susceptibility, further increasing the difficulties of managing deer in a time of a declining hunter population (McShea 2012). Recruitment and fawn survival are also important variables to consider when trying to determine population growth. Landscape composition and structure are known to influence predation risk, with certain land cover types facilitating predation and others mitigating predation (Gulsby et al. 2017). Heterogenous landscapes and temporal variability in space use by deer in relation to risk and resource availability present challenges for estimating and monitoring population size. Understanding the role that heterogeneity pays in white-tailed deer population dynamics can provide managers with useful information, particularly when presented with the challenges of managing deer across a changing landscape.

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Spatial and Temporal Variations in White-Tailed Deer Abundance and Detectability Across a Heterogeneous Landscape of Fear

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Abstract

Hunters, like predators, create a heterogeneous landscape of fear, within which prey can reduce the risk associated with predation by seeking refuge in low-risk areas. With the recent rise in private protected open space, understanding the degree to which these properties serve as refuge areas, and how refuge use might affect spatial variability in white-tailed deer abundance both seasonally and year-round is important to deer management. We used N-mixture models and 50 wildlife cameras to understand the role that hunting plays in creating spatial variability in white-tailed deer abundance across public open space; both open and closed to hunting. We also used kernel density functions on activity data and the Wald’s test to determine if significant differences in activity levels exist between sites and across seasons. Estimates of abundance suggest that it is unlikely that deer are shifting site use in response to risk at our scale of observation, with a 44.21% probability of a shift in abundance in year one and a 42.98% probability of a shift in year two. Detection probability estimates do support an observed difference in detectability between hunted and un-hunted deer during year one, with a 70.03% probability that detection was higher on un-hunted sites as opposed to hunted sites during the deer hunting season. Activity level analysis supports this finding, with a significant decline in activity levels on hunted sites during the hunting season when compared to the average, and a significant difference in activity between hunted and un-hunted sites across the entire sample year. Year 2 detection estimates did not show a difference in detectability between sites, with only a 44.58% probability of a difference between hunted and un-hunted sites during the hunting season. While we did not find evidence of deer shifting site use to avoid predation risk, our observed differences in detectability support fine-scale redistributions within sites to avoid the risk of being detected by hunters.
**Introduction**

Predator prey interactions can have both direct (death) and indirect effects on prey species (Creel and Christianson 2008). Due to the structured nature of predation across both space and time, predators create what is known as a heterogenous “landscape of fear” (Tolon et al. 2009). For prey species that can perceive this structured and dynamic landscape of fear, they have the potential to minimize risk by relocating to lower risk areas (Tolon et al. 2009). Low risk areas therefore serve as refuge from predation. The concept of ‘refuge’ or ‘refugia’ is widely used in the theories of ecology, biogeography, evolution and speciation and refers to a geographic area in which biota can grow and survive during adverse or unfavorable environmental conditions (Berryman et al. 2006, Birks 2016). The idea of refuge is suggested to be an essential concept, particularly in alleviating the role of population-level processes like predation (Berryman et al. 2006, Visscher et al. 2017). Changes in space use is one of the most common responses of prey to predation risk (Brown 1988, Abrahams and Dill 1989, Birks 2016). The scale at which prey respond to predation risk depends on the factors limiting individual fitness, however, areas of high heterogenous risk may influence space use more than other environmental factors (Rettie and Messier 2000, Tolon et al. 2009). Knowledge of low risk areas and or preys ability to shift to such areas given high predation risk likely influences prey space use (Tolon et al. 2009). With increases in fragmentation of land use and connectivity, ownership patterns and habitat change during the 21st century (Campa et al. 2011), low risk areas occur at higher densities and are more interspersed across the landscape, potentially increasing the prey’s ability to use these areas to avoid risk.

With the loss of apex predators, especially in Southern New England, humans took over the role as top predators and are considered to be the greatest source of annual mortality on most large mammals (Little et al. 2014). Most game species experience spatial and temporal
variability in risk due to restricted hunting seasons, daily times in which hunting pressure is the highest, hunter preference to stay close to roadways, and areas of higher human development (Cromsigt et al. 2013). If an individual’s fitness is determined mainly by the risk of being harvested, animals will then seek refuge during times of high risk, and subsequently modify space use in relation to resource availability when risk is low (Storm et al. 2007, Tolon et al. 2009, Quinn et al. 2013).

White-tailed deer hunters comprise 81% of all hunters 16 years of age and older, highlighting not only the importance of deer hunting, but also the amount of pressure put on deer across their range (Hewitt 2011). In response to hunters on the landscape white-tailed deer and other commonly harvested ungulates respond in markedly different ways across their geographic range. Changes in behavior, such as variation in activity levels and times (Proffitt et al. 2013, Little et al. 2016, Visscher et al. 2017), use of refuge areas (Tolon et al. 2009, Visscher et al. 2017), and changes in habitat use (Kilpatrick et al. 2001) are all possible responses to heterogenous hunter induced risk across the landscape. However, some evidence exists to suggest that some of the most heavily hunted species are not modifying behavior and space use in response to risk on the landscape (Reyna-Hurtado and Tanner 2007, Kays et al. 2017).

We had the unique opportunity to study the role that hunting plays in influencing space use by white-tailed deer as well as to determine the year-round effects of hunting on abundance. While much research exists on the short term effects of hunting on behavior of game species, little research exists on year round affects (Kays et al. 2017). The Connecticut landscape supports answering these questions due to the high fragmentation of land ownership. Connecticut consists of 32 state forests totaling 170,000 acres, 105 wildlife management areas totaling 32,000 acres, 10,000 acres of federal land, 82,146 acres of municipal property, and between 63,870 and
99,549 acres of land owned by non-profit land conservation organizations (NLCO) (Comprehensive Open Space Acquisition Strategy 2016). Hunting does not occur on much of the land owned by NLCO, which encompasses between 1.8% and 2.8% of all the land in Connecticut, while regulated hunting takes place in almost all state forests and wildlife management areas except for state parks. We believe that this highly interspersed landscape of hunted and un-hunted land provides deer with the opportunity to minimize exposure to hunting pressure and seek refuge outside of hunted sites.

Our goal for this study was to determine whether abundance of white-tailed deer varies across open space in relation to hunting as a management tool. We used wildlife camera data and N-mixture models in northeastern Connecticut to estimate abundance of unmarked individuals. Specifically, our objectives were 1) to determine if annual average estimates of abundance differed between hunted and un-hunted sites, 2) to quantify the relative magnitude that deer abundance shifts between hunted and un-hunted sites during the hunting season, and 3) to determine how hunting influences estimates of detection probabilities of white-tailed deer. We predict that regulated hunting will lead to higher abundance un-hunted sites as opposed to hunted sites year-round and that seasonal fluxes between hunted and un-hunted sites will be evident in response to the hunting season (Figure 1.1). We also predict that detection probability will decrease on hunted sites in response to hunters on the landscape while un-hunted site detection probability remains unchanged.

**Study Area**

Our research focused on six properties in north-eastern Connecticut that occur within deer management zone 5 (DMZ 5). This landscape is made up of primarily hardwood forests, interspersed with small amounts of agriculture and open fields. We selected this deer
management zone because of the large amount of land that is both open and closed to recreational hunting. To define the study area, we highlighted all open space parcels in DMZ 5 within ArcGIS (Environmental Systems Research Institute 2014). Parcels less than 61ha were removed. This minimum parcel size was based on the size of two doe home ranges estimated using 50% kernel density estimator (31 ha; unpublished data, CT DEEP). The remaining parcels were under the ownership of the following organizations: the Connecticut Department of Energy and Environmental Protection (CT DEEP) (James L Goodwin State Forest, Natchaug State Forest and Mashamoquet Brook State Park), The Nature Conservancy (Dennis Farm Preserve), The Audubon Society (Pomfret Center), Wyndham Land Trust (Valentine and Gellert Preserve), the New England Forestry Foundation (Chase-Kimball Memorial Forest) and the Boy Scouts of America (June Norcross Webster Scout Reservation).

Natchaug State Forest is just under 13,000 acres and is in the towns of Hampton, Chaplin, Eastford, Ashford, Pomfret and Brooklyn. Natchaug State Forest is open to deer hunting for bow, shotgun, and muzzleloader seasons, running from September to the end of December in addition to other forms of outdoor recreation. This piece of land is not contiguous and is therefore broken up into patches across the landscape. Our research focuses on two of these parcels, the main forest located in Eastford/Hampton and the Pumpkin Hill parcel located in Chaplin CT. The James L. Goodwin State Forest covers approximately 2,000 acres of land in the towns of Hampton and Chaplin. This state property is closed to all forms of hunting but is open to various other forms of public recreation. Mashamoquet Brook State Park, located in the town of Pomfret, is closed to hunting and is roughly 1,000 acres. Dennis Farm Preserve is in the town of Pomfret and includes 380 acres of land that is closed to hunting. The Audubon Center at Pomfret is closed to hunting and consists of roughly 700 acres of forest, open pasture, wetlands, and shrub.
scrub habitat. The Valentine property, which was recently acquired by the Wyndam Land Trust, secured 42.7 acres of land that abuts the 125-acre Gellert Preserve, both of which are closed to hunting. The Chase-Kimball Memorial Forest is 169 acres of land that does not allow hunting and is adjacent to the Gellert/Valentine Preserve. Since all three of these sites are contiguous this area was sampled as one large site. The June Norcross Webster Scout Reservation is closed to hunting and maintains 340 acres of land used actively during the summer months as a camp.

Past research conducted by CT DEEP estimated deer densities throughout the state at 26 deer/mi$^2$ on average (range 11 -40 deer/mi$^2$) (Andrew LaBonte, DEEP Personal Communication). Average annual temperature for north-eastern CT is 48 degrees Fahrenheit (average range 14-80 degrees Fahrenheit), and average rainfall is 51. 11 inches (U.S. Climate Data 2018).

**Methods**

**Study Design**

We used 50 Bushnell Trophy Cam HD wildlife cameras (Bushnell Outdoor Products, USA), able to capture 12 MP resolution photos, and up to 60 seconds of HD video with passive infrared motion sensors (PIR). These cameras also come equipped with an LED flash for clear nighttime photos. We created a camera trapping grid in ArcGIS over the study area, with each grid cell 31 ha in size or equivalent to the average core (50%) home-range of does in CT (CT DEEP unpublished data & Duquette et al. 2014). Cameras were spaced out relative to the average core home-range size of does in order to minimize the chance of detecting individual deer on more than one camera, which is an assumption of n-mixture models (Kery and Royle 2016). We then randomly assigned 25 cameras to grid cells located on properties that did not allow hunting, and 25 cameras to grid cells located on properties that were open to hunting (Figure 1.2). We deployed cameras in July 2016 such that they were fully operational by August
1st, 2016. Cameras were placed as close to the center of the grid cell as possible in areas that showed deer sign and/or game trails. This allowed for maximum detection probability without the use of bait, and therefore removing the known bias associated with baited sites (McCoy et al. 2011, Cusack et al. 2015, Braczkowski et al. 2016). We placed cameras 0.5 meters off the ground, facing cardinal north to reduce sun glare and observer bias in placement (McCoy et al. 2011, Keever 2014). Cameras were set with passive-infrared sensors at medium sensitivity and when triggered three photos were taken in a burst with a 30 second interval between trigger events. The cameras ran continuously from August 2016 through March 2018.

All camera photos were processed and entered into Camera Base, an access database designed to facilitate wildlife camera photo processing (Tobler 2013). We used a 40-minute time interval to group photos into unique detection events, such that individuals captured within 40 minutes of each other were considered the same event. This time frame is consistent with other studies that use 30 minute intervals but was extended to 40 minutes to allow for deer loafing or bedding down in an area for extended periods of time which happened occasionally with un-baited sites (Kelly and Holub 2008, O’Connor et al. 2017). We recorded the number of bucks, does and fawns in each detection event, as well as, the total number of deer observed in each detection event for two years of camera data (2016-2018). We considered a fawn to be an adult, after the initiation of the hunting season in September. Sampling periods, used for the analysis, consisted of six days, combined into three 48-hour occasions to increase detection probability and reduce the overall number of zeros in the data. We defined two pre-hunting season sample periods: pre-hunt 1 (1 – 6 August 2016) and pre-hunt 2 (1 – 6 September 2016), three hunting season sample periods: hunt 1 (1 – 6 October 2016), hunt 2 (1 – 6 November 2016 ) , and hunt 3 (14 –19 December 2016), and three sample periods post hunting season: post-hunt 1 (1– 6
January 2017), post-hunt 2 (1 – 6 February 2017), and post-hunt 3 (1 – 6 March 2017) (Figure 1.3). This sampling scheme was used again in year two with minor changes in the start and end dates for the white-tailed deer hunting season (2017 – 2018) (Figure 1.3). To assure population closure during our sample periods, we used data collected on hunter harvest near our camera sites to avoid days with high harvest, such as opening day of gun season (LaBonte and Kilpatrick 2016, 2017).

N-mixture Models
We estimated abundance from repeated count data using a Bayesian open population binomial mixture model that accounts for overdispersion in both abundance and detection by introducing a random site effect in log (abundance) and a random site-survey effect in logit (detection probability) (Kéry and Schaub 2012, Kery and Royle 2016). Open population mixture models are described by two conditional probability statements. Spatial variation in abundance \(N_{i,k}\) is described by a Poisson distribution with a rate parameter \(\lambda_{i,k}\) that varies over site and sample months (open portion of model). The observation process \(Y_{ijk}\) conditional on \(N_{ik}\) is represented by a binomial distribution (Kéry et al. 2009). Assumptions of N-mixture models are as follows; population closure during the sampling period, individual ID is ignored across occasions but not within occasions, individual detections are independent of each other and have equal detection probabilities, individuals are not counted at more than one site, and that count data is Poisson distributed and individual detections are binomially distributed (Royle and Dorazio 2008, Keever et al. 2017). We also sampled for three 48-hour occasions which we believe to be sufficient for a mammal species with relatively high survival rates during adulthood. Modeling the data in an open population framework allows for the analysis of trends in monthly abundance and detection probability while still maintaining closure during the daily sampling occasions (Kéry et al. 2009, Kéry and Royle 2010). Not baiting sites and only
surveying adult does ensures that all individuals have equal detection probabilities.

We used Program R (Team 2017) and the Markov chain Monte Carlo (MCMC) method and chose vague priors for all parameters. Normal distributions (0,0.1) were used for all covariates including site specific hunting (binary), season (pre-hunt, hunt, and post-hunt), interactions between site-specific hunting and season, atmospheric pressure, site specific buck occupancy, and site specific average doe group size as well as for the intercept terms in both detection and abundance. We used a normal distribution (0, tau) for the random effects on log (abundance) and logit (detection) with tau coming from a uniform distribution (0,3). We plotted posteriors over priors to ensure that the vague priors were not influencing the posteriors. To allow for quicker convergence, atmospheric pressure and site-specific doe group size were standardized. Missing covariate data related to infrequent camera failures during the study were given a prior distribution for all values and hyperparameters of that prior were estimated. This approach allows information from both the response and observed covariates to influence the missing values (Kery and Royle 2016). We used JAGS (Su and Yajima 2015) to run 3 parallel chains with 500,000 iterations each, discarded 50,000 in the burn-in and thinned by one in 500. We calculated the Bayesian P-value (0.406), which suggested good model fit (Kéry and Schaub 2012). The N-mixture model estimates abundance, and with assumptions made about the area surveyed and the area individuals occupy, we can estimate density. Because our model only used count data from adult does and we spaced cameras out by the average doe core home-range, we converted abundance to density by dividing the average site-specific abundance (λ) by 31ha and then converted this per hectare estimate to density per square mile. We realize the inherent bias in assuming a known sample area, including the potential for sampling “holes” and “edge effects” and acknowledge that our estimates of N are potentially underestimated due to the
likelihood that “holes” exist in our sampling design (Kery and Royle 2016).

**Activity Analysis**

We used the *activity* package in program R to fit kernel density functions to time series data collected on doe detections throughout each year of the study (Rowcliffe et al. 2014). We analyzed activity levels for the full sample year (1 August 2016 to 6 March 2017), during the white-tailed deer hunting season (15 September 2016 to 31 December 2016), and during the shotgun/rifle deer hunting season specifically (15 November 2016 to 6 December 2016), with minor variation in dates for year two (Figure 1.3). Prior to the analysis we converted all 24-hour time data into radial time and marked detections as either occurring on un-hunted or hunted sites (0,1) and whether they were during the pre-hunt, hunt or post-hunt season. We fit kernel density functions and estimated overall daily activity for each site as well as each season. We used the *compareAct* function to conduct a Wald’s test to compare activity estimates between hunted and un-hunted sites, hunted and un-hunted sites during the hunting season, hunted and un-hunted sites during the shotgun/rifle season, hunted sites between the pre-hunt and hunt season, and un-hunted sites between the pre-hunt and hunt season.

**Results**

Local abundance and detection probability varied considerably between sample periods during year one, with estimates of detection probability ranging from 0.05 to 0.42 and abundance estimates ranging from 0.75 to 9.56 does per 31 ha (Table 1.1 and 1.2). We estimated average detection probabilities below 0.10 during the post-hunt 3 sample period and we did not reach model convergence during the year one hunt 1 sample period, therefore inference in relation to abundance and detection probability is limited for these time-frames. We estimated average abundance of un-hunted sites to be 2.29 does per 31ha (0.93, 6.34) and 3.86 does per 31 ha across hunted sites (1.26, 12.25) (Table 1.3). We can say with 44.31% certainty that there is a
true difference in abundance between hunted and un-hunted sites on average based on posterior distributions (Figure 1.4). There is also a 44.23% probability that abundance shifted from hunted to un-hunted sites during the hunting season (Figure 1.4).

Average detection probability on un-hunted sites was 0.29 (0.12, 0.47) and 0.15 across hunted sites (0.04, 0.31) (Table 1.5). We estimated average cumulative detection probability at 0.22 (0.09, 0.36). Abundance on hunted sites declined from 9.56 does per 31 ha (2.51, 35.06) during the pre-hunt 2 sample period to 2.35 does per 31 ha (0.91, 5.32) during the hunt 1 sample period (Figure 1.4). Abundance estimates on un-hunted sites also declined from 5.63 does per 31 ha (1.93, 18.33) during pre-hunt 2 to 1.38 does per 31 ha (075, 2.53) during the hunt 1 sample period (Figure 1.4). Detection probability increased from 0.05 (0.01, 0.13) to 0.17 (0.05, 0.41) on hunted sites between pre-hunt 2 and hunt 1 sample periods and then declined during the hunt 2 sample period to 0.09 (0.02, 0.22) (Table 1.2). Detection probability on un-hunted sites increased, from 0.19 (0.04, 0.36) during pre-hunt 2 to 0.39 (0.09, 0.41) during the hunt 1 sample period and declined during the hunt 2 sample period to 0.25 (0.08, 0.42). However, this estimate is still 2.78 times higher than hunted sites during the hunt 2 sample period (Figure 1.5) with a 70.03% probability that detection is higher un-hunted sites compared to hunted sites during the hunting season.

Year two average abundance ranged from 1.22 to 5.75 does per 31 ha and detection probability ranged from 0.03 to 0.26 (Table 1.5 and 1.6). Detection probability was below 0.10 during the hunt 3 and post-hunt 1-3 sample periods and therefore inference of abundance is limited for these sample periods. Average abundance was higher on hunted sites at 4.60 does per 31 ha (0.92,19.23) than un-hunted sites at 2.67 does per 31 ha (0.66,10.68) (Table 1.3). We estimated a 42.98% probability of a shift in abundance from hunted to un-hunted sites during the
hunting season and a 43.08% probability that abundance is higher on un-hunted sites compared to hunted sites on average (Figure 1.4). Detection probability was 1.5 times higher on un-hunted sites at 0.14 (0.02, 0.28) than hunted sites at 0.09 (0.01, 0.24) (Figure 1.5). We estimated cumulative detection probability across all sites and sample periods to be 0.13 (0.02, 0.23) (Table 1.4). Abundance on hunted sites declined marginally between pre-hunt 2 and hunt 1 sample periods, with estimates of 5.75 does per 31 ha (1.02, 28.29) during pre-hunt 2 and 5.11 (1.28, 25.51) does per 31 ha during hunt 1 (Figure 1.4). Abundance on un-hunted sites declined marginally from 3.22 does per 31 ha (0.84, 14.39) during the pre-hunt 2 sample period to 3.08 (0.86, 15.15) during the hunt 1 sample (Figure 1.4). Detection probability remained constant between pre-hunt 1 and hunt 1 sample periods, with estimates of 0.12 (0.01, 0.27) during pre-hunt 1 and 0.12 (0.01, 0.27) during hunt 1 (Figure 1.5). However, detection declines by 5 times from the hunt 2 estimate of 0.15 (0.01, 0.33), to 0.03 (0.00, 0.10) during the hunt 3 sample period and remained low during the remained of the sample periods (Figure 1.5). A similar trend is also apparent on un-hunted sites with estimates declining marginally from 0.23 (0.03, 0.42) during pre-hunt 2 to 0.18 (0.02, 0.37) during hunt 1 (Figure 1.5). Detection probability also declined on un-hunted sites by just over four times from 0.22 (0.02, 0.45) during hunt 2 to 0.05 (0.00, 0.12) during hunt 3 and remained below 0.10 for the post-hunt 1-3 (Figure 1.5).

Covariate significance varied across sample periods and was evaluated at the 95% credible interval (CB) (Figure 1.6). Atmospheric pressure negatively affected detection probability by -0.91 (-2.06, -0.036) during the post-hunt 2 sample period in year one and positively influenced detection during the pre-hunt 2 sample period by 0.62 (0.10, 1.06) during year 2, proving insignificant during the subsequent sample periods. Average group size positively influence detection across all sample periods and across both years, with the strongest
effects occurring during hunt 3 to post-hunt 1-3 during year two in which detection probabilities estimates were some of the lowest observed across the two years. Buck occupancy positively influenced detection during pre-hunt 2 (1.57 (0.70, 2.27)), hunt 3 (0.70 (0.03, 1.21)), post-hunt 2 (1.65 (0.51, 2.60)) during year one. During year two, buck occupancy positively influenced detection during the hunt 3 (1.35 (0.67, 1.89)) sample period. Buck occupancy negatively influenced detection probability during hunt 1 (-0.92 (-1.81, -0.22)) and post-hunt 1 (-3.26 (-5.30, -1.72)) sample periods in year two. Whether or not sites were open or closed to hunting negatively influenced detection during the year one post-hunt 3 sample period by -2.23 (-4.63, -0.41) and was insignificant otherwise. The effects of season and site level hunting, along with the interaction between the two covariates did not prove significant in predicting abundance across all sample periods and years.

Comparison of activity levels during year one between hunted and un-hunted sites across all seasons resulted in a significant difference of 0.16 (SE=0.047) with a p-value of 0.00097 (Figure 1.7). However, during the hunting season, activity levels did not vary between sites with a difference of 0.041 (SE=0.064) with a p-value of 0.53 (Figure 1.8). During the shotgun/rifle season activity levels also did not vary between hunted and un-hunted sites with a difference of 0.004 (SE=0.12) and a p-value of 0.97 (Figure 1.9). Hunted site activity levels differed significantly between hunted season estimates and average activity level estimates with a decline in activity by -0.13 (SE=0.06) with a p-value of 0.035. Year two activity levels between hunted and un-hunted sites across all seasons varied by 0.018 (SE= 0.051) with a p-value of 0.72 (Figure 1.10). Activity levels between hunted and un-hunted sites during the hunting season varied by 0.081 (SE=0.67) with a p-value of 0.22 (Figure 1.11) and activity levels between hunted and un-
hunted sites during the rifle season varied by 0.04 (SE=0.12) with a p-value of 0.75 (Figure 1.12).

**Discussion**

Similar estimates in abundance across sample periods and years suggest that white-tailed deer are not responding to the hunting activity by shifting to un-hunted sites to avoid risk, supporting our null prediction. We estimated a 44.23% probability of a difference in abundance between hunted and un-hunted sites on average across all sample periods in year one, and a 44.31% probability of a shift in abundance from hunted to un-hunted sites during the hunting season in year one. Year two we estimated a 43.08% probability of a difference in average abundance between hunted and un-hunted sites and a 42.98% probability of a shift in abundance between hunted and un-hunted sites in response to the hunting season. Trends in detection probability suggest higher deer activity on un-hunted sites compared to hunted sites across both years of the study, with a greater difference in year one. Hunting season detection probability estimates were higher 70.03% of the time on un-hunted sites compared to hunted sites during year one. Year one average detection probability compared between sites was only 54.43% likely to differ. Year two estimates of detection probability only suggest a 55.60% probability that un-hunted sites had higher deer activity when compared to hunted sites during the hunting season, and only 53.80% probability of a difference on average. Activity level varied significantly during year one between hunted and un-hunted sites from 1 August 2016 to 6 March 2017. Activity levels were significantly higher on un-hunted sites as opposed to hunted sites during year one but did not vary between sites during the hunting season. We also estimated a significant difference in activity levels on hunted sites, with hunting season activity levels lower than year-round activity levels. We did not find significant differences in activity levels across year two.
We did not find evidence to support the theory that hunters cause spatial movements in white-tailed deer from hunted to un-hunted sites in response to risk and increased refuge areas on the landscape. Movement is based on both the distribution and abundance of resources and risk, eventually accumulating to represent space-use patterns at larger geographic scales (Dechen Quinn et al. 2013). Ungulates generally occupy smaller geographic areas, especially when fragmentation exists (Kie et al. 2002) and the need to move farther to access various resources is reduced (Dechen Quinn et al. 2013). Research suggests that white-tailed deer use smaller areas more intensively in response to the hunting season as well as reducing their overall movements (Little et al. 2016). Tolon et al. (2009) also found evidence that there is a threshold distance to which animals do not respond by shifting their home ranges toward a protected area. Our estimates support these findings suggesting that deer are not shifting sites in response to the hunting season, and are likely seeking refuge by occupying smaller areas of more dense cover or areas farther from human disturbance (Kilpatrick et al. 2001). Our findings are similar to research on white-tailed deer in Nebraska in which deer on hunted sites changed movement rates, but shifted centers of use that did not put them off hunted sites (Hygnstrom et al. 2011). While fine scale movements on sites closer to or bordering un-hunted sites is possible, this movement would be occurring at a finer scale than our data could detect. It is also possible that low risk associated with either low hunting pressure or passive hunting strategies common of traditional hunting methods does not impose a large enough risk to cause deer to shift from hunted to un-hunted sites (Cromsigt et al. 2013). We did not find evidence to suggest that increases in refugia that limit hunter access are affecting harvest susceptibility (Brown et al. 2000), however movement rates likely play more of a role in hunter success.
Trends in detection probability and the activity level analysis indicate that deer on un-hunted sites are more active across all seasons, with significant differences between hunted and un-hunted sites during year one. Year one detection probabilities were nearly 4.4 times lower during pre-hunt 2 when compared to pre-hunt 1 estimates on hunted sites. The pre-hunt 2 sample period occurred before the archery season in Connecticut, suggesting that the temporal predictability of hunting allows deer to respond by reducing movements, herd sizes and/or by avoiding hunting areas (Cromsigt et al. 2013, Little et al. 2016). We found evidence in detection probability trends to support the idea of hunting creating a landscape of fear that occurs across a smaller geographic area, resulting in adjustments to activity patterns and levels on hunted sites (Visscher et al. 2017). This landscape of fear is a result of the seasonal predictability from fixed hunting seasons with recurrent opening and closing dates, as well as human behavior that leads to higher hunting pressure in areas closer to roads and development (Proffitt et al. 2009, Cromsigt et al. 2013). During both year one and two, detection probabilities increased during the hunt 2 sample period, which occurs during peak breeding behavior for white-tailed deer in Connecticut. Does are thought to exhibit two strategies to maximize the quality of potential mates: restrict movement and concentrate activity in a central area, or increase activity and excursions (Sullivan et al. 2017). While buck occupancy did not significantly influence detection probability of does during the hunt 2 sample period, buck occupancy was significant during the hunt 3 sample period and supports the idea of increased doe activity in response to the breeding season. Group size was significantly related to detection probability with larger groups having higher detection probability. White-tailed deer among other ungulates are often detected in groups, therefore requiring additional model parameters to account for overdispersion of count data (Kéry et al. 2009, Martin et al. 2011). Our research highlights the importance of accounting
Detection probability estimates in year two declined during the hunt 3 sample period and never recovered. We think this is likely due to the increase in snow events observed during year two as opposed to year one. Between the hunt 3 sample period (December) and the post-hunt 3 sample period (March) we observed nine snow events in year two but only four snow events in year one. Snow depth is known to hinder movement of most large game species and restrict areas of use, shaping habitat selection (Gilbert et al. 1970, 2017). Habitat use under frequent snow conditions is completely reversed from low snow conditions, and for white-tailed deer in the north-east, Eastern Hemlock forests provide refuge during these adverse conditions (Lishawa et al. 2007, Gilbert et al. 2017). Eastern hemlock forests are known to significantly moderate extreme temperatures and snow depths (Lishawa et al. 2007). We only had one camera located in evergreen forests while 38 occurred in open hardwoods, likely contributing to the reduction in detections during the winter sample periods in year two, in which snow conditions forced deer to change habitat use. Our data suggests that when adverse weather conditions are present, space use is less likely to be influenced by hunters and more likely to be related to refuge from the natural elements.

Similar estimates in abundance between sites provides evidence that hunting in this area is not reducing population size. Hunter success on average for the 2016 deer hunting season was 22.2%, while success on state land averaged 8.9% (LaBonte and Kilpatrick 2016). Success was estimated by dividing the total deer harvest by the total permit issuance and multiplying by 100 (LaBonte and Kilpatrick 2016). The low success on state land likely explains our similar estimates of abundance between sites and across seasons and could be related to low hunter
density and low vulnerability of deer in contiguous habitats (Brown et al. 2000). With an aging hunter population and low recruitment of new hunters, it is likely that further declines in the hunter population are to be expected and will impact harvest success (Riley et al. 2003).

Large credible intervals surrounding both abundance and detection probability likely limits the successful use of N-mixture models in answering finite ecological questions. This is due to the inherent lack of information needed to provide estimates of abundance and detectability of unmarked individuals (Barker et al. 2018). We are confident in our estimates of relative abundance based on research showing the reliability of camera traps and N-mixture models at estimating relative abundance, however the lack of precision inhibited us from detecting highly significant differences between groups/landscapes (Royle 2004, McCoy et al. 2011, Duquette et al. 2014, Keever et al. 2017). Our results suggest that data collected on unmarked individuals can be used with N-mixture models to look at trends in relative abundance over time by incorporating the open population modeling aspect and would potentially improve with the incorporation of auxiliary data from marked individuals (Kéry and Schaub 2012, Kery and Royle 2016). Further research looking at deer movements with GPS collars would allow for the analysis of fine scale movements, potentially occurring within 24-hour periods, for which we could not account for. We also acknowledge that we were not able to get information on hunting pressure across our hunted sites. We only had 163 unique detection events of humans between 1 August 2016 and 6 March 2017 (year 1) and 134 unique detection events between 1 August 2017 and 6 March 2018 (year 2) photos of humans. However, we think that hunting pressure varied enough between sites with 85 deer harvested on our hunted sties during 2016 and 94 deer during 2017 (LaBonte and Kilpatrick 2016), and the assumption of no deer harvested on un-hunted sites, to adequately look at how hunting is influencing deer movements and behavior.
Management Implications

The rise in protected open space poses some interesting questions about white-tailed deer management, especially in New England. While we did not find evidence that these areas serve as refuge from hunting pressure, however we did find evidence that deer activity levels likely influenced harvest susceptibility on hunted sites. Our research supports the potential use of alternative hunting regimes that overcome the behavior associated with risk avoidance, such as creating spatial and temporal unpredictability (Cromsigt et al. 2013, Visscher et al. 2017). Our results also allow for a better understanding of deer behavior, as well as when deer would be most susceptible to hunters on the landscape to improve harvest numbers. We, along with others, highlight the use of wildlife cameras for monitoring trends in abundance over time for game species such as deer (Roberts et al. 2006, Curtis et al. 2009, Ikeda et al. 2013, Duquette et al. 2014, Keever et al. 2017).

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Tables

Table 1.1. N-mixture model abundance estimates (does/31 ha) and 95% credible intervals (CB) for cumulative (all sites), hunted and un-hunted site estimates during the sample periods in which cumulative detection probability was greater than 0.10 for year one in north-eastern Connecticut.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Sample Period</th>
<th>Abundance (does/31 ha)</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative Pre-Hunt 1</td>
<td>1.71</td>
<td>1.01</td>
<td>2.95</td>
<td></td>
</tr>
<tr>
<td>Cumulative Pre-Hunt 2</td>
<td>7.60</td>
<td>2.32</td>
<td>26.16</td>
<td></td>
</tr>
<tr>
<td>Cumulative Hunt 2</td>
<td>1.87</td>
<td>0.88</td>
<td>3.89</td>
<td></td>
</tr>
<tr>
<td>Cumulative Hunt 3</td>
<td>3.62</td>
<td>1.50</td>
<td>9.94</td>
<td></td>
</tr>
<tr>
<td>Cumulative Post-Hunt 1</td>
<td>2.65</td>
<td>0.78</td>
<td>10.12</td>
<td></td>
</tr>
<tr>
<td>Cumulative Post-Hunt 2</td>
<td>0.99</td>
<td>0.53</td>
<td>2.08</td>
<td></td>
</tr>
<tr>
<td>Hunted Pre-Hunt 1</td>
<td>2.13</td>
<td>1.07</td>
<td>3.94</td>
<td></td>
</tr>
<tr>
<td>Hunted Pre-Hunt 2</td>
<td>9.56</td>
<td>2.51</td>
<td>35.06</td>
<td></td>
</tr>
<tr>
<td>Hunted Hunt 2</td>
<td>2.35</td>
<td>0.91</td>
<td>5.32</td>
<td></td>
</tr>
<tr>
<td>Hunted Hunt 3</td>
<td>4.54</td>
<td>1.62</td>
<td>13.23</td>
<td></td>
</tr>
<tr>
<td>Hunted Post-Hunt 1</td>
<td>3.33</td>
<td>0.83</td>
<td>13.14</td>
<td></td>
</tr>
<tr>
<td>Hunted Post-Hunt 2</td>
<td>1.23</td>
<td>0.60</td>
<td>2.82</td>
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</tr>
<tr>
<td>Un-Hunted Pre-Hunt 1</td>
<td>1.29</td>
<td>0.79</td>
<td>2.08</td>
<td></td>
</tr>
<tr>
<td>Un-Hunted Pre-Hunt 2</td>
<td>5.63</td>
<td>1.93</td>
<td>18.33</td>
<td></td>
</tr>
<tr>
<td>Un-Hunted Hunt 2</td>
<td>1.38</td>
<td>0.75</td>
<td>2.53</td>
<td></td>
</tr>
<tr>
<td>Un-Hunted Hunt 3</td>
<td>2.70</td>
<td>1.25</td>
<td>7.01</td>
<td></td>
</tr>
<tr>
<td>Un-Hunted Post-Hunt 1</td>
<td>1.97</td>
<td>0.66</td>
<td>6.69</td>
<td></td>
</tr>
<tr>
<td>Un-Hunted Post-Hunt 2</td>
<td>0.75</td>
<td>0.40</td>
<td>1.37</td>
<td></td>
</tr>
</tbody>
</table>
Table 1.2. N-mixture model detection probability estimates and 95% credible intervals (CB) for cumulative (average across all sites), hunted and un-hunted estimates during the eight sample periods for year one in north-eastern Connecticut.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Sample Period</th>
<th>Detection Probability</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative</td>
<td>Pre-Hunt 1</td>
<td>0.32</td>
<td>0.19</td>
<td>0.44</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Pre-Hunt 2</td>
<td>0.12</td>
<td>0.03</td>
<td>0.23</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 2</td>
<td>0.28</td>
<td>0.13</td>
<td>0.44</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 3</td>
<td>0.17</td>
<td>0.05</td>
<td>0.29</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Post-Hunt 1</td>
<td>0.15</td>
<td>0.03</td>
<td>0.30</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Post-Hunt 2</td>
<td>0.37</td>
<td>0.18</td>
<td>0.53</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Post-Hunt 3</td>
<td>0.11</td>
<td>0.00</td>
<td>0.29</td>
</tr>
<tr>
<td>Hunted</td>
<td>Pre-Hunt 1</td>
<td>0.22</td>
<td>0.10</td>
<td>0.39</td>
</tr>
<tr>
<td>Hunted</td>
<td>Pre-Hunt 2</td>
<td>0.05</td>
<td>0.01</td>
<td>0.13</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 2</td>
<td>0.17</td>
<td>0.05</td>
<td>0.41</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 3</td>
<td>0.09</td>
<td>0.02</td>
<td>0.22</td>
</tr>
<tr>
<td>Hunted</td>
<td>Post-Hunt 1</td>
<td>0.08</td>
<td>0.01</td>
<td>0.22</td>
</tr>
<tr>
<td>Hunted</td>
<td>Post-Hunt 2</td>
<td>0.33</td>
<td>0.10</td>
<td>0.59</td>
</tr>
<tr>
<td>Hunted</td>
<td>Post-Hunt 3</td>
<td>0.07</td>
<td>0.00</td>
<td>0.21</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Pre-Hunt 1</td>
<td>0.42</td>
<td>0.25</td>
<td>0.57</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Pre-Hunt 2</td>
<td>0.19</td>
<td>0.04</td>
<td>0.36</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Hunt 2</td>
<td>0.39</td>
<td>0.21</td>
<td>0.54</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Hunt 3</td>
<td>0.25</td>
<td>0.08</td>
<td>0.42</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Post-Hunt 1</td>
<td>0.23</td>
<td>0.04</td>
<td>0.43</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Post-Hunt 2</td>
<td>0.40</td>
<td>0.22</td>
<td>0.59</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Post-Hunt 3</td>
<td>0.15</td>
<td>0.00</td>
<td>0.41</td>
</tr>
</tbody>
</table>
Table 1.3. N-mixture model density (does/sq. mile) and abundance (does/31 ha) estimates and associated 95% credible intervals (CB) averaged across sample periods with cumulative detection probabilities greater than 0.10 for cumulative, hunted and un-hunted estimates for year one (A) and year 2 (B) in north-eastern Connecticut.

A.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Density (does/sq. mile)</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
<th>Abundance (does/ 31 ha)</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative</td>
<td>25.67</td>
<td>9.79</td>
<td>76.79</td>
<td>3.07</td>
<td>1.17</td>
<td>9.19</td>
</tr>
<tr>
<td>Hunted</td>
<td>32.24</td>
<td>10.51</td>
<td>102.35</td>
<td>3.86</td>
<td>1.26</td>
<td>12.25</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>19.10</td>
<td>8.06</td>
<td>52.94</td>
<td>2.29</td>
<td>0.93</td>
<td>6.34</td>
</tr>
</tbody>
</table>

B.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Density (does/sq. mile)</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
<th>Abundance (does/ 31 ha)</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative</td>
<td>30.35</td>
<td>6.90</td>
<td>124.40</td>
<td>3.63</td>
<td>0.83</td>
<td>14.89</td>
</tr>
<tr>
<td>Hunted</td>
<td>38.41</td>
<td>7.70</td>
<td>160.70</td>
<td>4.60</td>
<td>0.92</td>
<td>19.23</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>22.29</td>
<td>5.50</td>
<td>89.22</td>
<td>2.67</td>
<td>0.66</td>
<td>10.68</td>
</tr>
</tbody>
</table>
Table 1.4. N-mixture model detection probability with 95% credible intervals (CB) across all sites (cumulative), hunted sites, and un-hunted sites, for year one and year 2 in north-eastern Connecticut.

<table>
<thead>
<tr>
<th>Year</th>
<th>Estimate</th>
<th>Detection Probability</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cumulative</td>
<td>0.22</td>
<td>0.09</td>
<td>0.36</td>
</tr>
<tr>
<td>1</td>
<td>Hunted</td>
<td>0.15</td>
<td>0.04</td>
<td>0.31</td>
</tr>
<tr>
<td>1</td>
<td>Un-Hunter</td>
<td>0.29</td>
<td>0.12</td>
<td>0.47</td>
</tr>
<tr>
<td>2</td>
<td>Cumulative</td>
<td>0.13</td>
<td>0.02</td>
<td>0.23</td>
</tr>
<tr>
<td>2</td>
<td>Hunted</td>
<td>0.09</td>
<td>0.01</td>
<td>0.24</td>
</tr>
<tr>
<td>2</td>
<td>Un-Hunter</td>
<td>0.14</td>
<td>0.02</td>
<td>0.28</td>
</tr>
</tbody>
</table>
Table 1.5. N-mixture model abundance estimates (does/31 ha) and 95% credible intervals (CB) for cumulative (all sites), hunted and un-hunted site estimates during the sample periods in which cumulative detection probability was greater than 0.10 for year two in north eastern Connecticut.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Sample Period</th>
<th>Abundance (does/31ha)</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative</td>
<td>Pre-Hunt 1</td>
<td>1.63</td>
<td>0.67</td>
<td>5.31</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Pre-Hunt 2</td>
<td>4.49</td>
<td>0.98</td>
<td>21.55</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 1</td>
<td>4.09</td>
<td>1.11</td>
<td>19.83</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 2</td>
<td>4.32</td>
<td>0.55</td>
<td>12.87</td>
</tr>
<tr>
<td>Hunted</td>
<td>Pre-Hunt 1</td>
<td>2.05</td>
<td>0.75</td>
<td>6.86</td>
</tr>
<tr>
<td>Hunted</td>
<td>Pre-Hunt 2</td>
<td>5.75</td>
<td>1.02</td>
<td>28.29</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 1</td>
<td>5.11</td>
<td>1.28</td>
<td>25.51</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 2</td>
<td>5.48</td>
<td>0.63</td>
<td>16.29</td>
</tr>
<tr>
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<td>Pre-Hunt 1</td>
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<td>0.51</td>
<td>3.64</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Pre-Hunt 2</td>
<td>3.22</td>
<td>0.84</td>
<td>14.39</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Hunt 1</td>
<td>3.08</td>
<td>0.86</td>
<td>15.15</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Hunt 2</td>
<td>3.16</td>
<td>0.41</td>
<td>9.53</td>
</tr>
</tbody>
</table>
Table 1.6. N-mixture model detection probability estimates and 95% credible intervals (CB) for cumulative (average across all sites), hunted and un-hunted estimates during the eight sample periods for year two in north-eastern Connecticut.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Sample Period</th>
<th>Detection Probability</th>
<th>2.5% CB</th>
<th>97.5% CB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative</td>
<td>Pre-Hunt 1</td>
<td>0.24</td>
<td>0.06</td>
<td>0.41</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Pre-Hunt 2</td>
<td>0.18</td>
<td>0.02</td>
<td>0.39</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 1</td>
<td>0.15</td>
<td>0.02</td>
<td>0.30</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 2</td>
<td>0.19</td>
<td>0.02</td>
<td>0.36</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Hunt 3</td>
<td>0.04</td>
<td>0.00</td>
<td>0.09</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Post-Hunt 1</td>
<td>0.06</td>
<td>0.01</td>
<td>0.12</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Post-Hunt 2</td>
<td>0.04</td>
<td>0.00</td>
<td>0.11</td>
</tr>
<tr>
<td>Cumulative</td>
<td>Post-Hunt 3</td>
<td>0.03</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>Hunted</td>
<td>Pre-Hunt 1</td>
<td>0.22</td>
<td>0.04</td>
<td>0.47</td>
</tr>
<tr>
<td>Hunted</td>
<td>Pre-Hunt 2</td>
<td>0.12</td>
<td>0.01</td>
<td>0.41</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 1</td>
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<td>0.01</td>
<td>0.27</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 2</td>
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<td>0.01</td>
<td>0.33</td>
</tr>
<tr>
<td>Hunted</td>
<td>Hunt 3</td>
<td>0.03</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Hunted</td>
<td>Post-Hunt 1</td>
<td>0.04</td>
<td>0.00</td>
<td>0.13</td>
</tr>
<tr>
<td>Hunted</td>
<td>Post-Hunt 2</td>
<td>0.03</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>Hunted</td>
<td>Post-Hunt 3</td>
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<td>0.00</td>
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<td>0.03</td>
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<td>0.02</td>
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<td>Hunt 3</td>
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<td>0.00</td>
<td>0.12</td>
</tr>
<tr>
<td>Un-Hunted</td>
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<td>0.01</td>
<td>0.16</td>
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<td>Post-Hunt 2</td>
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<td>0.00</td>
<td>0.18</td>
</tr>
<tr>
<td>Un-Hunted</td>
<td>Post-Hunt 3</td>
<td>0.04</td>
<td>0.00</td>
<td>0.10</td>
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</tbody>
</table>
Figures

Figure 1.1. Hypothesized abundance trends for n-mixture models of doe camera trapping count data in north-eastern Connecticut. Plot A represents a shift in abundance from hunted to un-hunted sites in response to the hunting season but no average difference in abundance between hunted and un-hunted sites. Plot B represents no shift in abundance from hunted to un-hunted sites in response to the hunting season and no average difference in abundance. Plot C represents a shift in abundance from hunted to un-hunted sites in response to the hunting season and an average difference in abundance between sites.
Figure 1.2. Highlighted open space parcels with 31 ha sample grid, derived from the core home range of adult doe white-tailed deer (CT DEEP, unpublished data). Sites were randomly selected (25 hunted (green) and 25 un-hunted (orange)), and cameras placed as close to the center point as possible in areas with deer sign present. Cameras face north, 0.5-2 meters off the ground and are set to take 3-photo bursts with a 30 second trigger interval.
A.

B.

Figure 1.3. Sample period start dates (six days in length) for the 2016-2017 (A) and 2017-2018 (B) wildlife camera data collection years with respect to the white-tailed deer hunting season dates in Connecticut.
Figure 1.4. N-mixture model abundance estimates (does/31 ha) and 95% credible intervals for hunted and un-hunted sites for sample periods in which cumulative (all sites) average detection probability was greater than 0.2 for years one (A) and two (B) in north-eastern Connecticut.
Figure 1.5. N-mixture model detection probability estimates with 95% credible intervals for hunted and un-hunted sites across all sample periods for years one (A) and two (B) in north-eastern Connecticut.
Figure 1.6. N-mixture model beta estimates and 85% credible intervals for the interaction of site hunting and season and season alone on abundance (A), site hunting on abundance (B), site hunting on detection probability (C), buck occupancy on detection probability (D), average group size on detection probability (E) and average daily atmospheric pressure on detection probability (F) both years one and two in north-eastern Connecticut.
Figure 1.7. Year one activity curves for wildlife camera detections of white-tailed deer does on hunted (A) and un-hunted (B) sites with a significant difference in activity times from August 1st, 2016 to March 6th, 2017 in north-eastern Connecticut.

Figure 1.8. Year one activity curves for wildlife camera detections of white-tailed deer does on hunted (A) and un-hunted (B) sites with an insignificant difference in activity times during the white-tailed deer hunting season in north-eastern Connecticut.
**Figure 1.9.** Year one activity curves for wildlife camera detections of white-tailed deer does on hunted (A) and un-hunted (B) sites with insignificant differences in activity times during the shotgun/rifle white-tailed deer season in north-eastern Connecticut.

**Figure 1.10.** Year two activity curves for wildlife camera detections of white-tailed deer does on hunted (A) and un-hunted (B) sites with an insignificant difference in activity times from August 1st, 2017 to March 6th, 2018 in north-eastern Connecticut.
Figure 1.11. Year two activity curves for wildlife camera detections of white-tailed deer does on hunted (A) and un-hunted (B) sites with an insignificant difference in activity times during the white-tailed deer hunting season in north-eastern Connecticut.

Figure 1.12. Year two activity curves for wildlife camera detections of white-tailed deer does on hunted (A) and un-hunted (B) sites with an insignificant difference in activity times during the shotgun/rifle white-tailed deer season in north-eastern Connecticut.
Fawn Survival in the Exurban, Heterogeneous, Predator Rich Landscape of North-Western Connecticut

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Abstract
Landscape heterogeneity affects both predator and prey distributions. Recent increases in predator populations across the eastern United States along with increased human densities and landscape heterogeneity raises concerns for managers of ungulate populations. Extensive research supports the negative effects of predators on fawn survival and has even lead to reductions in harvest tags as well as the implementation of extensive predator control strategies. While certain landscape features are known to mitigate predation, the spatial scale at which landscape features exhibit the greatest influence on both survival and predation of fawns is not well understood. We had the opportunity to study fawn survival in an area of north-west Connecticut characterized by a predator rich, heterogenous landscape. We used cox-proportional hazard models to determine the best spatial scale (15, 30, 60 and 100 HA circular buffers) for analysis of landscape variables (model set 1) that best predict fawn survival. We also investigated the effects of biological (model set 2) and weather variables (model set 3) on fawn survival. We then compared top models across the three model sets to determine the overall top model predicting fawn survival to 90 days. Model set 1 indicated that survival was best predicted by the percent forest cover at the 15ha scale, with survival decreasing by 10% with every 1% increase in forest cover (HR = 1.02, 95% CI = (1.012, 1.031)). Model set 2 indicated that fawn sex and weight best predict survival, with a 96% decrease in survival for males (HR = 1.96, 95% CI = (1.08, 3.50)) and a 61% increase in survival for every 1kg increase in fawn weight (HR = 0.39, 95% CI = (0.21, 0.72)). We did not find support for effects of weather on fawn survival, with the null model less than 2 AICc values from the top model. Overall doe selection of birthing sites and the subsequent landscape composition within a 15ha buffer had the strongest influence on fawn survival. Our
findings support the importance of investigating both landscape and patch level variables at varying spatial scales on fawn survival.

**Introduction**

Modern human development and emigration from urban epicenters has increased the ability of wildlife species to persist and thrive in these environments (Ditchkoff et al. 2006, Saalfeld and Ditchkoff 2007). The interspersion of forests, farms and suburban communities creates a heterogenous landscape, defined by the complexity and variability in ecological properties (Kie et al. 2002). This variability in macrohabitat is known to affect survival of wildlife species through the distribution and density of predators as well as predator efficiency when hunting (Rohm et al. 2007, Grovenburg et al. 2011). Therefore prey space use is in part related to the degree of landscape heterogeneity and the distribution and abundance of predators (Kie et al. 2002, Resetarits et al. 2018). Understanding the relationship between landscape interspersion and impacts of predators on prey species is particularly important for wildlife managers tasked with maintaining healthy game species populations. One such species, the white-tailed deer is now found across fragmented and contiguous forests, agricultural lands, and highly developed landscapes (Dechen Quinn et al. 2013). Due to the high susceptibility of mortality at the fawn life stage, understanding fawn survival within exurban landscapes is important and currently not well understood (Saalfeld and Ditchkoff 2007, Shuman et al. 2017). Research supports the role of macrohabitat and its effects on fawn survival (Rohm et al. 2007, Grovenburg et al. 2012), yet the relationships between macrohabitat conditions at various landscape scales on fawn survival and predation is not well understood.

Predation on fawns is a growing concern across much of the south-eastern United States, with recent research indicating low survival and high mortality (Kilgo et al. 2012, Gulsby et al.
2015, Shuman et al. 2017). Recent research on fawn survival in the north-eastern United States is limited (Williams and Gregonis 2015) and of importance as this area is characterized by both increasing human and predator populations. The expansion of coyotes into the north-east within the past 100 years ignites a call for a greater understanding of the role that predators play in white-tailed deer recruitment (Robinson et al. 2014). Many states have already experienced decreased fawn survival due to increases in predator populations, leading to reduction in doe harvest tags and the implementation of predator control strategies (Robinson et al. 2014, Chitwood et al. 2015). While much research exists on the factors affecting fawn survival, including a combination of weather, biological and landscape covariates, the relative importance of these covariates in comparison to each other vary based on geographic location and their influence on predation is unclear (Rohm et al. 2007, Grovenburg et al. 2012, Shuman et al. 2017, Warbington et al. 2017).

We had the unique opportunity to investigate fawn survival across a heterogenous landscape within a three-predator system. Black bears, coyotes, and bobcats are among the many large mammals once uncommon in much of the New England forests (Foster et al. 2002). These species are now commonly encountered through the woods and backyards of Connecticut and likely play a role in fawn recruitment. Our goal was to determine the top models for three model sets; landscape variables across varying scales, biological and weather models. We then compared top models from each of the three model sets to determine the overall top model for predicting risk to fawn survival. We predict that biological variables will best predict survival, as they relate to overall herd health going into the breeding season.
Study Area
We conducted our study in western Connecticut, more specifically in Litchfield County which is referred to as deer management zone one (DMZ 1) (Figure 2.1). This DMZ is bordered by Massachusetts to the north and New York to the west. Human population density averaged 30.5 people/km\(^2\) (Connecticut Economic Resource Center 2010). DMZ 1 is primarily forested (62%), 19% developed, 14% turf, grass in large lawns or agricultural field, 3% wetlands (non-forested and forested), and 3% water. Dominant tree species comprising Connecticut forests by net volume are, red maple (Acer rubrum) (21%), red oak (Quercus rubra) (14%), white pine (Pinus strobus) (8%), black oak (Quercus veluntina) (7%), black birch (Betula lenta) (7%), white oak (Quercus alba) (7%), eastern hemlock (Tsuga canadensis) (5%), white ash (Frasinus Americana) (5%), sugar maple (Acer saccharum) (4%), scarlet oak (Quercus coccinea) (4%) and various other species (18%) (Hochholzer 2010). Predator densities of eastern coyote, black bear and bobcat in DMZ 1 are some of the highest in the state (Paul Rego, Connecticut Department of Energy and Environmental Protection, personal communication). Annual average temperature for DMZ 1 is 49.25°F with average annual precipitation of 53.42 inches and average annual snowfall of 31 inches (U.S. Climate Data 2018).

Methods
Capture and Monitoring
White-tailed deer capture work began in the winter of 2012 and continued through the winter of 2015. We darted 25-26 female deer each year over baited sites using a dart gun (model 171c or 389, Pneu-Dart Inc., Williamsport, PA) and a 2-cc disposable, wire-barbed, dart equipped with radio transmitters (Pneu-Dart Inc., Williamsport, PA). We immobilized deer using a combination of Telazol (280 mg) and Xylazine (315 mg). We radio collared and implanted adult female deer with temperature-activated vaginal implant transmitters (VIT) (Models
M2920B and M3930; Advanced Telemetry Systems Inc., Isanti, MN). The VIT’s detected a change in temperature and were equipped with a timer, recording the number of 30-minute intervals that passed since expulsion (Shuman et al. 2017). We recorded information on age, condition of the doe and location of capture site. After processing was complete, we reversed xylazine hydrochloride with tolazoline hydrochloride (200mg intravenous).

We monitored the very high frequency collars and the VIT signals daily from early May each year (2012-2015) until all VIT’s dropped. When we detected a change in the VIT signal, indicating the transmitter had been expelled during birth, we would locate the transmitter and search the surrounding area for fawns (Warbington et al. 2017). If fawns were located, we would immediately blind fold them and place them in a mesh sling filled with natural vegetation to reduce scent transfer while wearing non-scented latex gloves (Rohm et al. 2007, Grovenburg et al. 2012, Shuman et al. 2017, Warbington et al. 2017). We measured and recorded fawn weight, hoof growth, inner ear length, tail length and hind leg length, as well as, location of VIT and fawns using a global positioning system (GPS). We continued to locate fawns and does daily using radio-telemetry gear and the process of bi-angulation. We recorded locations of fawns and does for 90 days post capture, and then 3-times per week thereafter until the end of the hunting season (December 31). When the mortality signal activated, we would hone in on the collar and record the GPS location. We documented mortality events with photographs and classified the source of mortality as bear when very little remains were left and bear scat was near the kill site, as coyotes when remains were scattered and no obvious neck could be found, as bobcats when obvious puncture wounds were located on the fawn’s necks and remains were cached. We classified predation as unknown when no obvious scat could be found and remains exhibited a combination of the previous classifications making it difficult to determine the primary predator.
responsible. Mortality classified as a natural event occurred when fawns were located at birth sites, with no obvious predation signs and no other physical damage. We classified the cause of mortality as human when kill sites did not fit any of the previous predator classifications and as poached when obvious human sign was discovered at the mortality site and wounds to the fawn were created by man-made objects. We classified mortality as farming equipment when fawns and or collars were found either in freshly mowed fields or hay bales. Unknown mortality occurred when it was not clear whether it was human or predator.

**Landscape and Weather Variables**

To assess the relative importance of landscape scale on fawn survival we created circular buffers at 15, 30, 60 and 100 ha intervals around the GPS birth site locations of fawns in ArcGIS (Environmental Systems Research Institute 2014) (Figure 2.1). Due to the lack of research that looks at the effects of landscape variables at different scales on fawn survival, we selected intervals that related to the average 50% fixed kernel home range of does collared during this study (31ha). We created buffers both smaller and larger than the core home-range to capture potential variability in the effects and relative importance of landscape variables. We used FRAGSTATS Version 3.3 (McGarigal and Marks 1995) in ArcGIS and the National Land Cover Database (Homer et al. 2015) to calculate both class and landscape level variables. Land cover classes were generalized and included forested (deciduous, conifer and mixed), developed (developed open space, low, medium and high development), barren (rock/sand/clay), shrubland (dwarf shrub and shrub/scrub), Herbaceous (grassland/herbaceous, sedge/herbaceous, lichens and moss), planted/cultivated (pasture/hay, and cultivated crops), and wetlands (woody wetlands, emergent herbaceous wetlands). We selected a set of both landscape and class-level variables based on previous research on the effects of macrohabitat variables on survival and basic neonate ecology (Rohm et al. 2007, Grovenburg et al. 2011, 2012) and on habitat types that varied the
most across fawn buffers. Class metrics included patch density (PD; number of patches/100 ha of the habitat category), %habitat (percent of the buffer comprised of the habitat category of interest), and landscape shape index (LSI; total edge associated with the corresponding habitat category, divided by the minimum total length of edge possible). Landscape metrics included the number of patches (NP; total number of patches in the area), landscape shape index (LSI; total length of edge in the landscape, divided by the minimum total length of edge possible), and the interspersion and juxtaposition index (IJI; index of patch adjacency and relates to the mixing of patch types on the landscape). We used Pearson’s correlation coefficients to evaluate potential collinearity between landscape variables. Variables with correlation coefficients greater than 0.7 were not included in the same models.

We used daily low temperature (°F), daily average wind speed (mph), and daily rain totals (inches) from Weather Underground (Weather Underground 2018) for our weather variables based on findings from other studies (Grovenburg et al. 2012, Warbington et al. 2017). We accessed the weather data from the closest (38 miles north) weather station (Pittsfield Municipal, Pittsfield MA) to our study area that provided continuous historical data from 2012-2015.

**Analysis**

We used cox-proportional hazard models and the *survival* package in program R (Therneau 2015 and R Core Team 2017) to estimate survival and predation to 90 days and to determine the relative importance of landscape scale, as well as the effects of landscape, biological and weather variables on predicting survival. We choose 90 days because the most accurate data occurred during this time frame, as we switched to monitoring fawns three days a
week after 90 days as well as the fact that after 119 days, fawns are accessible to hunters and are therefore considered recruited into the population at this time (Shuman et al. 2017).

Model set 1 consisted of 19 a-priori models constructed of all possible combinations of habitat variables, excluding combinations in which variables were correlated. We ran these 19 a-priori models for each of the four buffers (15, 30, 60 and 100 ha). Model set 2 consisted of 16 a-prior models, or all possible combinations of biological covariates and model set 3 consisted of 8 a-prior models of all possible combinations of weather variables. Biological covariates included fawn sex, birth weight, whether a fawn was born a twin, and the year of capture. We initially ran model set 1 for each of the selected buffers (15, 30, 60 and 100 ha) to determine the most supported landscape scale and variables related to fawn survival using Akaike’s Information Criterion corrected for small sample size (Burnham and Anderson 2002). We considered competing models to be those with ≤ 2.0 AICc units from the top model (Burnham and Anderson 2002). We also used AICc model selection to determine the most supported model from model set 2 (biological) and model set 3 (weather). Finally, we used AICc model selection to determine the overall most supported model based on the top ranked models from each model set and the global model.

Results
Fawns were successfully captured from 56 of the 103 does with VIT’s (54%), which included 28 singletons, 24 twins and one triplet for a total of 79 fawns. One fawn was removed from the analysis due to missing data on capture location, which prevented calculations of covariates, bringing the total number in the analysis to 78 fawns. Reasons for unsuccessful captures resulted from does dispersing from the study area, premature expulsion of the transmitters, the inability to locate the VIT’s in less than 4 hours, and the inability to locate
fawns. Doe parturition dates occurred from May 20\textsuperscript{th} through July 1\textsuperscript{st} with peak fawning occurring on June 2\textsuperscript{nd} (n=11) (2012-2015). Mean birth weight was significantly different among years (F\textsubscript{3} = 3.67, P=0.016), with a mean birth weight of 3.4kg (SD=0.11) in 2012, 3.2kg (SD=0.12) in 2013, 3.6kg (SD=0.11) in 2014, and 3.1kg (SD=0.10) in 2015. Mean birth weight also was significantly different among twins (3.2kg, SD=0.39) and singletons (3.4kg, SD=0.68) (F\textsubscript{1} = 4.69, P=0.033) but did not differ between sexes.

Cause-Specific Mortality
A total of 56 fawn mortality events were recorded during the study: 12 during 2012, 13 during 2013, 9 during 2014 and 22 during 2015. Of the 35 fawns predated upon from 2012-2015, 40\% were classified as bobcat (N=14), 11\% as coyote (N=4), 37\% as bear (N=13) and 11\% as unknown predation (N=4) (Table 2.1). Fawn mortality events classified as natural included five during 2012, one during 2013, none during 2014 and one during 2015. A total of five fawns from 2012 to 2015 were classified as poached, as well as another two mortality events as human caused. Farming equipment was another common source of mortality, with five total mortality events occurring during 2012-2015. Of the fawns that survived past the 90 days, only one was harvested during the subsequent hunting season (Table 2.1).

Survival Analysis

Landscape Covariates
The landscape model and scale that best predicted survival was percent forest at 15 ha (Table 2.2). We estimated two competing top models, however models were nested, with the second model only adding an additional parameter (forest patch density (PD)), and therefore model averaging was not warranted (Arnold 2010). Percent forest occurred in eight of the 18 models, all of which made up the top eight models, suggesting overwhelming support for the
effect of forest cover on fawn survival. Model \{\%forest 15 \text{ ha}\} had the lowest AICc value and the weight of evidence was 2.6 times greater than the second-best model and 2.9 times better than the third-best model. Cox-proportional hazard ratios suggest that percent forest within the 15ha buffer increased the hazard ratio such that for every 1% increase in forest cover survival decreased by 10\% (HR=1.022, 95\% CI = (1.012,1.031) (Table 2.3 and Figure 2.3). The amount of forest within the 15ha buffer ranges from 0 to 100 \% in this study.

**Biological Covariates**

For model set 2 we identified three competing top models (i.e. within 2 AICc units) with all three of the top models including weight and sex (Table 2.4). Competing models were nested, only adding an additional parameter when compared to the top model, therefore we did not model average between the top three models. Weight and sex were in the top eight models suggesting strong support for their effects on fawn survival. Weight of evidence for model\{weight+sex\} was 2.6 times higher than the second model and 2.8 times higher than the third model. Cox proportional hazard ratios suggest that males are associated with an increase in the hazard and therefore a decrease in survival days by 95\% (HR= 1.96, 95\% CI = 1.08-3.50) (Table 2.5 and Figure 2.4). Survival increased with weight (HR=0.39, 95\% CI = 0.21-0.72) such that for every 1kg increase in weight, fawn survival increased by 61\% (Table 2.5 and Figure 2.5). Both covariates are significant, with hazard ratios not overlapping 1.

**Weather Covariates**

For model set 3, we identified four top models which included the null model suggesting that weather variables likely have little to no effect on fawn survival (Table 2.6). Top models included all the covariates; daily low temperature, daily rain and average wind with the null model only 1.92 AICc’s from the top model. We therefore excluded model set three from further consideration.
Overall Survival Model
Ranking of the models from model set 1 and 2 as well as the global model and null model resulted in competing models between the global model and the most supported landscape model (Table 2.7). Weight of evidence for both models suggest week support for the top ranked model with an evidence ratio of 1.5 ($W_1/W_2$). We reported survival estimates from the most parsimonious model of percent forest cover in 15ha buffers.

Survival rates
Overall 90 day survival from the most supported cox-proportional hazard model was 0.36 (95% CI = 0.25-0.52). Survival was 94% (95% CI = 0.84-1.00) during the first week, 86% (95% CI = 0.73-1.00) during the second week and declined to 50% (95% CI = 0.377-0.675) by day 39 (Figure 2.2).

Discussion

Cause-specific mortality
Our study provides an analysis of white-tailed deer fawn survival in an area of the northeastern United States with 3 sympatric predators (black bears, bobcats and coyotes). We estimated a survival rate of 36% on average across the four-year study based on the most supported cox-proportional hazard model. This survival rate is comparable to the estimated survival of soft released rehabilitated fawns in Connecticut (30.8%) (Scott and Gregonis 2015) and the survival rate of 27% in the southeastern US with the same primary three predators (Shuman et al 2017). It is also comparable to other 2-predator systems in the southeastern United States (Saalfeld and Ditchkoff 2007, Kilgo et al. 2012, Chitwood et al. 2015), and also the fawn survival of 40% in Maine (Long et al. 1998). In comparison, fawn survival rates from the Midwest are generally higher at 87% in Minnesota and South Dakota (Grovenburg et al. 2011), 94%-54% in north-central South Dakota (Grovenburg et al. 2012), 77% in Southwestern Lower
Michigan (Burroughs et al. 2006), and 59% in Southern Illinois (Rohm et al. 2007). Based on classification of mortality sources within this study, predation was the greatest source of mortality in northwest Connecticut (62.5%), with the largest source of predation from bobcats (40%) and bears (37%), with only 11% of predation events classified as coyote. Our estimates of survival are greater than some of the 2-predator system studies, but similar to findings from research on another three predator system in the south-eastern U.S. (Shuman et al. 2017). Research supports risk-reducing effects associated with multiple predator systems, resulting in lower consumption than expected based on the independent effects of each predator (Sih et al. 1998).

**Landscape Scale**

While habitat characteristics are known to affect deer distributions and abundance (Anderson et al. 2011) the impact of habitat on fawn survival has only been recently investigated at limited scales. We found that 15ha buffers best predicted the effects of landscape covariates on fawn survival. Our research is the first to use varying buffers around birth sites to determine the most appropriate landscape scale for studying fawn survival. One other study conducted in Louisiana considered the importance of the proximity to certain land cover types by calculating the distance to the nearest cover type or edge in 100 meter increments from fawn locations (Shuman et al. 2017). Some studies ignore landscape variables all together (Carstensen et al. 2009, Warbington et al. 2017), potentially missing out on key factors affecting fawn survival, particularly if these landscapes are heterogeneous or predator rich. Research focusing on fine scale cover variability at birth sites received weak support suggesting that mitigating the effects of predation is likely more complicated than just managing for increased hiding cover (Chitwood et al. 2015). Our results along with the weak support of characteristics at bedsites suggest that habitat at scales larger than the location of the fawn likely influences fawn predation risks, as
larger spatial scales capture predator distribution and abundance (Tolon et al. 2012). Home range of the fawn may be a biologically appropriate way to define the spatial scale, but high mortality within short time hindered us and others from attaining the appropriate data for home range estimation (Rohm et al. 2007, Grovenburg et al. 2012, Gulsby et al. 2017).

**Habitat covariates**

Model selection results from model set 1 as well as comparisons between models sets indicate that variability in fawn survival is best predicted by percent forest in 15ha buffers around birth sites. Buffers with increased survival were characterized by low forest cover when compared to buffers with mortality events. We found similar results to Grovenburg et al. (2012), that surviving fawns had less forest cover in their home-ranges than fawns that died, and opposite findings compared to fawn survival in Southern Illinois where areas with high survival had few relatively large irregular forest patches (Rohm et al. 2007). Homogeneous landscapes may force does to increase home range size to include more areas of cover, resulting in reduced maternal care and defense (Grovenburg et al. 2009, 2012). Landscapes defined by high interspersion of habitat types and edges allow deer to acquire the necessary resources while occupying a small geographic area (Kie et al. 2002). Homogenous landscapes increase movement rates and distances for does and subsequently fawns (at later life stages), increasing fawn susceptibility to predation. Our study and others (Rohm et al. 2007, Grovenburg et al. 2012, Gulsby et al. 2017) highlight the positive influence of landscape heterogeneity on mitigating predation resulting in increased survival.

A large portion of the mortality events were classified as predation, particularly from bobcats and black bears. Certain landscape features and cover types have the potential to influence the hunting efficiency of predators (Dijak and Thompson 2000). Our observed increase
in the hazard associated with forest cover may be a representation of landscape conditions in which bobcats and black bears are the most efficient. Conversely our relatively low coyote depredation could be attributed to low hunting efficiency in forested cover (Rohm et al. 2007, Grovenburg et al. 2012). Research suggests that bobcats are more likely to select for forest cover compared to other habitat classes, and in some cases were twice as likely to select forest cover over other habitats (Nielsen and Woolf 2002, Tucker et al. 2008). Bobcats are an opportunistic predator, however fawns move little during the first few weeks of life, potentially making detection far easier in forested areas with little to no understory (Litvaitis et al. 1986). While bobcats are considered habitat generalists, bobcat may avoid row crop areas (Tucker et al. 2008).

We found moderate support for a correlation between forest cover and percent agriculture (cultivated crops and hay pasture) (-0.67, p-value = 2.2e-16) based on the Pearson correlation coefficient, such that an increase in forest cover corresponds to a decrease in agriculture (Figure 2.6). Interestingly, while not in our most supported models, the percent agriculture within the 15ha buffer model was significant in predicting survival and a post hoc run of a single variable model indicates that percent agriculture reduces the hazard ratio, therefore increasing survival by 1.53% for every 1% increase in agriculture (HR = 0.98, 95% CI = 0.97 – 0.99). Agriculture in this region is often hay fields, which may provide increased concealment for fawns and agricultural fields are generally associated with lower predator abundance than forested areas.

Predation by black bear was the second greatest cause of mortality in our study. Black bear distributions in our intermixed ecosystem were best predicted by human housing density and not related to forest cover (Evans et al. 2017). However, black bear densities in our study area are some of the highest in the state (Evans et al. 2017), likely leading to increased
encounters with fawns and therefore increased predation events (Shuman et al. 2017). Again, the low concealment in Connecticut forests also likely increases black bear encounters with fawns.

**Biological covariates**

While models with biological covariates explained little when ranked against models of landscape covariates, the highest ranking biological model contained covariates that are significant on survival. Weight and fawn sex best predicted risk to fawn survival with weight increasing survival, and male fawns exhibiting lower survival than females. Fawn weight is related to doe weight, and is viewed as an indication of overall health and access to resources either related to social hierarchy or food availability (Therrien et al. 2008, Taillon et al. 2012, Michel et al. 2015). Fawns with low birth mass spend more time and energy feeding, which then increases the time does spend foraging for resources and results in reduced fitness and survival of fawns (Therrien et al. 2008). When resources are limited, adult does are more likely to favor their own survival over that years reproductive success, generally resulting in lower than normal fawn growth rates and survival (Therrien et al. 2007, Hewitt 2011). The increased feeding time of low birth mass fawns could potentially increase visibility of does and thus predation risk (Therrien et al. 2008, Panzacchi et al. 2010). We also found significant evidence that survival is lower in male fawns then female fawns, which conflicts with previous research finding no sex differences (Rohm et al. 2007, Saalfeld and Ditchkoff 2007, Kilgo et al. 2012). Male fawn activity is higher than female fawn activity, which could increase their visibility to predators, particularly in forested landscapes with low concealment (Jackson et al. 1972, Warbington et al. 2017). Independence is achieved earlier in male fawns, and results in increased distance and decreased association with adult does when compared to female fawns (Schwede et al. 1994). We think our observed increase in the hazard ratio with respect to male fawns is associated with increased activity and decreased association with adult does increasing their susceptibility to
predation and reducing overall survival, particularly in a predator dense system (Warbington et al. 2017).

The importance of landscape heterogeneity on fawn survival is evident based on our research and others (Rohm et al. 2007, Grovenburg et al. 2012). Landscape heterogeneity likely influences predator distributions, abundance and hunting efficiency. With predation as the leading cause of mortality in our study, understanding how landscape features either mitigate or exasperate predation risk is important. Our findings suggest that percent forest cover, associated with homogenous landscapes, at a larger scale than fawn location likely influences predator distributions, and lead to a reduction in concealment and fitness of does and subsequently fawns associated with increased movements to access resources.

**Management Implications**

Our research provides the first estimates of fawn survival for white-tailed deer in Connecticut, with the exception of estimates of survival for rehabilitated fawns (Scott and Gregonis 2015). Estimating fawn survival and understanding what factors influence survival is important for managers who set harvest regulations on white-tailed deer. Most of the eastern United States is faced with overabundant deer populations and understanding what factors are hindering or promoting survival and recruitment allow for improved management actions.

Predator densities will likely remain high in Connecticut, with no current strategies to mitigate their impacts on prey species. We found that predation on fawns will be greater in areas of mature, closed-canopy forests, which make up most of the forested landscape in Connecticut, where only moderately intense forest harvest is occurring (Foster et al. 2002). Continued research on the degree to which forests and other landscape variables impact fawn survival are encouraged to improve management.
Literature Cited


Environmental Systems Research Institute, I. 2014. ArcGIS. Redlands, California.


### Tables

**Table 2.1.** Cause specific-mortality of white-tailed deer fawns from 2012-2015 in Litchfield County, Connecticut.

<table>
<thead>
<tr>
<th>Mortality Cause</th>
<th>Male</th>
<th>Female</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bobcat</td>
<td>7</td>
<td>7</td>
<td>14</td>
</tr>
<tr>
<td>Coyote</td>
<td>3</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Bear</td>
<td>8</td>
<td>6</td>
<td>13</td>
</tr>
<tr>
<td>Unknown Predator</td>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Natural Causes</td>
<td>5</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>Poached</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Suspicious</td>
<td>2</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Unknown</td>
<td>2</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Farming Equipment</td>
<td>4</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>34</strong></td>
<td><strong>20</strong></td>
<td><strong>55</strong></td>
</tr>
</tbody>
</table>
Table 2.2. Four top ranked cox-proportional hazard models and the null model for white-tailed deer fawns in Litchfield County, Connecticut for model set 1 (landscape).

<table>
<thead>
<tr>
<th>Model Name</th>
<th>K</th>
<th>AICₖ</th>
<th>ΔAICₖ</th>
<th>ωᵢ</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>%Forest (15HA)</td>
<td>1</td>
<td>361.07</td>
<td>0.00</td>
<td>0.46</td>
<td>-179.53</td>
</tr>
<tr>
<td>ForestPD+%Forest (15HA)</td>
<td>2</td>
<td>362.90</td>
<td>1.83</td>
<td>0.18</td>
<td>-179.45</td>
</tr>
<tr>
<td>%Forest (30 HA)</td>
<td>1</td>
<td>363.11</td>
<td>2.04</td>
<td>0.16</td>
<td>-180.56</td>
</tr>
<tr>
<td>ForestPD+%Forest (30 HA)</td>
<td>2</td>
<td>364.44</td>
<td>3.37</td>
<td>0.08</td>
<td>-180.22</td>
</tr>
<tr>
<td>Null Model</td>
<td>0</td>
<td>380.99</td>
<td>19.92</td>
<td>0.00</td>
<td>-190.09</td>
</tr>
</tbody>
</table>

Table 2.3. Coefficients, standard errors, hazard ratios and 95% confidence intervals for covariates from the most supported model from model set 1 predicting risk to white tailed deer fawn survival in Litchfield County, Connecticut.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Coefficient</th>
<th>SE</th>
<th>HR</th>
<th>HR 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Forest (15 ha)</td>
<td>0.021</td>
<td>1.02</td>
<td>1.022</td>
<td>1.012 - 1.031</td>
</tr>
</tbody>
</table>

Table 2.4. Four top ranked cox-proportional hazard models and the null model of white-tailed deer fawns in Litchfield County, Connecticut for model set 2 (survival).

<table>
<thead>
<tr>
<th>Model Name</th>
<th>K</th>
<th>AICₖ</th>
<th>ΔAICₖ</th>
<th>ωᵢ</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight + Sex</td>
<td>2</td>
<td>372.72</td>
<td>0.00</td>
<td>0.35</td>
<td>-183.01</td>
</tr>
<tr>
<td>Weight + Sex +Year</td>
<td>5</td>
<td>374.55</td>
<td>1.83</td>
<td>0.14</td>
<td>-180.66</td>
</tr>
<tr>
<td>Weight + Sex +Twin</td>
<td>3</td>
<td>374.71</td>
<td>1.99</td>
<td>0.13</td>
<td>-182.99</td>
</tr>
<tr>
<td>Sex + Year</td>
<td>4</td>
<td>375.07</td>
<td>2.35</td>
<td>0.11</td>
<td>-182.31</td>
</tr>
<tr>
<td>Null Model</td>
<td>0</td>
<td>380.99</td>
<td>7.45</td>
<td>0.01</td>
<td>-190.09</td>
</tr>
</tbody>
</table>
Table 2.5. Coefficients, standard errors, hazard ratios and 95% confidence intervals for covariates in top model from model set 2 predicting risk to white-tailed deer fawn survival in Litchfield County, Connecticut.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Coefficient</th>
<th>SE</th>
<th>HR</th>
<th>HR 95% CI Lower</th>
<th>HR 95% CI Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>-0.85</td>
<td>0.35</td>
<td>0.43</td>
<td>0.21</td>
<td>0.85</td>
</tr>
<tr>
<td>Sex (Male)</td>
<td>0.70</td>
<td>0.31</td>
<td>2.01</td>
<td>1.09</td>
<td>3.67</td>
</tr>
</tbody>
</table>

Table 2.6. Top ranked cox-proportional hazard models of white-tailed deer fawns in Litchfield County, Connecticut for model set 3 (weather).

<table>
<thead>
<tr>
<th>Model Name</th>
<th>K</th>
<th>AIC&lt;sub&gt;c&lt;/sub&gt;</th>
<th>ΔAIC&lt;sub&gt;c&lt;/sub&gt;</th>
<th>( \omega_i )</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>LowTemp</td>
<td>1</td>
<td>378.25</td>
<td>0.00</td>
<td>0.37</td>
<td>-188.12</td>
</tr>
<tr>
<td>Rain+LowTemp</td>
<td>2</td>
<td>380.08</td>
<td>1.84</td>
<td>0.15</td>
<td>-188.04</td>
</tr>
<tr>
<td>AvgWind+LowTemp</td>
<td>2</td>
<td>380.17</td>
<td>1.92</td>
<td>0.14</td>
<td>-188.08</td>
</tr>
<tr>
<td>Null Model</td>
<td>0</td>
<td>380.17</td>
<td>1.92</td>
<td>0.14</td>
<td>-190.09</td>
</tr>
<tr>
<td>Rain+AvgWind+LowTemp</td>
<td>3</td>
<td>382.00</td>
<td>3.75</td>
<td>0.06</td>
<td>-188.00</td>
</tr>
</tbody>
</table>

Table 2.7. Model comparison between the most supported models from both model set 1 (landscape) and model set 2 (biological), including the global and null model for cox proportional hazard survival models for white-tailed deer fawns in Litchfield County, Connecticut between.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>K</th>
<th>AIC&lt;sub&gt;c&lt;/sub&gt;</th>
<th>ΔAIC&lt;sub&gt;c&lt;/sub&gt;</th>
<th>( \omega_i )</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>%Forest15HA+Weight+Sex</td>
<td>3</td>
<td>360.27</td>
<td>0.00</td>
<td>0.60</td>
<td>-177.13</td>
</tr>
<tr>
<td>%Forest15HA</td>
<td>1</td>
<td>361.07</td>
<td>0.80</td>
<td>0.40</td>
<td>-179.53</td>
</tr>
<tr>
<td>Weight+Sex</td>
<td>2</td>
<td>370.02</td>
<td>10.25</td>
<td>0.00</td>
<td>-183.01</td>
</tr>
<tr>
<td>Null Model</td>
<td>1</td>
<td>380.17</td>
<td>19.10</td>
<td>0.00</td>
<td>-190.09</td>
</tr>
</tbody>
</table>
Figures

Figure 2.1. White-tailed deer fawn birth sites (black dots), with 15, 30, 60 and 100 ha buffers for landscape variable analysis in Litchfield County, Connecticut using a condensed version of National Land Cover Data (2011) using general land cover categories.
Figure 2.2. Cumulative survival and 95% confidence band based on the most parsimonious cox-proportional hazard model for white-tailed deer fawn survival in north-western Connecticut from 2012-2015.
Figure 2.3. Simulated effects, of percent forest cover on the hazard ratio from the most supported cox-proportional hazard model and most supported model from model set 1 (landscape) predicting white tailed deer fawn mortality in north-western Connecticut from 2012-2015. The extent of the predictions was limited to the range of observed values. The dotted line represents the value at which hazards are equal ($y = 1$), light grey ribbons represent the lower (0.075) and upper (93.5) quantiles whereas dark blue ribbons represent the central 50% of values.
Figure 2.4. Survival curves for male and female fawns based on the most supported cox proportional hazards model from model set 2 (biological) with 95% confidence bands for fawn survival in north western Connecticut from 2012-2015.
Figure 2.5. Simulated effects of fawn birth weight (kg) on the hazard ratio from the most supported cox-proportional hazard from model set 2 (biological) predicting white-tailed deer fawn mortality in north-western Connecticut from 2012-2015. The extent of the predictions was limited to the range of observed values. The dotted line represents the value at which hazards are equal (y = 1), light grey ribbons represent the lower (0.075) and upper (93.5) quantiles whereas dark blue ribbons represent the central 50% of values.
Figure 2.6. Relationship between percent agriculture and percent forest cover within the 15ha buffer around fawn birth sites from north-western Connecticut with a Pearson correlation coefficient of -0.67 (p-value 2.2e-16).
Accounting for Bias in White-tailed Deer Aerial Surveys Through the Calibration of a Sightability Model in Connecticut

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Abstract

Aerial surveys are a common tool used to estimate population size of large mammals across large geographic areas. However, biased estimates occur due to the influences of terrain, vegetation, animal activity and various other factors affecting detection probability. Sightability models attempt to account for these biases by conducting repeated flights over collared animals, recording information on variables likely to affect detection probability. Informed estimates of detection probability are then used to estimate population size. We attempted to calibrate a sightability model for the Connecticut landscape, accounting for animal behavior, group size, cover type, understory, and weather conditions. We used AICc model selection to determine the best detection probability model and used this to estimate population size in deer management zone 5 in Connecticut. Preliminary results indicate that deciduous and conifer cover observed from the helicopter are the most important factors affecting sightability with conifer hindering sightability and deciduous cover increasing sightability of deer. Preliminary estimates of 790 deer (481, 1,496) per 6.42 square miles, along with large variance estimates (44,880) associated with operational flights indicate the need to increase replications of operational flights in future years to improve abundance estimate accuracy and precision. The continuation of sightability flights and the incorporation of additional cover types will only improve the model for future years and increase its applicability across the Connecticut landscape.

Introduction

Aerial surveys are typically used when population estimates of large mammals are needed over large geographic areas, however these counts are often biased low (Zabransky et al. 2016). Biased estimates of population size are due to the influence of terrain, vegetation, animal activity and other factors on detection probability (Caughley 1974, Samuel et al. 1987, Zabransky et al. 2016). Accounting for these potential biases is important, as policy and
management decisions are based on population size, requiring accurate and precise estimates (Haroldson et al. 2003, Jacques et al. 2014). A common method to correct for bias in estimates is the use of sightability models or modified Horvitz-Thompson estimators, first used for estimating elk population size in Idaho (Samuel et al. 1987). Sightability models are generally developed by conducting repeated flights over collared animals, taking measurements of the variables likely to influence detection. Variable selection methods are used to determine the best model at predicting detection probability (Giudice et al. 2012). Population size is estimated by summing the quotients of complete counts of groups observed during a survey divided by their detection probability as determined through the sightability model (Walsh et al. 2011). Recent advances in the sightability model include accounting for correlation between stratum-specific estimates when a common detection model is used across all strata (Fieberg and Giudice 2008, Walsh et al. 2011).

Aerial surveys and sightability models have been used for a wide range of taxa and across various geographic locations (Haroldson et al. 2003, Buckland et al. 2012, Fieberg and Lenarz 2012, Habib et al. 2012, Jacques et al. 2014, Zabransky et al. 2016), however we are not aware of research on the creation of a sightability model for white-tailed deer in the forested region of New England. We had the opportunity to calibrate a sightability model for white-tailed deer in a portion of north-eastern Connecticut. Previous correction factors for aerials surveys in Connecticut, established in a coastal region, was estimated to be 2.2 based on the ratio of marked to un-marked deer observed during the aerial surveys (Kilpatrick et al. 2001). Factors such as land cover, animal behavior and group size are all known to influence detection and were not accounted for in previous correction estimates. Furthermore, advancements in technology allow for the use of GPS collars (global positioning system) to locate deer on the landscape during
flights to better understand the role of certain variables on detection probability of marked deer. Our objective was to use the *Sightability* package in program R (Fieberg 2012, R Core Team 2017) and GPS collared deer to determine which factors (cover type, group size, animal behavior and understory presence) best predict detection probability of white-tailed deer during aerial surveys. We then plan to use the best model based on AICc model selection to estimate population size across deer management zones (DMZ) in Connecticut.

**Methods**

Twenty-five to 35 adult female white-tailed deer were collared by the Connecticut Department of Energy and Environmental Protection making up our sightability sample size between 2017 and 2018. We conducted sightability trials and operational surveys for white-tailed deer in the same Deer Management Zone (5). Flights took place on different days and followed different sampling designs. We used information collected on collared deer to create a predictive sightability model while operational surveys were standard aerial counts of deer on randomly selected transects consistent with the simple estimate survey design (Caughley 1977) with no attempt to locate marked individuals (Giudice et al. 2012).

Surveys began in year two of the study (December 2017), when snow depth (>4”) and weather conditions, notably wind speed (<15mph), permitted. Both operation and sightability flights were conducted using an R44 helicopter, flying 70m above ground level at 16-24 km/hour flying east-west transects when wind direction and speed permitted. GPS collars were set to take locations every fifteen minutes and download fixes every four hours just prior to flights. We created one square mile rectangular survey plots over GPS collared deer locations during the morning of sightability flights using ArcGIS (Environmental Systems Research Institute 2014). Transects were placed, 500ft apart, within each survey plot and four transects were selected to
fly for each GPS collared deer that maximized the chances of detecting that deer (Figure 3.1). Flights consisted of a pilot and an observer, both experienced with conducting white-tailed deer aerial surveys (Griffin et al. 2013, Zabransky et al. 2016). Individuals responsible for determining survey plots and transects were not involved in the sightability flights to reduce bias (Giudice et al. 2012). When a group of deer was observed the primary observer recorded the GPS location, along with the cover type (conifer, deciduous, mixed forest, open, residential) and understory presence (0 or 1) within a nine-meter radius around the first observed deer, as well as that deer’s behavior (active or inactive), total group size and the presence of collared deer. We also noted the wind speeds, snow cover (inches) and cloud cover (%) during the flights. If we did not observe the collared deer in the survey plot upon completion of the transects, the primary observer used telemetry to locate the animal. If the animal was in the test plot the primary observer recorded the same information as for the observed deer, noting that the collared deer was not sighted during the initial flight.

For operational flights we used ArcGIS to overlay transects spaced 1 km apart over DMZ 5, resulting in a total of 37 potential transects. We randomly selected the first transect and then evenly selected five more transects for a total of six transects (Figure 3.2). We randomly trimmed transects in ArcGIS so that they were roughly 10 miles in length to complete the survey in one day. The flights consisted of a pilot and primary observer. If a group of deer was detected, the primary observer would record the GPS location as well as the same variables recorded during the sightability trials including weather conditions during the flight.

**Sightability Model**

We used the c to determine the best predictors of detection probability as well as to estimate abundance in DMZ 5. Sightability models are binary logistic-regression models, with
detection probability based on the sightability flights and covariates (Fieberg 2012). The fitted detection model is used to adjust counts of animals missed during surveys. A modified Horvitz-Thompson estimator is used to estimate abundance (Fieberg 2012). Due to limited sightability data (29 total observations), we looked at the relative importance of cover type (conifer, deciduous, and mixed), behavior, snow cover (inches), and understory presence as single covariate models. We used AICc model selection to determine the best model (Arnold 2010, Burnham et al. 2011). We intended to include group size as a covariate for model selection, however the relationship between this covariate and detection probability was not linear, and therefore the limited data meant that this variable had to be excluded from model selection. Density was estimated by dividing the model estimate of abundance by the total area flown. We assumed a 500ft strip width for each of the six transects.

**Results**

We surveyed a total of 29 collared deer between December 2017-February 2018. The proportion of marked deer detected was 0.53 with 19 observed collared deer and 10 un-observed collared deer. We flew one operational flight and detected a total of 101 deer across the six transects.

**Sightability Models**

Based on AICc model selection, we identified two possible competing models (i.e. within 2 AICc units) that predicted sightability (Table 3.1). The most supported models included both conifer and deciduous cover types suggesting that cover type best predicts sightability, as opposed to animal behavior and understory presence (Table 3.2). The model averaged beta estimate for conifer was -2.89 (SE=1.21) therefore negatively influencing detection probability, while deciduous cover positively influenced sightability with a beta estimate of 2.74 (SE=1.15) (Table 3.2).
Population Estimates
The sightability model estimated abundance at 790 deer (481, 1,496) per 6.42 square miles. Sampling variance was estimated at 44,880 while sightability variance was 8,102 and model variance was 2,307.

Discussion
Preliminary results suggest that landcover determined from the air has a strong influence on detection probability of white-tailed deer in Connecticut. We demonstrated that dense conifer stands negatively impact detection while deciduous forests have a positive effect on detection probability. These results are comparable to other studies looking at vegetation and its impact on detection probability, even if vegetation types vary across geographic areas (Rice et al. 2009, Griffin et al. 2013). The importance of cover types on detection reinforces the need to develop sightability models across the landscapes in which they will be applied (Zabransky et al. 2016). Behavior of deer during the survey did not come out in the most supported models and group size did not exhibit a linear relationship with detection probability, even though other research suggests the importance of these covariates (Rice et al. 2009, Griffin et al. 2013, Jacques et al. 2014). However, animal activity did not affect detection for all studies (Samuel et al. 1987, Anderson et al. 1998), with Anderson et al. (1998) suggesting that activity might not influence detection probability during surveys with snow cover. Snow cover generally reduces movements of deer and therefore behavior likely varies little between observations during our winter surveys.

Survey variance was high for our one operational survey. The high survey variance likely resulted in biased estimates of abundance and large confidence intervals around the current estimate, and thus the current estimate is not useable for management decisions. Only one operation flight was flown during the current year, however once the sightability model is
finalized, in future years most of flights will be operational flights. Future operational surveys need to occur over several days to ensure that a large proportion of the study area (i.e., deer management zone) is surveyed. Obtaining enough data such that vegetation classes can be incorporated into the estimate of detection probability is the most important step that would allow the sightability model to be applied across all the Connecticut deer management zones.

**Literature Cited**


Environmental Systems Research Institute, I. 2014. ArcGIS. Redlands, California.


Tables

Table 3.1. Candidate model set for white-tailed deer sightability in north-eastern Connecticut considered a priori with the number of parameters (K), AICc, ΔAICc, log likelihood, and cumulative model weights.

<table>
<thead>
<tr>
<th>Model Names</th>
<th>K</th>
<th>AICc</th>
<th>ΔAICc</th>
<th>AICcWt</th>
<th>LL</th>
<th>Cum.Wt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conifer</td>
<td>2</td>
<td>33.44</td>
<td>0.00</td>
<td>0.51</td>
<td>-14.49</td>
<td>0.51</td>
</tr>
<tr>
<td>Deciduous</td>
<td>2</td>
<td>33.95</td>
<td>0.51</td>
<td>0.40</td>
<td>-14.75</td>
<td>0.91</td>
</tr>
<tr>
<td>Behavior</td>
<td>2</td>
<td>39.17</td>
<td>5.73</td>
<td>0.03</td>
<td>-17.36</td>
<td>0.94</td>
</tr>
<tr>
<td>Null Model</td>
<td>1</td>
<td>39.51</td>
<td>6.07</td>
<td>0.02</td>
<td>-18.68</td>
<td>0.96</td>
</tr>
<tr>
<td>Snow Depth</td>
<td>2</td>
<td>40.19</td>
<td>6.75</td>
<td>0.02</td>
<td>-17.87</td>
<td>0.98</td>
</tr>
<tr>
<td>(inches)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Understory</td>
<td>2</td>
<td>41.22</td>
<td>7.78</td>
<td>0.01</td>
<td>-18.38</td>
<td>0.99</td>
</tr>
<tr>
<td>Mixed Forest</td>
<td>2</td>
<td>41.62</td>
<td>8.18</td>
<td>0.01</td>
<td>-18.58</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table 3.2. Model averaged parameter estimates, standard errors and p-values for most supported sightability models of white-tailed deer in north-eastern Connecticut.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Estimate</th>
<th>Std.Error</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.42</td>
<td>0.91</td>
<td>0.65</td>
</tr>
<tr>
<td>Deciduous</td>
<td>2.74</td>
<td>1.16</td>
<td>0.024</td>
</tr>
<tr>
<td>Conifer</td>
<td>-2.89</td>
<td>1.20</td>
<td>0.022</td>
</tr>
</tbody>
</table>
Figure 3.1. Example sightability flight transects in north-eastern Connecticut established by placing a 1 square mile rectangular buffer around the last known GPS location of white tailed deer. Transects were placed in the buffer, spaced 500ft apart, and four transects were selected that maximized the chances of detecting the collared deer during the survey.
**Figure 3.2.** Operational flight transects, spaced 1km apart, in deer management zone 5, with six randomly selected transects for flights over white-tailed deer.