Whittell Research

Researchers conducted three studies focusing on wildlife occupancy modeling in Nevada's Whittell Forest & Study Area. The first study examined black bear occurrence and habitat selection using trail cameras. Results indicated that distance to roads significantly influenced black bear occupancy probability, while time affected detection probability. The study emphasized the importance of protecting bear habitat from road disturbances to preserve this native species. In the second study, trail cameras were used to investigate mule deer occupancy patterns. Findings revealed a positive correlation between mule deer occupancy and elevation, with distance from roads also impacting occupancy. Time of day emerged as a significant factor affecting detection probability. These insights are valuable for wildlife management and conservation efforts, emphasizing the importance of elevation and road proximity in predicting mule deer habitat use. The third study focused on squirrel occupancy modeling, identifying distance to road and time as key predictors of squirrel occupancy. Squirrels were found to exhibit higher tolerance towards edges, suggesting management implications for maintaining habitat quality near roads. Future research could explore additional covariates to enhance understanding of squirrel occupancy patterns and support conservation efforts. Collectively, these studies contribute to the understanding of wildlife occupancy patterns and provide insights for effective wildlife management and conservation in the study areas.

TABLE OF CONTENTS

18 Dec 2023

Modeling Black Bear Occupancy in Whittell Forest

DiDiAlice Coker[1], Delynn Fath[1]

[1]University of Nevada-Reno, 1664 N. Virginia Street, Reno, NV 89557, USA

ABSTRACT

Black bears are a native species to the state of Nevada, historically having populations across the entire state. The species has been locally extinct in the eastern range for more than 80 years, with the only remaining populations occurring in western parts of the state. Occupancy modeling was conducted to inform researchers on black bear occurrence and habitat selection. Researchers used trail cameras to record animal occupancy in Whittell Forest & Study Area. Distance to roads, elevation, vegetation type, and time were recorded and iterated as covariates into occupancy models. Using the 'unmarked' package in R, 13 hypotheses were analyzed to compare the differing effects of each covariate. Models suggest that distance to roads has the greatest effect on black bear occupancy probability and that time has an effect on detection probability. To preserve this native species, land managers should protect bear habitat from road disturbance and prevent the new construction of roads through current and potential ranges.

INTRODUCTION

The forests surrounding Lake Tahoe in Nevada and California are known for the presence of black bears (*Ursus americanus*). Historically, black bear ranges have existed throughout the state of Nevada, however, likely due to anthropogenic disturbance, bears are now only found in the western parts of the state (Lackey et al. 2011). Existing bears are not able to successfully recolonize the eastern mountain range of Nevada due to lack of suitable habitats between the ranges. If land managers want to work towards the restoration of Nevada to its historic conditions, determining the current abundance and occupancy habits of black bears in the state is vital.

Using observation data gathered from trail cameras, habitat data, and spatial data, we model occupancy of black bears in Whittell Forest & Wildlife Area. We developed 16 hypotheses considering the effects vegetation type, elevation, and distance to roads on black bear occupation and time on detection. Understanding how these variables affect occupancy will provide insight on black bear habitat selection and reveal what kinds of habitats should be protected for use by bears.

Sultaire et al. (2023) conducted a very similar study recently, where they sought to determine occupancy *and* density of black bears across Nevada. Sultaire et al. used 100 camera traps, hair snags, genetic sequencing, and radio telemetry to detect individuals and prevent overestimation of density; they found that occupancy was highest in mixed conifer forest, followed by pinyon-juniper forest and low-elevation shrub/grassland (Sultaire et al. 2023)

STUDY SITE

Whittell Forest & Wildlife Area (2,650 acres) is inside the Carson Range of the Sierra Nevada mountains which lies between approximately 1960 to 2300 meters in elevation. Mixed-conifer and Jeffrey pine forest are the most abundant habitats with some meadows also present (Fig. 1). Snow is abundant in winters, whereas summers are very dry. Portions of the area are prone to disturbance via wildfires and paths/dirt roads host mild human activity disturbance in the form of frequent foot traffic and vehicles driving through about every day during the sampling period.

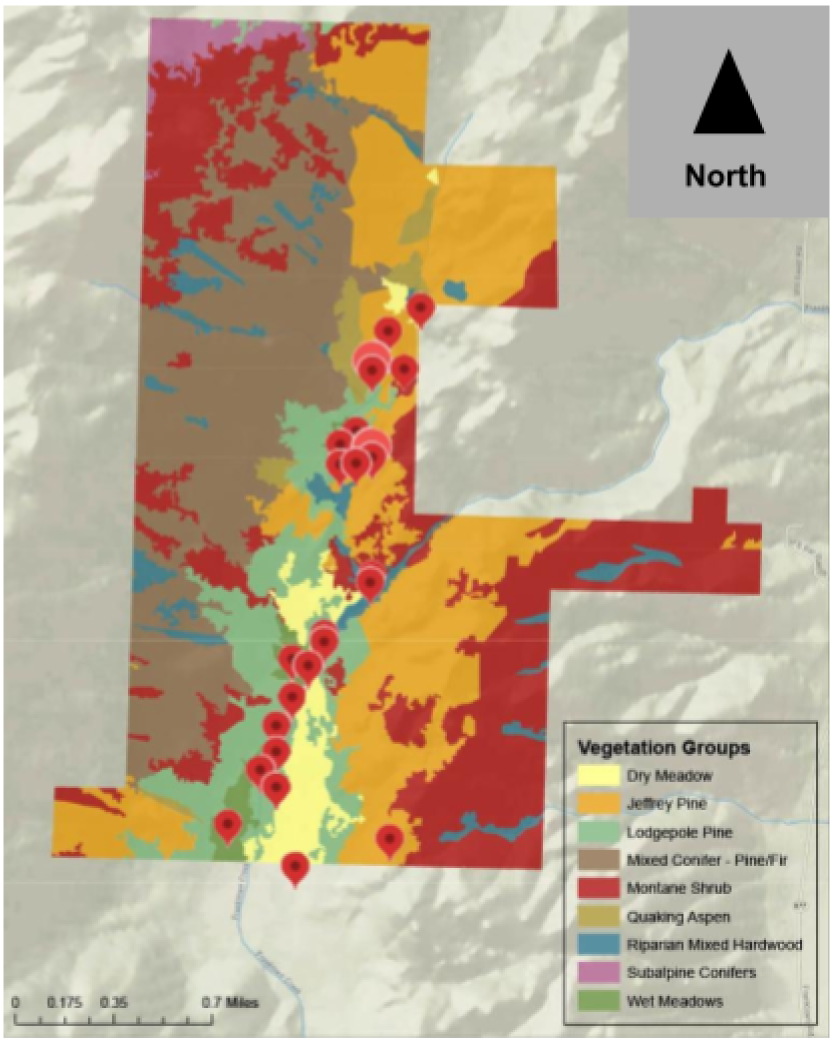


Figure 1. Map of Whittell Forest showing approximate locations of 27 camera traps and vegetation types.

OBJECTIVES

Researchers set out 26 trail cameras around the study site before noon on September 23, 2023. Our specific study sites were located in habitats with six vegetation types: Jeffrey pine, riparian mixed hardwood, dry meadow, wet meadow, lodgepole pine, and montane shrub (Fig.

1). Cameras were retrieved before noon on November 11, 2023. Researchers manually looked through captured photographs and identified species. The presence of bears on certain dates and the time of first observation on these dates were recorded. Distance from the road, elevation, and vegetation type were recorded for each camera site.

Elevation, vegetation type, distance from road, and time were used as covariates to predict site occupation by bears. Elevation and distance were scaled to increase ease of model fitting. We formulated 16 hypotheses and aimed to fit 16 corresponding models using the R package 'unmarked' (Fiske & Chandler 2011). Hypotheses/models are as follows: model 1 is the null model, which states that none of these variables influence bear occupancy; model 2 examines the effect vegetation type has on the probability of occupancy; model 3 analyzes elevations as a variable affecting occupancy probability; model 4 considers the joint effects elevation and distance to roads have on the probability of occupancy; model 5 looks at the effects distance to roads alone has on occupancy probability; model 6 analyzes the combined effects elevation and vegetation type have on occupancy probability; model 7 examines how distance to roads, vegetation type, and elevation affect occupation probability; model 8 analyzes the effects distance to roads and vegetation type together have on occupation probability; models 9-16 correlate respectively with models 1-8, but assess the additional effect of time on detection (see Table 1).

We hypothesize that bear occupancy will be higher in forested vegetation types than in meadow and shrubland, at higher elevations (per Sultaire et al. 2023), and will increase with distance from the road. We hypothesize that time impacts detection more than not. We also expect that factors like vegetation type will have significant effects on occupation (Sultaire et al. 2023).

The seed was set at '5' to ensure models fitted consistently and parameters were reproducible. AIC scores, delta AIC, and model weights were calculated for each model and put into a table (Table 1). Detection and occupation probabilities were calculated from log odds (parameters) using an inverse logit ($\frac{e^{logit(\Psi)}}{1+e^{logit(\Psi)}}$; $\frac{e^{logit(p)}}{1+e^{logit(p)}}$). Confidence intervals were calculated through back transformations.

Table 1. Table with description, parameter number, AIC score, delta AIC, and weight of each model. The most parsimonious model is highlighted in yellow.

Model	**K**	**AIC**	**ΔAIC**	**Weight**
Model 1: Ψ{.}, p{.}	0	251.54	13.70	0.00
Model 2: Ψ{vegtype}, p{.}	5	257.64	19.80	0.00
Model 3: Ψ{elevation}, p{.}	1	254.08	16.24	0.00
Model 4: Ψ{distroad+elevation}, p{.}	2	250.22	12.38	0.00
Model 5: Ψ{distroad}, p{.}	1	240.91	3.07	0.13

Model 6: Ψ{elevation+vegtype}, p{.}	6	264.08	26.24	0.00
Model 7: Ψ{elevation+vegtype+distroad}, p{.}	7	247.49	9.65	0.00
Model 8: Ψ{distroad+vegtype}, p{.}	6	264.08	26.24	0.00
Model 9: Ψ{.}, p{time}	1	248.45	10.61	0.00
Model 10: Ψ {vegtype}, p{time}	6	254.42	16.58	0.00
Model 11: Ψ{elevation}, p{time}	2	245.98	8.14	0.01
Model 12: Ψ{distroad+elevation}, p{time}	3	240.25	2.41	0.19
Model 13: Ψ{distroad}, p{time}	2	237.84	0.00	0.62
Model 14: Ψ{elevation+vegtype}, p{time}	7	261.08	23.24	0.00
Model 15: Ψ{elevation+vegtype+distroad}, p{time}	8	244.32	6.48	0.02
Model 16: Ψ{distroad+vegtype}, p{time}	7	245.14	7.30	0.02

RESULTS

Model 13, which accounts for the effects of distance from the road on occupation and time on detection, was the most parsimonious. Model 13's weight indicates a 62% chance of this model being the best fit for these data. The y-intercept log odds of occupancy show a 1.00 probability (95% CI $1\text{-}6.26*10^{-39}$ – $1+6.26*10^{-39}$) of this area being occupied by bears when on the road (0 distance units away) (β_0=93.4). With each scaled distance unit from the road, the log odds of occupancy increase by 146.1 (Fig. 2; Table 2). The y-intercept log odds of detection show a 0.0099 probability of detection (95% CI -0.0001–0.0199) at midnight (time 0) (β_0= -4.61). The log odds of detection increase by 0.0675 with each hour (Fig. 3; Table 2). Parameters for both occupancy and detection are in Tables 2 and 4.

Black bears were detected in fifteen of the 26 sites, and a maximum of 4 observations occurred at a site that had Jeffrey pine vegetation. The mean and median for time of detection were between noon and 1p.m.

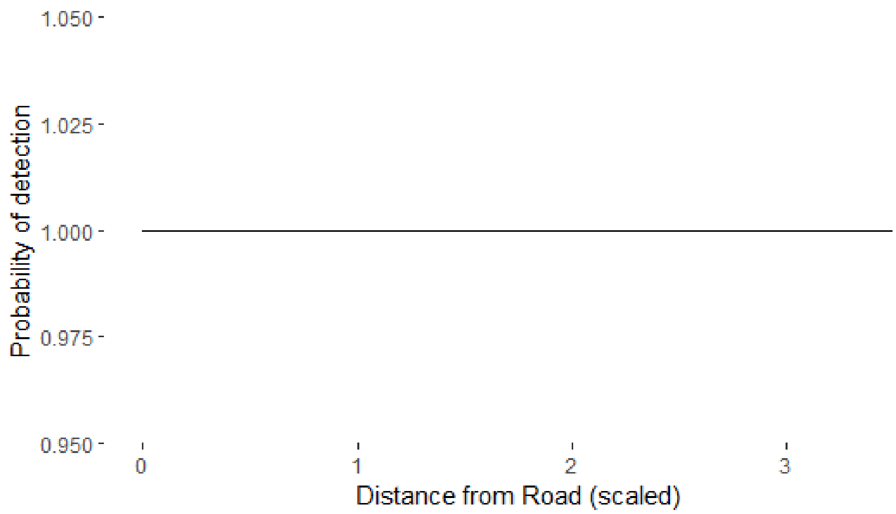


Figure 2. Mean and 95% confidence intervals for black bear occupancy probability over time. Lower and upper bounds are too small to be visible, but see Table 2 for all limits.

Table 2. Mean and lower and upper limits (at 95% significance) for occupancy probabilities at increasing distances from the road.

Distance from road (scaled)	Lower bound	Mean	Upper bound
0.0	$1-6.26*10^{-39}$	1	$1+6.26*10^{-39}$
0.5	$1-2.1*10^{-70}$	1	$1+2.1*10^{-70}$
1.0	$1-5.68*10^{-102}$	1	$1+5.68*10^{-102}$
1.5	$1-1.398*10^{-133}$	1	$1+1.398*10^{-133}$
2.0	0	1	0
2.5	0	1	0
3.0	0	1	0
3.5	0	1	0

Table 3. Parameter estimates, probability (inverse logit of estimates), and upper and lower 95% confidence interval values for occupancy and detection.

	Estimate	Probability	Lower bound	Upper bound
$\Psi\ \beta_0$	93.4	1.00	$1\text{-}6.26*10^{-39}$	$1+6.26*10^{-39}$
Ψ(distroad)	146.1	1.00	–	–
p β_0	-4.6076	0.0099	-0.00012	0.01988
p (time)	0.0675	0.0106	–	–

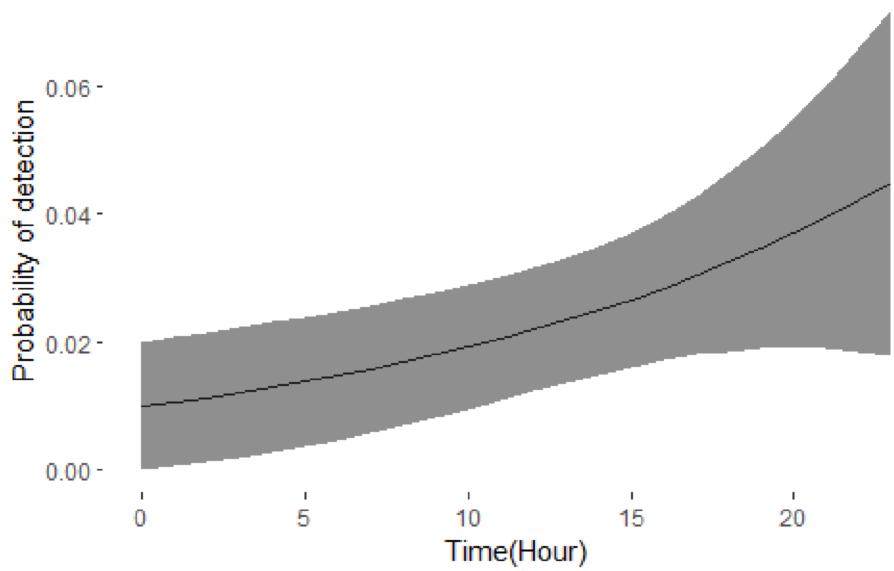


Figure 3. Mean and 95% confidence intervals for black bear detection probability over time.

Table 4. Full equations for both occupancy and detection.

Occupancy	logit(Ψ)= 93.4+146.1*distfromroad
Detection	logit(p)= -4.6076+0.0675*time

DISCUSSION

Model-fitting revealed that distance from the road had the greatest impact on occupancy and time had more of an effect on detection than not. At zero distance units from the road, the probability of occupancy is 100% and remains constant with distance, which is unexpected. However, as shown in Table 2, variation is greater nearer to the road and disappears further from the road. These results are also incongruent with Sultaire et al's (2023) findings that black bear occupancy differs with vegetation type and possibly elevation. Vegetation type nor elevation explained our observations in this study; thus the results of Sultaire et al's study support our hypotheses, but the results of our own study do not. Sultaire et al. (2023) had a larger sample size

(100 locations sampled across *all* of Nevada), measured density, and collected data over two years. They also lured their camera traps, which we did not do to avoid overestimation of occupancy. Though Sultaire et al. (2023) also acquired data from outside of our study site, much of their observation data was within the Sierra Nevada mountains, so it is reasonable to compare this study to ours. In the context of Sultaire et al's results, our findings are highly unusual.

Most of the camera traps were concentrated around the road, which could have skewed the effects of distance from the road. Having cameras further away from the road would better capture variation in occupancy and allow us to better determine if distance from the road is having a real effect. Additionally, cameras were not spread through habitat types equally, with pine habitats having 13 of the 26 cameras and habitats like meadows and montane shrub having 5 and 2, respectively. Spreading the cameras across vegetation types more equally would prevent overrepresentation of occupancy in certain habitats or underestimation of a habitat's influence on occupancy. The package 'unmarked' additionally presented many issues when fitting models, which may have resulted in the parameters of each model featured here not being the best-fitting possible; that is, other randomization seeds yield smaller or larger AIC scores than are reported in this paper. There was far too much randomness and the ability of the analysis program/package too limited to provide an unambiguous answer about which model(s) fit best.

CONCLUSION

Utilizing data gathered from trail cameras in Whittell Forest & Study Area researchers recorded elevation, habitat type, distance to roads, and time. These data points were used to create occupancy models for multiple different species. This study compared the effects these covariates had on black bear occupancy and detection probability. Models suggest that distance to roads has the greatest effect on black bear occupancy. Models also suggest that time has an effect on detection probability. These results suggest that the best way to protect black bears is to prevent road disturbance around bear habitat.

In the future, more research should go into black bear habitat selection to better determine what areas should be prioritized for bear conservation. Future methods should seek to better capture natural variation in the area's features. This data could also be utilized if land managers ever attempt to reintroduce black bears into their historical ranges in the eastern parts of Nevada. Occupancy studies should be conducted in the Tahoe National Forest areas due to the high rates of black bear-human interactions.

APPENDIX

R code is attached with this document.

REFERENCES

Fiske, I. J. and R. B. Chandler. 2011. Unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance. Journal of Statistical Software, 43(10):1-23. https://doi.org/10.18637/jss.v043.i10

Lackey, C. W., J. P. Beckmann, and J. Sedinger. 2013. Bear historical ranges revisited: Documenting the increase of a once-extirpated population in Nevada. The Journal of Wildlife Management, 77(4):812-820. https://doi.org/10.1002/jwmg.548

Sultaire, S. M., Y. Kawai‐Harada, A. Kimmel, E. M. Greeson, P. J. Jackson, C. H. Contag, C. W. Lackey, J. P. Beckmann, J. J. Millspaugh, and R. A. Montgomery. 2023. Black bear density and habitat use variation at the Sierra Nevada‐Great Basin Desert transition. The Journal of Wildlife Management 87:e22358. https://doi-org.unr.idm.oclc.org/10.1002/jwmg.22358

Using Trail Cameras to Estimate the Occupancy of Mule Deer (*Odocoileus hemionus*) in the Whittell Forest and Wildlife Area

M. Haar and C. Davis

December 18, 2023

Abstract

This study used trail cameras to investigate the occupancy of mule deer in the Whittell Forest and Wildlife Area. Occupancy surveys play a pivotal role in scientific research, aiding in ecosystem understanding and wildlife management. The trail cameras, capturing diverse species simultaneously, were strategically placed based on vegetation type, animal use indicators, and varied elevations. Data from the images were analyzed through 16 occupancy models to estimate the probability of mule deer occurrence and assess associated environmental factors. The study's primary objective was to discern the influence of independent variables such as habitat, elevation, and distance from the road on both occupancy and detection probabilities. Models revealed a positive correlation between mule deer occupancy and elevation, suggesting a preference for higher elevations. Additionally, distance from the road impacted occupancy, highlighting potential human disturbance effects. Time of day emerged as a significant factor affecting detection probability, with higher probabilities earlier in the day. The results offer valuable insights for wildlife management and conservation efforts in the Whittell Forest, emphasizing the importance of elevation and road proximity in predicting mule deer habitat use.

Introduction

Background

Occupancy surveys of mule deer in the Whittell Forest and Wildlife Area provide crucial data for a variety of scientific purposes contributing to our understanding of ecosystems, biodiversity and the factors influencing deer populations. The data collected and interpretation of the data can be used for wildlife management and conservation. To understand the occupancy of mule deer in the Whittell Forest, trail cameras were used as a tool to help us better understand regions these deer inhabit. Camera traps are an increasingly popular tool for studying animal occurrence because they collect data on many different species simultaneously and can cover broad spatial scales (Parsons et al. 2017). The information from the photos will be translated into data which will be used in conjunction with 16 occupancy models. Occupancy models are used to estimate the probability of occurrence within a predefined region while assessing environmental factors associated with the occurrence patterns, making them an ideal statistical framework when estimating habitat and space-use patterns with camera trap data (Bassing et al. 2023).

Objectives

The main objective of this study was to examine the effects of several independent variables including habitat and topographic features on both the occupancy probability and detection probability of mule deer in the Whittell Forest. Our goal was to learn how to implement trail cameras to collect presence/absence data to determine which areas of the Whittell Forest are used by mule deer. This study was designed to take the information that we had learned from our lecture and apply it to a real-world scenario. We wanted to be able to effectively use occupancy modeling to predict where mule deer would most likely be found in the Whittell Forest.

Literature Review

When choosing locations for the cameras, Parsons et al. (2017) chose locations at random without regard for distance to the trailhead and faced them in the clearest direction to maximize detection distance. Our study included these concepts along with choosing locations based on vegetation type and looking for areas with animal use. Mori et al. (2021) used a similar approach in R Studio to calculate occupancy models using the "unmarked" package along with the "occu" function to fit occurrence models with no linkage between abundance and detection. Along with this, Mori et al. (2021) used binary numbers as a 1 indicated the detection of roe deer and a 0 indicated non-detection. These methodologies align with ours even though their study focused on occupancy of Siberian roe deer and presence of large carnivores. Bassing et al. (2022) used camera traps to determine occupancy of mule deer along with 12 other species using a wide range of elevations. Mule deer and white-tailed deer had the highest probability of site use (63–92%) and detection (35–67%) elevation ranging 225–2790 m. Our occupancy for the average elevation was 47.2% which is like their findings, but our detection probability was 7.49%. This could be due to our study having 15 times less camera traps with a constrained elevation band and much less variable vegetation.

Methods

Study Area

Our study was conducted within the boundaries of the Whittell Forest and Wildlife Area, which is a 2,650-acre (10.72 km^2) piece of property owned by the University of Nevada, Reno (Whittell Forest & Wildlife Area | Research & Innovation n.d.). The Whittell Forest is in the Little Valley of the Carson Range in the Sierra Nevada Mountains of Nevada. It is surrounded by Humboldt-Toiyabe National Forest land and is characterized by a variety of vegetation types. The area primarily consists of Jeffrey pine (*Pinus jeffreyi*) and mixed conifer forest types, but also has large areas of lodgepole pine (*Pinus contorta*) and montane shrub. The elevation ranges from 1,490 to 2,500 meters, with a valley in the middle and mountainous terrain on each side. In the middle of the valley there is a 120-acre meadow system, consisting of wet and dry meadows and riparian mixed hardwoods. The climate is semi-arid with hot, dry summers and cold winters with large amounts of snow. There is a road that goes through the middle of the property, allowing access for researchers and managers.

Conceptual Hypotheses

We developed a set of 16 hypotheses to test the effects of several independent variables on occupancy probability (Ψ) and detection probability (p). The independent variables we used to influence occupancy probability were vegetation type, elevation (meters), and distance from the road (meters). The independent variable we used to influence detection probability was time of day. Hypothesis 1 was the null model, in which both occupancy probability and detection probability were held constant. Hypotheses 2-8 kept detection probability constant but incorporated independent variables to influence occupancy probability. Hypotheses 9-16 were the same as models 2-8, except detection probability was also varied across time of day for each model.

Hypothesis 1: Null Model- p(.)Ψ(.)

Null (H0): None of the factors (vegetation type, elevation, or distance from road) have a significant effect on the detection probability or occupancy probability of mule deer. Detection and occupancy are not influenced by these factors, and any observed relationships are due to random chance or unrelated to these factors.

Alternative (Ha): At least one of the factors (vegetation type, elevation, or slope) has a significant effect on occupancy probability by mule deer. Occupancy and detection are influenced by one or more of these factors.

Hypothesis 2: Vegetation Type- p(.)Ψ(vegtype)

Null (H0): Vegetation type has no significant effect on the occupancy probability of mule deer.

Alternative (Ha): Vegetation type does have a significant effect on the occupancy probability of mule deer.

Hypothesis 3: Elevation- p(.)Ψ(elevation)

Null (H0): The elevation of the locations has no significant effect on the occupancy probability of mule deer.

Alternative (Ha): The elevation of the locations does have a significant effect on the occupancy probability of mule deer.

Hypothesis 4: Distance from road- p(.)Ψ(distance)

Null (H0): The distance from the road of the camera locations has no significant effect on the occupancy probability of mule deer.

Alternative (Ha): The distance from the road of the camera locations does have a significant effect on the occupancy probability of mule deer.

Hypothesis 5: Vegetation type and elevation- p(.)Ψ(vegtype + elevation)

Null (H0): Neither the vegetation type nor the elevation of the locations has a significant effect on the occupancy probability of mule deer.

Alternative (Ha): Both vegetation type and the elevation of the locations have a significant effect on the occupancy probability of mule deer.

Hypothesis 6: Vegetation type and distance from road- p(.)Ψ(vegtype + distance)

Null (H0): Neither vegetation type nor the distance from road of the camera locations has a significant effect on the occupancy probability of mule deer.

Alternative (Ha): Both vegetation type and the distance from the road of the camera locations have a significant effect on the occupancy probability of mule deer.

Hypothesis 7: Elevation and distance from road- p(.)Ψ(elevation + distance)

Null (H0): Neither the elevation nor the distance from the road of the locations has a significant effect on the occupancy probability of mule deer.

Alternative (Ha): Both the elevation and the distance from the road of the locations have a significant effect on the occupancy probability of mule deer.

Hypothesis 8: Vegetation type, elevation, and distance from road- p(.)Ψ(vegtype + elevation + distance)

Null (H0): None of the factors (vegetation type, elevation, or distance from road) have a significant effect on occupancy probability of mule deer.

Alternative (Ha): At least one of the factors (vegetation type, elevation, or slope) has a significant effect on the occupancy probability of mule deer.

Hypothesis 9: Detection varies with time of day- p(time)Ψ(.)

Null (H0): The time of day has no significant effect on the detection probability of mule deer. None of the factors (vegetation type, elevation, or distance from road) have a significant effect on the occupancy probability of mule deer. Occupancy is not influenced by these factors, and any observed relationships are due to random chance or unrelated to these factors.

Alternative (Ha): Time of day has a significant effect on detection probability of mule deer. At least one of the factors (vegetation type, elevation, or slope) has a significant effect on occupancy probability of mule deer. Occupancy is influenced by one or more of these factors.

Hypothesis 10: Time of day and vegetation type- p(time)Ψ(vegtype)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. Vegetation type has no significant effect on the occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. Vegetation type does have a significant effect on the occupancy probability of mule deer.

Hypothesis 11: Time of day and elevation- p(time)Ψ(elevation)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. The elevation of the locations has no significant effect on the occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. The elevation of the locations does have a significant effect on the occupancy probability of mule deer.

Hypothesis 12: Time of day and distance from road- p(time)Ψ(distance)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. The distance from the road of the camera locations has no significant effect on the occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. The distance from the road of the camera locations does have a significant effect on the occupancy probability of mule deer.

Hypothesis 13: Time of day, vegetation type and elevation- p(time)Ψ(vegtype + elevation)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. Neither the vegetation type nor the elevation of the locations has a significant effect on the occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. Both vegetation type and the elevation of the locations have a significant effect on the occupancy probability of mule deer.

Hypothesis 14: Time of day, vegetation type and distance from road- p(time)Ψ(vegtype + distance)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. Neither vegetation type nor the distance from road of the camera locations has a significant effect on the occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. Both vegetation type and the distance from the road of the camera locations have a significant effect on the occupancy probability of mule deer.

Hypothesis 15: Time of day, elevation and distance from road- - p(time)Ψ(elevation + distance)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. Neither the elevation nor the distance from the road of the locations has a significant effect on the occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. Both the elevation and the distance from the road of the locations have a significant effect on the occupancy probability of mule deer.

Hypothesis 16: Time of day, vegetation type, elevation, and distance from road- p(time)Ψ(vegtype + elevation + distance)

Null (H0): Time of day has no significant effect on the detection probability of mule deer. None of the factors (vegetation type, elevation, or distance from road) have a significant effect on occupancy probability of mule deer.

Alternative (Ha): Time of day does have a significant effect on the detection probability of mule deer. At least one of the factors (vegetation type, elevation, or slope) has a significant effect on the occupancy probability of mule deer.

Field Methods

Data collection began on September 23, 2023 when we placed the game cameras out in the study area. Data was collected until November 10, 2023 when the cameras were retrieved. We used a total of 30 Browning Model BTC-8E-HP4 game cameras equipped with SD memory cards and motion sensors to collect the data. The cameras were all set to the same settings. They were put into trail cam mode with medium (8 MP) photo quality. The photo delay was set to 5 seconds and the camera would take 3 photos at a time. They were set to a medium range of 60 feet. We placed the cameras out in the field across varying vegetation types and locations (Figure 1). We chose camera locations based on vegetation type to be able to analyze possible effects of different habitats on the occupancy and detection probabilities of mule deer. We also looked for places that had signs of high animal use, such as trails, scat, broken branches, and other disturbances so that we would have the highest chance of capturing pictures of animals at each location. We divided the cameras up among several groups, and each group took their cameras to different areas of the Whittell Forest. The groups were spread out along the road and directed to walk no more than a few hundred meters into the surrounding landscape (to make it easier for retrieval). When a location was chosen, each camera was turned on and strapped to a tree. Information about the site was recorded, along with GPS coordinates.

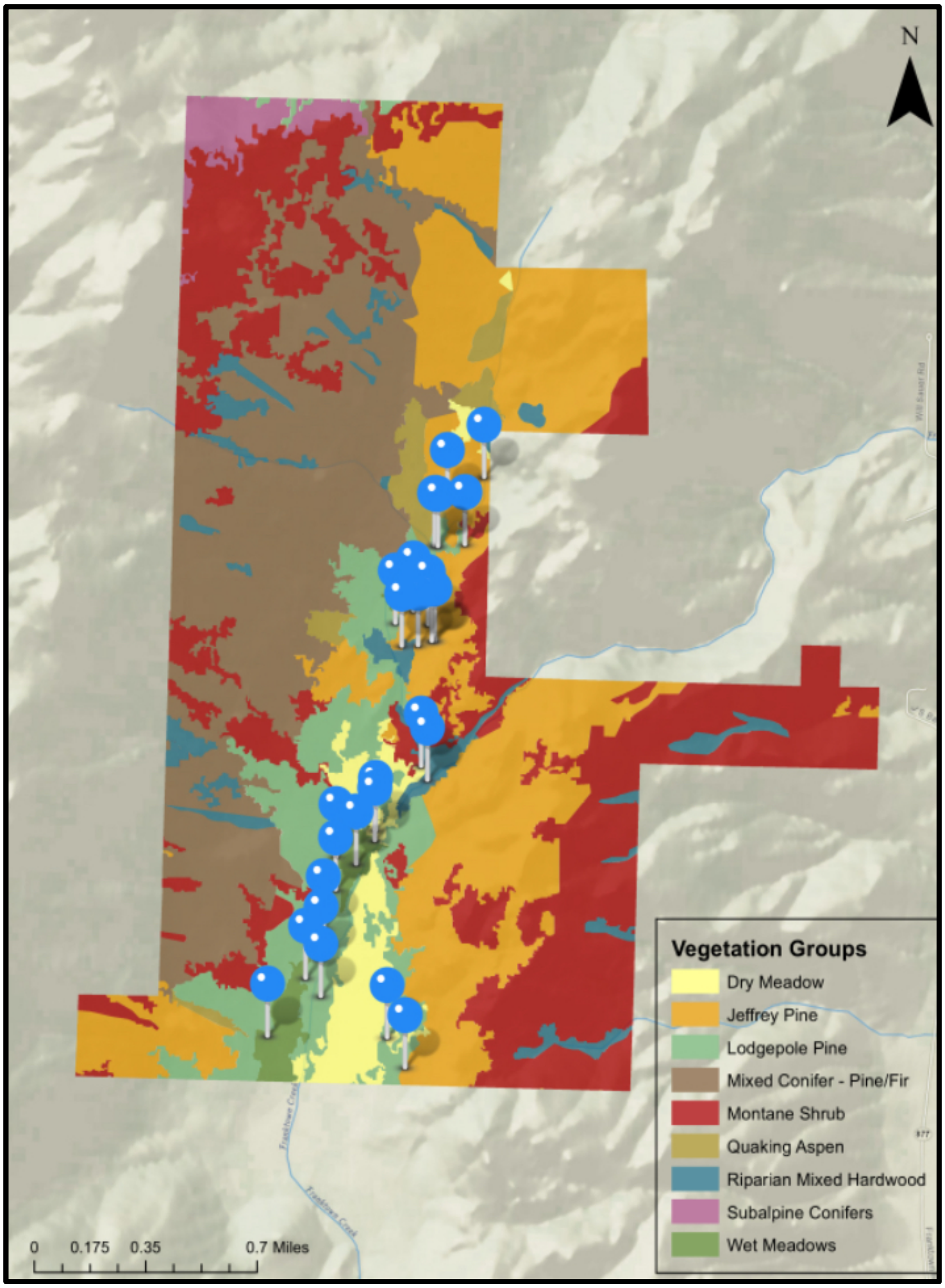


Figure 1. A vegetation map of the study area in the Whittell Forest. Each color corresponds to a different vegetation type as seen in the key. The blue pins represent the locations where each camera was placed inside the study area.

After the cameras had been retrieved, we sorted through the pictures that were taken. We went through the memory card of each camera to look for pictures with animals in them. If a picture had an animal, it was saved to a folder for each individual camera. We also sorted pictures based on species. Then, after all the pictures were sorted, the data was input into a different excel file for each species, with data for each camera. If a species was present for a camera, it received a 1, and if nothing was there it received a 0. If we had uncertainty about a certain animal, we did not use the picture because we wanted to avoid false positives that might influence the data. We only used data collected on mule deer for this study. We also recorded the elevation of each camera and what vegetation type it was placed in (Appendix B). If more than one individual from a species was spotted for a camera, it was not recorded because we were only looking for the presence or absence of a species. We also record the time of day of each animal sighting to use as another independent variable.

Analysis Methods

We analyzed our data by developing occupancy models for each of the hypotheses mentioned above. The general model statement for occupancy models is:

$$y_{i,t} \sim \begin{cases} \text{Bernoulli}\ (p_{i,t}) & z_i = 1, \\ 0 & z_i = 0 \end{cases}$$

$$z_{i,t} \sim \text{Bernoulli}(\Psi_i)$$

$$\text{logit}(p_{i,t}) = \beta_{p,0}$$

$$\text{logit}(\Psi_i) = \beta_{\Psi,0}$$

We analyzed our data using the ‘unmarked’ package in R, making sure to first format our data properly using the ‘unmarkedFrameOccu’ function (Appendix A). We created objects for each of the independent variables and transformed vegetation type by using the ‘factor’ function (Appendix A). We also transformed the elevation variable by using the ‘scale’ function. Since we incorporated time of day into our analysis, we had to convert the time variable from military time into a decimal format (Appendix A). Once this was done, we developed 16 occupancy models using the ‘occu’ function. We used AIC to determine the top model based on maximizing model fit and minimizing model complexity. The top model was further analyzed to get estimates for occupancy probability and detection probability using the ‘backTransform’ function (Appendix A).

Results

The results of our AIC analysis showed that model 3 was the top model (Table 1). There were three other models that fell within 2 AIC units of the top model, and they were models 4, 7, and 11, which are statistically significant (Table 1). The occupancy model statement for model 3 is:

$$y_{i,t} \sim \begin{cases} \text{Bernoulli}(p_{i,t}) & z_i = 1, \\ 0 & z_i = 0 \end{cases}$$

$$z_{i,t} \sim \text{Bernoulli}(\Psi_i)$$

$$\text{logit}(p_{i,t}) = \beta_{p,0}$$

$$\text{logit}(\Psi_i) = \beta_{\Psi,0} + \beta_1(\text{elevation})$$

Table 1. The models used to evaluate the effects of several independent variables on both the occupancy probability (Ψ) and detection probability (p) of mule deer in the Whittell Forest. The independent variables used were vegetation type, elevation, and distance from road, which were put together in several combinations to measure their combined effects on occupancy probability. Time of day was also used as an independent variable for detection probability. Each model is described with the variables used to influence occupancy and detection probability. AIC and ΔAIC values were calculated for each model to determine the most parsimonious model. The top model was model 3, which had an AIC score of 358.16. This model best minimizes model complexity while maximizing model fit to explain the data. Three models fell within 2 AIC units of the top model, and they were models 4, 7, and 11, which are statistically significant. Model 4 measured occupancy probability as a function of distance from the road. Model 7 evaluated occupancy probability as a function of elevation and distance from road. Model 11 evaluated detection probability as a function of time of day, and occupancy probability as a function of elevation. Model 3 made up 32% of the model weight, and models 4, 7, and 12 made up 20% and 12%, and 14%, respectively.

ID	Model	K	AIC	ΔAIC	Model weight (w)
1	p(.) Ψ(.)	2	391.34	33.18	0.00
2	p(.) Ψ(vegtype)	3	394.30	36.14	0.00
3	**p(.) Ψ(elevation)**	**3**	**358.16**	**0.00**	**0.32**
4	**p(.) Ψ(distance)**	**3**	**359.11**	**0.95**	**0.20**
5	p(.) Ψ(vegtype+elevation)	4	363.42	5.26	0.02

6	p(.) Ψ(vegtype+distance)	4	363.47	5.30	0.023
7	**p(.) Ψ(elevation+distance)**	**4**	**360.14**	**1.98**	**0.12**
8	p(.) Ψ(vegtype+elevation+distance)	5	365.29	7.12	0.01
9	p(time) Ψ(.)	3	393.11	34.95	0.00
10	p(time) Ψ(vegtype)	4	396.07	37.91	0.00
11	**p(time) Ψ(elevation)**	**4**	**359.86**	**1.70**	**0.14**
12	p(time) Ψ(distance)	4	360.81	2.65	0.09
13	p(time) Ψ(vegtype+elevation)	5	365.13	6.96	0.01
14	p(time) Ψ(vegtype+distance)	5	365.17	7.01	0.01
15	p(time) Ψ(elevation+distance)	5	361.84	3.68	0.05
16	p(time) Ψ(vegtype+elevation+distance)	6	367.04	8.88	0.00

The parameter estimates for the top model are displayed in Table 2. The intercept for occupancy probability equals -0.113 when elevation is equal to 0. The 95% confidence intervals for the intercept overlap 0, so there is some uncertainty about the true value. The relationship between elevation and occupancy probability is positive. This means for each unit increase in elevation, the log-odds of occupancy probability increases by 0.411. The confidence intervals for this value overlap 0, so there is some uncertainty about the true relationship between occupancy probability and elevation. Detection probability was held constant for this model, with a value of -2.51. The 95% confidence intervals for this value do not overlap 0, so we are confident that the true relationship between elevation and detection probability is negative.

Table 2. Beta values of the top model (model 3) along with 95% confidence intervals for each value. Psi is the occupancy probability of mule deer and p is detection probability. Model 3 measured the effect of elevation on occupancy probability as detection probability was held constant. If the 95% confidence interval overlaps zero, there is uncertainty about the true relationship between the variables.

		95% Confidence Intervals	
	Estimate	Lower Bound	Upper Bound
Psi.(Intercept)	-0.113	-0.9171717	0.690457
Psi.(elevation.scale)	0.411	-0.4204626	1.243326
p.(Intercept)	-2.5140625	-2.832046	-2.196079

The estimate for occupancy probability of the average elevation of the sites using the inverse logit function is 0.472. This means that 47.2% of the sites at the average elevation are occupied by mule deer. The estimate for detection probability is 0.0749. This means that there is a 7.49% chance of detecting a mule deer at the average elevation. The occupancy probability for each scaled elevation was calculated to examine the relationship between occupancy and elevation (Figure 2). We found that higher elevations had a positive effect on the occupancy probability of mule deer in the Whittell Forest. Occupancy probability ranged from 36.5% at low elevations to 70% at high elevations.

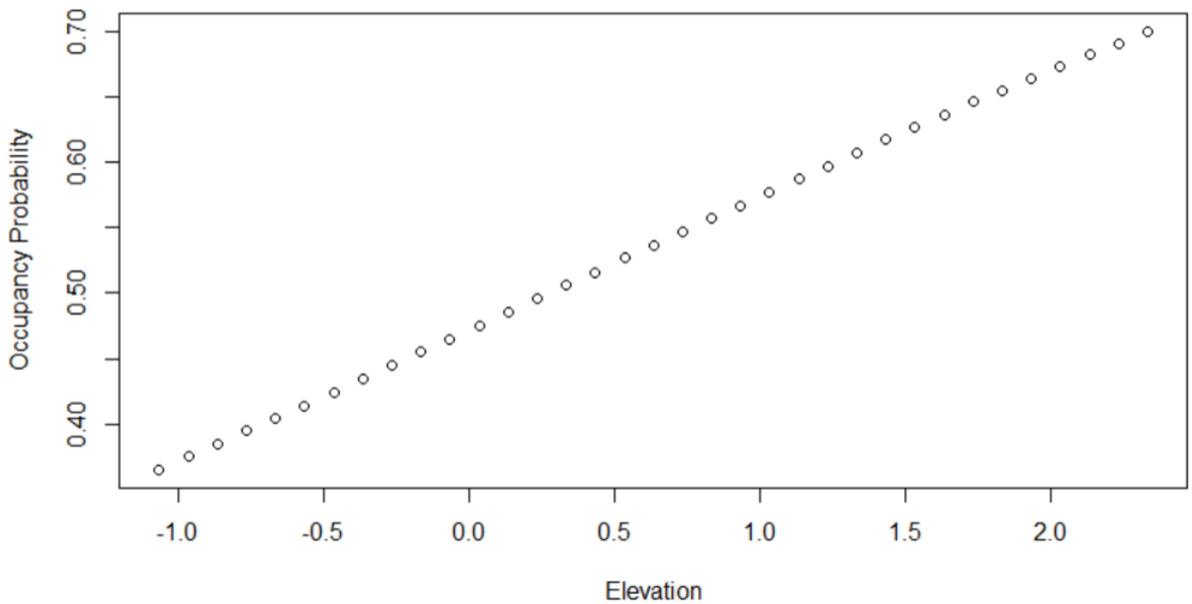


Figure 2. The computed occupancy for each elevation that a camera was placed at. The elevation is the independent variable and was transformed using the scale function. Occupancy is the dependent variable and was computed in R using the BackTransform function for each elevation. The graph shows that the relationship between elevation and occupancy is positive, with higher elevations having a higher occupancy. The range of values are higher than the occupancy of the average elevation, which was 0.472.

Three other models, 4, 7, and 11 were also statistically significant. Model 4 examined the relationship between the distance from the road and occupancy probability. This model showed that the relationship between distance from road and occupancy was negative, with a β_1 value of -0.0003. The estimate for occupancy using the inverse logit function was 0.488 and the estimate for detection probability was 0.0748. Model 7 examined the combined effects of elevation and distance from the road. The relationship with elevation was positive, with a β_1 value of 0.433. The relationship with distance from the road was positive, with β_1 value of 0.00027. Model 11 examined the effects of elevation on occupancy probability and time of day on detection probability. The relationship between elevation and occupancy probability was positive, with a β_1 value of 0.412. The relationship between time of day and detection probability was negative with a β_1 value of -0.0122.

Discussion

Interpretation of Results

We fit 16 occupancy models to the camera trap data. The rejection of the null hypothesis suggests that at least one factor (vegetation type, elevation, and distance from the road) had an impact on mule deer occupancy and detection probabilities. This means that these variables contribute to variations in occupancy probabilities. Our models showed a positive relationship between occupancy probability of mule deer and elevation which is our top model, model 3. This suggests that mule deer prefer higher elevations in the Whittell Forest. This could be due to food availability during this time of year or possible terrain preferences. The negative relationship between elevation and detection probability implies that as elevation increases, the likelihood of detecting a mule deer decreases. The estimate for the occupancy probability of 47.2% at the average elevation provides a baseline of mule deer presence in our study area. Other variables influenced mule deer occupancy that fell within 2 AIC units but were still significant. Model 4 has a negative relationship between distance from the road and occupancy probability indicating that mule deer are less likely to occupy areas further from roads. This could be related to human disturbance or accessibility to resources. Model 7 shows the positive effect of elevation plus distance from a road on occupancy probability. This indicates that certain areas with specific elevations closer to roads are more favorable to mule deer. When looking at model 11, we saw a positive relationship between elevation and occupancy probability and a negative relationship between time of day and detection probability. This tells us that mule deer are more likely to be present at higher elevations and detection probability decreases during later times of the day.

Comparison with Previous Studies

Camera traps have been a tool used by researchers for many years to collect data without being present. Researchers can collect data which is free of human interference. Previous studies have been conducted that are similar to ours. Baribeau et al. (2022) used camera traps to predict the probability of occupancy and detection of white-tailed deer. This study found the maximum detection probability varied between 12 and 19%. Our detection probability was also low at 7.49% at the average elevation. Baribeau et al. (2022) stated that single species data with low survey detection probabilities ($p < 15\%$) may lead to uncertainty in occupancy parameters. O'Connor et al. (2017) suggested to target detection probabilities larger than 40%. It is recommended to increase the length of the survey to increase detection probabilities. With the limited number of camera traps and days the camera traps were set up, we had a greater chance of having a lower detection probability.

Limitations

Limitations in the study design helps provide context when interpreting the results. Our accessibility to the limited number of trail cameras might limit the representation of the entire habitat and the coverage may not capture all vegetation types and elevation gradients. Due to the bias of choosing camera locations in areas of high animal use may not be representative of the entire landscape, affecting the estimation of occupancy probabilities. While the time of day was considered as a variable, the study may not capture long-term temporal trends due to the short data collection period. Seasonal variations and behavioral changes over the year, the rut for example, may have influences on time-dependent effects. The use of presence or absence for detection probability also might not capture deer activity levels leading to an underestimation in detection probabilities because we excluded photos of uncertainty. Lastly, the study's findings are only applicable to the Whittell Forest and may not represent other regions with different ecological conditions. Future research can address these limitations to further enhance occupancy modeling in similar contexts.

Conclusion

Our study found that elevation and the distance that a camera was placed from the road were the two most important factors affecting occupancy probability of mule deer in the Whittell Forest. Higher elevations tended to have higher mule deer occupancy probabilities, and further distances from the road had lower occupancy probabilities. We also found that time of day was a significant factor in affecting the detection probability. Our analysis found that later time of day had a lower detection probability. It was interesting that our results showed higher occupancy closer to the road. This suggests that the road may be an important feature that deer use to travel. They may also favor the habitats near the road. Further research could be done to see if cameras placed even further from the road would change occupancy probability because our study was limited by how far we placed cameras from the road. This also has important implications for managers because they need to consider the importance of the road and how human disturbances by using the road may affect deer behavior. Managers should focus on the higher elevation areas of the Whittell Forest and see if the habitat types in those elevations are correlated with deer occupancy. Higher priority should be given to any restoration projects in the higher elevation areas. Although we captured many pictures of deer during the night, our results showed higher detection probability earlier in the day. This is important for future researchers to know because when trying to study deer they will have the highest chance of sighting or capturing deer early in the day.

References

Baribeau, A., J. Tremblay, and S. D. Côté. 2022. Occupancy modeling of habitat use by white-tailed deer after more than a decade of exclusion in the boreal forest. Wildlife Biology 2022. <https://onlinelibrary.wiley.com/doi/10.1002/wlb3.01049>. Accessed 11 Dec 2023.

Bassing, S. B., M. DeVivo, T. R. Ganz, B. N. Kertson, L. R. Prugh, T. Roussin, L. Satterfield, R. M. Windell, A. J. Wirsing, and B. Gardner. 2023. Are we telling the same story? Comparing inferences made from camera trap and telemetry data for wildlife monitoring. Ecological Applications 33:e2745. <https://esajournals.onlinelibrary.wiley.com/doi/10.1002/eap.2745>. Accessed 12 Dec 2023.

Gerber, B. D., P. J. Williams, and L. L. Bailey. 2014. Primates and cameras: Noninvasive sampling to make population-level inferences while accounting for imperfect detection. International Journal of Primatology 35:841–858. <http://link.springer.com/10.1007/s10764-014-9761-9>. Accessed 11 Dec 2023.

Mori, E., M. Cicero, S. Lovari, M. Zaccaroni, S. Salomoni, A. Vendramin, and C. Augugliaro. 2021. Occupancy and activity rhythms of the Siberian roe deer. Biologia 76:2991–2999. <https://link.springer.com/10.1007/s11756-021-00790-1>. Accessed 11 Dec 2023.

O'Connor, K. M., L. R. Nathan, M. R. Liberati, M. W. Tingley, J. C. Vokoun, and T. A. G. Rittenhouse. 2017. Camera trap arrays improve detection probability of wildlife: Investigating study design considerations using an empirical dataset. PLOS ONE 12:e0175684. <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0175684>. Accessed 17 Dec 2023.

Parsons, A. W., T. Forrester, W. J. McShea, M. C. Baker-Whatton, J. J. Millspaugh, and R. Kays. 2017. Do occupancy or detection rates from camera traps reflect deer density? Journal of Mammalogy 98:1547–1557. <https://academic.oup.com/jmammal/article/98/6/1547/4430381>. Accessed 11 Dec 2023.

Whittell Forest & Wildlife Area | Research & Innovation. n.d. University of Nevada, Reno. <https://www.unr.edu/whittell>. Accessed 11 Dec 2023.

Acknowledgements

We would like to thank Professor P.J. Williams and J. Schuyler for sharing all their knowledge and expertise with us. We greatly appreciate all the help that they gave us while using R to create our occupancy models. We could not have completed this project without them.

Appendices

Appendix A. R Code

Independent Variables:

```
vegtype=factor(deer.data$Vegtype)
table(vegtype)
elevation=deer.data$Elevation_m
elevation.scale=scale(elevation)
road=deer.data$DistanceRoad_m
siteCovs=data.frame(vegtype,elevation.scale,road)
```

Formatting Data for unmarked package:

```
## format data for unmarked

deer.data.occ=unmarkedFrameOccu(y=y,siteCovs=siteCovs, obsCovs=obsCovs)
summary(deer.data.occ)
```

Time Conversion:

```
time0=deer.data[,56:104]
time.tmp=time0[!is.na(time0)]


# Function to convert military time to decimal hours
convertMilitaryTimeToDecimal <- function(military_time) {
  # Extract hours and minutes
  hours <- as.numeric(substr(military_time, 1, nchar(military_time) - 2))
  minutes <- as.numeric(substr(military_time, nchar(military_time) - 1, nchar(military_time)))

  # Convert minutes to decimal
  decimal_minutes <- minutes / 60

  # Calculate total decimal hours
  decimal_hours <- hours + decimal_minutes

  return(decimal_hours)
}

time0[!is.na(time0)] <- convertMilitaryTimeToDecimal(time.tmp)
hist(time0[!is.na(time0)])
time=time0
time[is.na(time0)]=runif(length(time[is.na(time0)]), 0 ,24)
time

obsCovs=list(time=time)
```

Top Model:

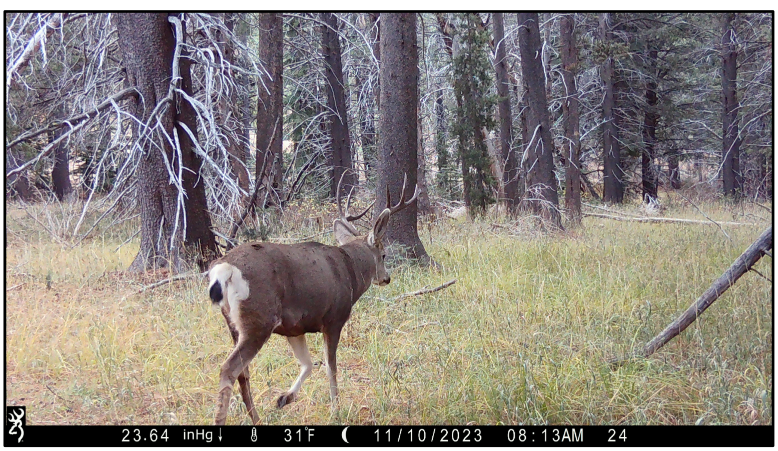
```
###
### {psi(elevation)p(.)}
###


model3=occu(~1 ~elevation.scale, deer.data.occ)
summary(model3)
confint(model3, type= 'state')
confint(model3, type= 'det')

backTransform(linearComb(model3, type='state', coefficients=c(1, 0)))
```

```
backTransform(model3,'det')
```

Appendix B. Data

Vegtype	Elevation_m	DistanceRoad_m
LodgepolePine	1968	280
RiparianMixedHardwood	1987	76
JeffreyPine	2014	101
RiparianMixedHardwood	1968	21
MontaneShrub	2037	86
LodgepolePine	1974	38
MontaneShrub	1999	64
RiparianMixedHardwood	1970	16
RiparianMixedHardwood	1972	275
DryMeadow	1969	157
RiparianMixedHardwood	1967	26
JeffreyPine	1991	13
DryMeadow	1981	215
WetMeadow	1971	144
LodgepolePine	1976	570
JeffreyPine	1997	128
JeffreyPine	1986	4
WetMeadow	1994	106
DryMeadow	1976	756
JeffreyPine	1999	64
JeffreyPine	2025	124
JeffreyPine	2027	41
RiparianMixedHardwood	1973	423
LodgepolePine	1975	887
LodgepolePine	2013	68
JeffreyPine	2001	0

Appendix C. Pictures




23.86 inHg↑ 32°F 10/17/2023 09:10AM CAMERA15


23.86 inHg↑ 13°F 11/09/2023 07:22AM 13


24.01 inHg↑ 37°F 10/05/2023 09:52AM CAMERA09


23.87 inHg - 50°F 10/14/2023 07:54PM CAMERA09

18 Dec 2023

Estimating occupancy of squirrels in Nevada using non-invasive sampling techniques

Jorge Esparza, University of Nevada - Reno, 1664 North Virginia Street, Reno, NV 89557, USA

Ryan Murphy, University of Nevada - Reno, 1664 North Virginia Street, Reno, NV 89557, USA

Correspondence: Jorge Esparza, University of Nevada – Reno, 1664 North Virginia Street, Reno, NV 89557, USA. Email: jorgee@nevada.unr.edu; Ryan Murphy, University of Nevada – Reno, 1664 North Virginia Street, Reno, NV 89557, USA. Email: rkmurphy@nevada.unr.edu

Abstract

Squirrels are among one of countless species of wildlife vulnerable to human impacts such as deforestation and urbanization. Given the uncertain future, an emerging need exists to model and predict population dynamics of wildlife populations to further understand their biological systems and inform wildlife managers about appropriate conservation actions. This study attempted to gain increased knowledge of a biological system through a practical application of estimating squirrel occupancy in Whittell Forest & Wildlife Area, located in northern Nevada. Camera traps were deployed in Whittell Forest by University of Nevada, Reno students to capture photographs of detected wildlife over a two-month period between September and November 2023. Photographs were binarily sorted into squirrel presence or absence across all cameras for all days on Excel. Then, the data was analyzed in R-Studio to determine if elevation, distance to road, vegetation type, time, or any combination of the covariates had the greatest influence in determining squirrel occupancy. The study used Akaike Information Criterion (AIC) over a wide range of defined models to select the best model in estimating squirrel occupancy. Distance to road and time were determined as the most important predictors of squirrel occupancy, where squirrels were later determined to be more edge tolerant. Management implications suggest maintaining habitat quality near roads will be most beneficial for maintaining squirrel populations. However, future research could focus on understanding the influence of additional undescribed covariates, such as slope and aspect, to acquire a greater biological understanding of squirrel occupancy patterns and aid conservation efforts.

Keywords: squirrels, occupancy modeling, camera trapping methods, non-invasive sampling, detection probability, population dynamics

Squirrels are a widespread species of mammal found across the Americas, Eurasia, and Africa. As the globe undergoes the severe impacts of anthropogenically-induced global warming and climate change, the populations of countless wildlife populations, including squirrels, are jeopardized toward vulnerable and endangered statuses. Examples of human-related activities that have triggered the declines of wildlife populations include deforestation, urbanization, and agriculture, which have contributed to habitat loss, degradation, fragmentation, pollution, and overall increased mortality of wildlife species. Given that wildlife populations, including squirrels, are subject to increased future mortality rates, an ever-growing significance arises to model and predict the population dynamics of wildlife species to better understand the factors (e.g., slope, distance to road) that influence habitat selection, species distribution, and overall population sizes. Acquisitions of knowledge regarding the population dynamics of wildlife species, as was investigated in this study with squirrels, can be useful in helping develop the solutions and initiatives necessary to mitigate the impacts of the anthropogenically driven sixth mass extinction.

The objective of this study was to determine the factors that most influenced squirrel occupancy around Whittell Forest & Wildlife Area, located in northern Nevada, by utilizing occupancy modeling and camera trapping techniques while accounting for imperfect detection probability. Two primary advantages of using camera trapping techniques were that both the animal and observer do not have to be in the same location during observation and the cameras can be deployed continuously for weeks or months at a time at large spatial scales (Gerber et al. 2014). The fact that observers and animals do not have to be in the same location during observation is a cost-friendly benefit that also minimizes interactions (Gerber et al. 2014). The terrain for wildlife population studies can often be described as remote and difficult to reach, which can render frequent site visits costly (Gerber et al. 2014). Furthermore, one also must consider that interactions between the observer and animal can potentially influence the probability of detecting the animal again in the future (Gerber et al. 2014). An animal may change its behavior after it sees a human so that it is more difficult to be seen or vice versa (Gerber et al. 2014). The influences that animal-observer interactions pose on future animal behaviors may create bias or skew the count-based data, which can further affect the analysis of studies (Gerber et al. 2014). The ability for cameras to be deployed at a long-term spatial scale can be significant for acquiring an abundance of count-based species data, which can further be analyzed to make inferences about the species of interest at larger spatial scales (Gerber et al. 2014). The long-term deployment also helps increase the probability of detecting a rare or endangered species that likely may not be spotted often if the counts were conducted physically at the field site (Gerber et al. 2014). As a result, camera trapping techniques functioned appropriately as a non-invasive sampling technique that maximizes data collection under limited resources (Gerber et al. 2014).

The primary significance behind selecting the occupancy model to understand squirrel distribution patterns was to account for imperfect detection probabilities of the animal during the counting process (Gerber et al. 2014). Occupancy can be defined as the probability that a habitat or site is occupied by a target species during a specific period (Gerber et al. 2014). In other studies that have used different sampling techniques such as distance sampling or mark-recapture, one of the biased assumptions is that all the individuals have been counted and that there are no individuals missing within an area (Gerber et al. 2014). However, the reality of counting animals or individuals is that the observer is usually unable to count all the animals because some animals may be rare, cryptic, or generally difficult to spot or find (Gerber et al. 2014). Other count-based data collection methods tend to fail to distinguish between a site that did not contain any animals (true absence) versus a site that had animals, but the observer failed to detect them (false-absence) (Gerber et al. 2014). The occupancy modeling framework works to consider imperfect detection (Gerber et al. 2014). The occupancy model further assumes sites are closed to occupancy status changes during the study period, the occupancy and detection probabilities are constant, and detection histories of sites are independent (Gerber et al. 2014). Taken together, the occupancy modeling framework functions to mimic the human nature of imperfect detection of animals across large spatial and temporal scales (Gerber et al. 2014).

For this study, squirrel occupancy data was collected across camera sites in Whittell Forest & Wildlife Area, which is located near Lake Tahoe in northern Nevada. Field methods involved placing 29 camera traps as evenly dispersed as possible across the different vegetation zones of the study area. The camera traps were deployed for a period of two months from September to November of 2023. Data collection involved manually reviewing the pictures taken and recording whether squirrels occupied a site on a given day for all sites. Excel and R-Studio were used for data input and analysis. Elevation, distance to road, and vegetation type characteristics were also recorded for each camera site. 16 occupancy models using the environmental characteristics described above plus time were created. The best model for estimating occupancy was chosen using the Akaike Information Criterion (AIC) model selection method. The top model was further analyzed by evaluating its coefficients and 95% confidence intervals to further understand its implications on squirrel distribution patterns and conservation/management.

Study Area

The camera trapping methods performed in this study were implemented in Whittell Forest & Wildlife Area, which is in northern Nevada near Lake Tahoe. Whittell Forest & Wildlife Area (Whittell) is a forested property at a size of 2,650 acres owned by the University of Nevada, Reno for the purposes of research, instruction, and community outreach (Whittell Forest & Wildlife Area | Research & Innovation, 2023). The property was designated as a natural wildlife area in 1961 by the Board of Regents (BOR) (Whittell Forest & Wildlife Area | Research & Innovation, 2023). Whittell Forest is situated in the Little Valley of the Carson Range bordered by the Tahoe Rim to the west and Washoe Valley to the east (Whittell Forest & Wildlife Area | Research & Innovation, 2023). Whittell Forest can be environmentally characterized as a hanging valley that primarily consists of a Jeffrey pine/mixed-conifer forest type (Whittell Forest & Wildlife Area | Research & Innovation, 2023). The climate at Whittell Forest can be described as semi-arid with dry summers and wet winters (Whittell Forest & Wildlife Area | Research & Innovation, 2023). Access to Whittell Forest is limited to a four-wheel drive road, which takes one and a half hours to reach from the University of Nevada, Reno (Whittell Forest & Wildlife Area | Research & Innovation, 2023). The operation of private recreational vehicles is strictly prohibited in Whittell Forest and access to the property requires an approved application granted by the University of Nevada, Reno for research or educational purposes (Whittell Forest & Wildlife Area | Research & Innovation, 2023). Figure 1 shows a satellite map that illustrates the extent of Whittell Forest, where the valleys to the east represent Washoe Valley and the mountains plus lake to the west represent Tahoe Rim. Figure 2 shows a photograph of the landscape within Whittell Forest. Figure 3 shows the scenery of Washoe Valley (east) viewed from Whittell Forest.

Figure 1. Satellite map of Whittell Forest & Wildlife Area, 2023. Washoe Valley lies to the east and Tahoe Rim lies to the west.

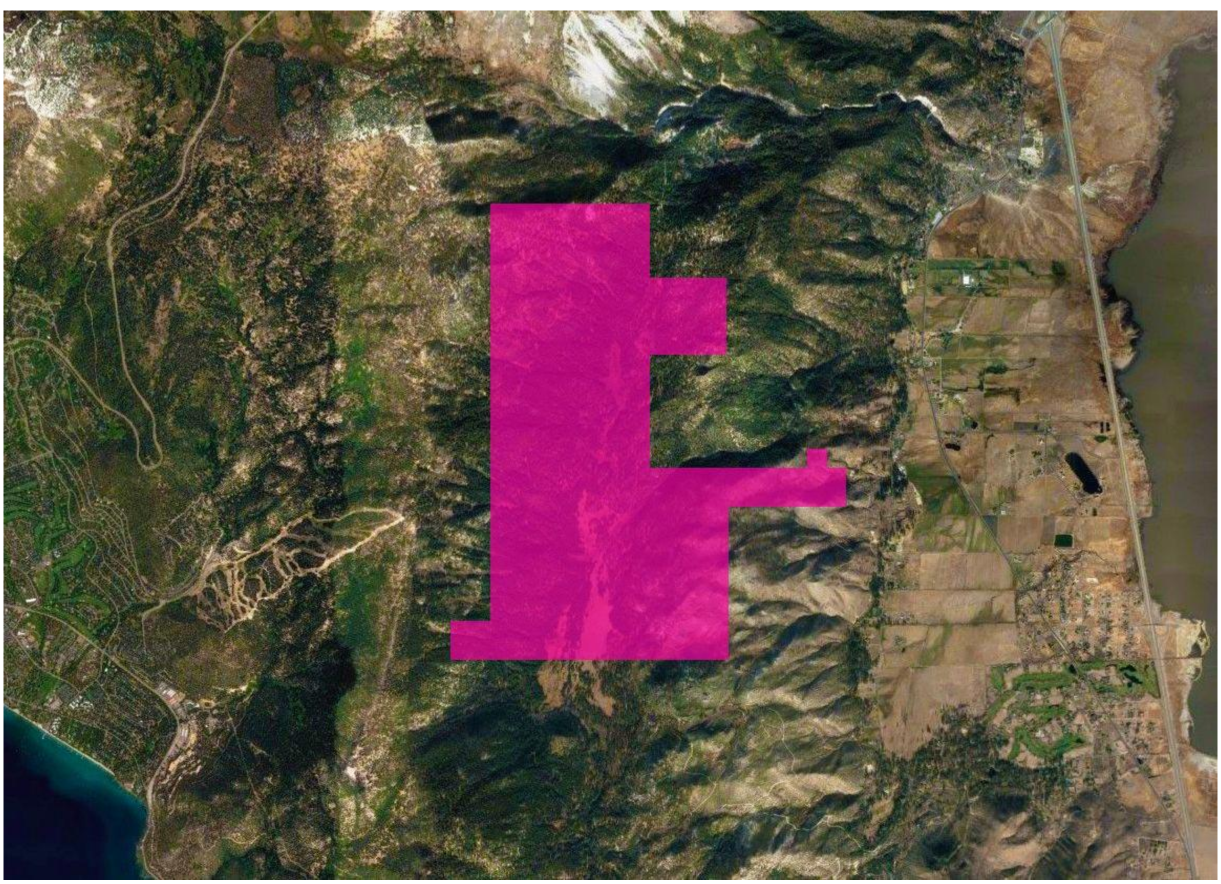


Figure 2. Photograph of Whittell Forest landscape, 2023. Whittell Forest is characterized by Jeffrey pine and mixed conifer trees.

Figure 3. Photograph of Washoe Valley (east) seen from Whittell Forest, 2023. The areas to the east can be characterized by drier, more arid conditions.

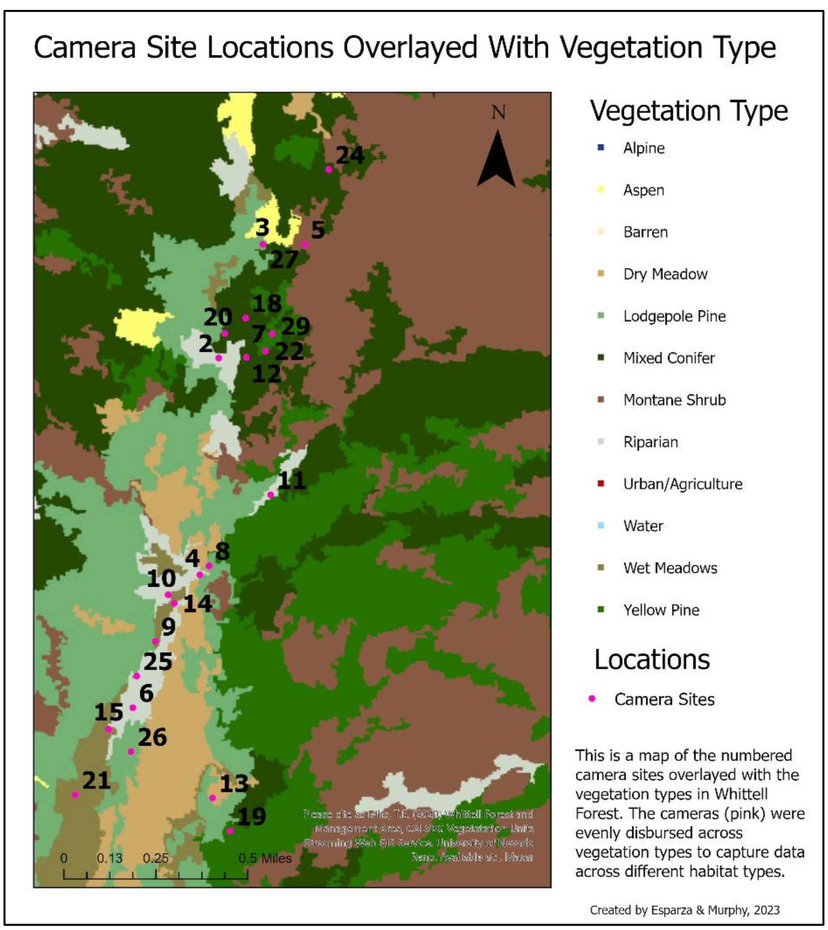
Methods

Students from the University of Nevada, Reno who were enrolled in a course that took part in the study worked together to facilitate the camera trap setup and data collection processes. 29 camera traps were set up in Whittell Forest around tree trunks to capture photographic data of spotted wildlife. The type of cameras used were of the Browning brand, as shown in Figure 4. The camera traps took pictures of spotted wildlife during the period between September 23rd, 2023, to November 11th, 2023. All cameras were programmed to have the same settings, including medium photo quality, normal motion detection range, 4-shot standard multi-shot model, a one-minute photo delay, and the operation mode as trail cam. The coordinate information for each camera, except for two, was collected for finding and retrieval purposes.

Figure 4. Browning trail camera. The Browning trail cameras were set up around tree trunks.

The different vegetation zones that could be found in Whittell Forest were used as basis for the main criteria for camera trap selection. The nine vegetation types that could be found in Whittell Forest include Dry Meadow, Jeffrey Pine, Lodgepole Pine, Mixed Conifer – Pine/Fir, Montane Shrub, Quaking Aspen, Riparian Mixed Hardwood, Subalpine Conifers, and Wet Meadows. The lower elevation (central) portions of Whittell Forest were divided into 40 subregions that encompassed the nine vegetation types described above. The goal was to disperse 29 different cameras anywhere across the subregions so the sites had a diversity of vegetation types that could capture unique data relevant to the study. Figure 5 shows a map of the camera sites across Whittell Forest overlayed with the different vegetation zones to illustrate the cameras were implemented across different vegetation zones. It is important to note that due to data entry errors, the locations of two camera locations could not be illustrated on the map.

Figure 5. Map of camera sites overlayed with vegetation zones. The cameras were placed in a diversity of vegetation zones in Whittell Forest.



After the cameras were retrieved at the end of the two-month period, the data were entered and analyzed using Excel and R-Studio, which was also a collaborative process between students. Excel was used to create a data table that contained information about each camera site such as coordinates (lat/long), vegetation type, elevation, distance to road, binary data representing whether a squirrel was detected on a given day, and the time of day in military time that detected squirrels were captured by the camera, and the observer responsible for setting up the camera. The data on vegetation type, elevation, and distance to road were collected after the cameras were retrieved by using software tools including Google Earth and the Whittell Forest GIS Database. The main part of the data entry process revolved around the binary aspects of squirrel detection. The pictures captured by each camera were uploaded as folders onto a computer, where each folder represented all the pictures taken by a specific camera. The pictures were manually reviewed one-by-one. For the days where at least one squirrel was detected, the cell on the spreadsheet corresponding to the specific day for the specified camera would be assigned a 1. For example, if at least one squirrel was detected by camera #13 on October 17th, the cell corresponding to the row with camera #13 and the column of October 17th would be assigned a value of 1 to represent that camera #13 detected at least one squirrel on October 17th. The time of detection was also noted in a separate series of rows and columns to the right of the main binary data. In cases where squirrels were not detected on a given day by a given camera, the value of the cell would be assigned a 0. Therefore, 1 represents that at least one squirrel was detected on a given day by a given camera whereas 0 represents that no squirrels were detected on a given day by a given camera. This manual labor process was implemented for all cameras and all days during the study period.

The Excel data regarding squirrel occupancy at each camera site was imported into R-Studio for further analysis and processing. The package "unmarked" was used as an essential tool for being able to run the occupancy functions on R-Studio. All the binary data columns of squirrel presence or absence were assigned as dependent variables. The covariates of elevation, vegetation type, and distance to road were modeled as potential predictors of squirrel occupancy. Furthermore, time was also incorporated as a covariate for the purpose of understanding whether squirrel detection was influenced by the dynamics of time. The military time of each squirrel observation was converted into a sine curve to more accurately reflect cyclical trends that are more realistic in space. The unmarkedFrameOccu () function was then used as an unmarked occupancy model that served the foundation for all created models in the subsequent steps. The occupancy framework/equation can be defined by the following expressions:

$$\text{logit}(\psi_i) = \beta_{\psi,0} + \beta_{\psi,1} x_i$$

$$\text{logit}(p_{i,t}) = \beta_{p,0} + \beta_{p,1} x_i$$

The upper equation represents occupancy probability (ψ_i) whereas the lower equation represents detection probability ($p_{i,t}$) and both may be functions of specific covariates, such as elevation or distance to road. Occupancy probability can be defined as the probability that an animal occupies a certain site for a specific period. Detection probability can be defined as the probability of an observer successfully detecting and identifying an individual animal. With the data that was obtained, 16 models were constructed to represent different hypotheses for estimating occupancy probabilities for squirrel populations at Whittell Forest. The 16 occupancy models are based on all combinations of the covariates described above, which are elevation, distance to road, vegetation type, and time. The occu () function was used to create all 16 occupancy models described. It is important to note that within the results of the summarized occupancy models, the occupancy probability estimate is labeled as "Psi ()", and the detection probability estimate is labeled as "p ()". The implementation of the covariates of elevation, distance to road, and vegetation type correspond to the "Psi ()" parameter in the occu () function, whereas the covariate of time corresponds to the "p ()" parameter in the occu () function. The first model was a null model, which modeled that squirrel occupancy was a function of neither covariate. Null models are used as a baseline or control group that the other models can compare themselves to. The 16 models or hypotheses to estimate survival rates used in this study are detailed below:

- Model 1: Null Model → p(.) and psi(.)
    - Description: Is squirrel occupancy a function of neither covariates?
- Model 2: Vegetation Type Model → p(.) and psi(VegType)
    - Description: Is squirrel occupancy a function of vegetation type?
- Model 3: Elevation Model → p(.) and psi(Elevation)
    - Description: Is squirrel occupancy a function of elevation?
- Model 4: Distance to Road Model → p(.) and psi(Distance_Road)
    - Description: Is squirrel occupancy a function of distance to road?
- Model 5: Distance to Road & Elevation Model → p(.) and psi(Distance_Road+Elevation)
    - Description: Is squirrel occupancy a function of distance to road and elevation?
- Model 6: Elevation & Vegetation Type Model → p(.) and psi(Elevation+VegType)
    - Description: Is squirrel occupancy a function of elevation and vegetation type?
- Model 7: Elevation & Vegetation Type & Distance to Road Model → p(.) and psi(Elevation+VegType+Distance_Road)
    - Description: Is squirrel occupancy a function of elevation, vegetation type, and distance to road?

- Model 8: Distance to Road & Vegetation Type Model → p(.) and psi(Distance_Road+VegType)
  - Description: Is squirrel occupancy a function of distance to road and vegetation type?
- Model 9: Time Model → p(time) and psi(.)
  - Description: Is squirrel occupancy a function of time?
- Model 10: Vegetation Type & Time Model → p(time) and psi(VegType)
  - Description: Is squirrel occupancy a function of vegetation type and time?
- Model 11: Elevation & Time Model → p(time) and psi(Elevation)
  - Description: Is squirrel occupancy a function of elevation and time?
- Model 12: Distance to Road & Time Model → p(time) and psi(Distance_Road)
  - Description: Is squirrel occupancy a function of distance to road and time?
- Model 13: Distance to Road & Elevation & Time Model → p(time) and psi(Distance_Road+Elevation)
  - Description: Is squirrel occupancy a function of distance to road, elevation, and time?
- Model 14: Elevation & Vegetation Type & Time Model → p(time) and psi(Elevation+VegType)
  - Description: Is squirrel occupancy a function of elevation, vegetation type, and time?
- Model 15: Elevation & Vegetation Type & Distance to Road & Time Model → p(time) and psi(Elevation+VegType+Distance_Road))

  - Description: Is squirrel occupancy a function of elevation, vegetation type, distance to road, and time?
- Model 16: Distance to Road & Vegetation Type & Time Model → p(time) and psi(Distance_Road+VegType)
  - Description: Is squirrel occupancy a function of distance to road, vegetation type, and time?

For all 16 models, the Akaike Information Criterion (AIC) value was determined. AIC is a method of model selection, where the top model is one that maximizes fit and minimizes complexity. The model with the lowest AIC value was the best for modeling amongst the parameters examined. The top model was back transformed using the backTransform () function. For the top model selected, 95% confidence intervals were constructed to evaluate ranges of certainty and statistical significance. The "confint ()" function was used to determine the upper and lower bounds of the confidence intervals for both occupancy and detection probability. The betas or parameter estimates for the top model were then plugged into the occupancy model equation for practical use and evaluation. The top model was further assessed regarding its conservation and management implications on squirrel population dynamics at Whittell Forest.

Results

Table 1. AIC Comparison table ranked from highest to lowest by model. Includes model type, AIC, Delta AIC, Weights, and number of parameters within the model.

Model	AIC	ΔAIC	Weights	Parameters
Psi.Distance_Road and p.time (12)	**343.74**	**0**	**0.25**	**4**
Psi.null and p.time (9)	344.39	0.69	0.18	3
Psi.Elevation and p.time (11)	345.03	1.29	0.13	4
Psi.Distance_Road and p.null (4)	345.26	1.52	0.12	3
Psi.Distance_Road + Elevation and p.time (13)	345.59	1.85	0.10	5
Psi.null and p.null (1)	345.91	2.17	0.09	2
Psi.Elevation and p.null (3)	346.55	2.81	0.06	3
Psi.Distance_Road + Elevation and p.null (5)	347.11	3.37	0.05	4
Psi.Distance_Road + VegType and p.time (16)	351.74	8.00	0	10
Psi.Elevation + Vegetation + Distance_Road and p.time (15)	352.47	8.73	0	11
Psi.Distance_Road + VegType and p.null (8)	353.26	9.52	0	9
Psi.VegType and p.time (10)	353.53	9.79	0	9
Psi.Elevation + VegType and p.time (14)	353.92	10.18	0	10
Psi.VegType and p.null (2)	355.06	11.32	0	8
Psi.Elevation + VegType + Distance_Road and p.null (7)	355.44	11.70	0	10
Psi.Elevation + VegType and p.null (6)	357.62	13.88	0	9

The top model regarding squirrel occupancy was found to include distance to road for occupancy and time for detection probability with the lowest AIC score of 343.74 (Table 1). There were four other competing models that fell under a 2 ΔAIC score. These models included null occupancy and time for detection probability, elevation occupancy and time for detection probability, distance to road occupancy and null detection probability, and distance to road and elevation occupancy and null detection probability.

Table 2. Table that includes the best model's (Phi.Distance_Road and p.time) pre-transformed parameters, estimates, and 95% confidence intervals. Lcl represents the lower confidence limit while ucl represents the upper confidence limit. The estimate values were transformed using an inverse logit function.

Parameter	Estimate Probability	lcl	ucl
Psi(Intercept)	-0.944	-1.909	0.022
Psi(Distance_Road)	-0.831	-2.304	0.643
p(Intercept)	-1.4037	-1.980	-0.827
p(Time)	-0.0437	-0.090	0.003

Table 3. Table that includes the top model's estimates for occupancy (psi) and detection probability (p). For this model, psi is represented by distance to road while p is represented by time (military). The low value for psi represents sites that are closer to the road while mean is the average distance they were found at, and max represents the sites farthest from the road. Time was given early morning (6:00), midday (12:00), and evening (18:00) values.

Betas	Estimate (Occupancy/Detection)
Psi(min)	0.426
Psi(mean)	0.28
Psi(max)	0.0301
p(6:00)	0.159
p(12:00)	0.127
p(18.00)	0.101

For the top model, squirrels were more likely to occupy spaces closer to the road shown with the estimate being 0.426 (Table 3). The estimates for the other distances were lower with the mean being 0.28 and the max distance from the road being 0.0301. For detection probability, it decreased as time progressed through the day from morning with 0.159, midday with 0.127, and evening with 0.101 (Table 3). This relationship between these variables is visualized below. The negative relationship between occupancy and distance to road is depicted with a higher slope near the lower values (Figure 6). There is a normal distribution for the relationship between detection probability and time with the highest detection point being ~10:00 (Figure 7).

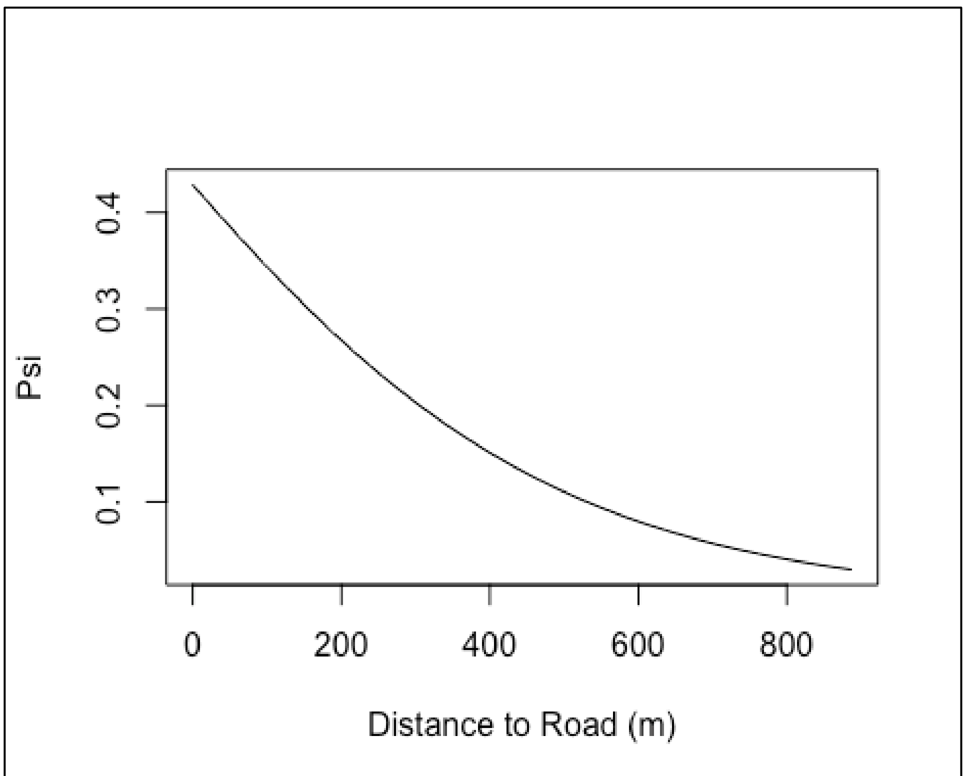


Figure 6. Graph depicting relationship between distance to road and occupancy (psi). The x-axis is represented by distance to a road measured in meters. The y-axis is represented by occupancy estimates. There is a negative relationship between the two variables.

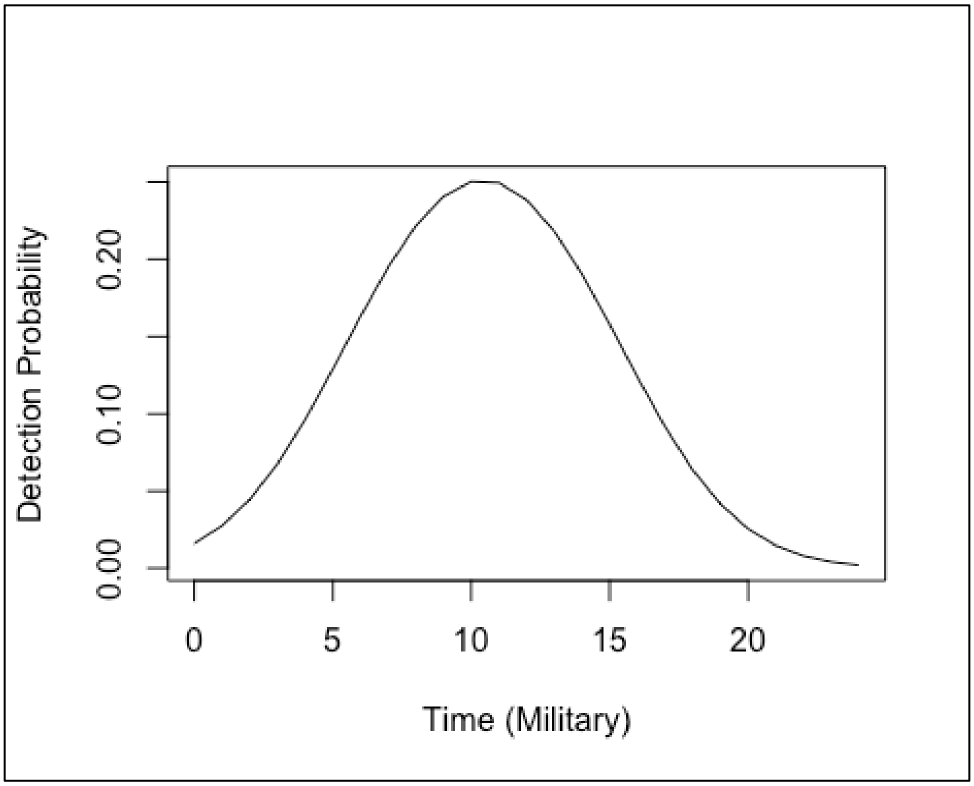


Figure 7. Graph depicting the relationship between time (military) and detection probability derived from an equation transformation from linear to polynomial. The x-axis is represented by time while the y-axis is represented by detection probability. The graph depicts a normal distribution.

Discussion

The study supported the 12th model that proposed that the distance to the road is important for occupancy while the time of day is also important for detection probability (Table 1). It was found that there were higher occupancies closer to the road and decreased as the site was farther away, depicting a negative relationship (Figure 6). Detection probability was also found to have a linear relationship with time. Earlier times in the day had higher probabilities for the detection of squirrels and decreased as time increased (Table 3). When plotted, this resulted in a linear relationship that did not align with biological and ecological concepts. There would be a jump in estimation from 0 at 24:00 to the largest estimate at 0:00 within a minute. To combat this, another model was made based on the top model that was a polynomial function with time^2 as the extra variable. This solved the problem as revealed that detection probabilities were highest at ~10:00 (Figure 7). This accomplishes the previously mentioned objective by determining which variables have a profound impact on squirrels within the Whittell forest area. Models 9, 11, 4 and 13 were also found to be competing models due to their closeness in AIC value. These models imply that besides distance to road, elevation could also be another factor that affects squirrel occupancies within the study area. 75% of the competing models (9, 11, and 13) also had time as the variable for the detection probability, further supporting that it is crucial to detection probability.

There are both similarities and differences between this study and others. There was another study performed where squirrels were also found in higher abundance closer to roads (Chen and Koprowski, 2016). One of the squirrel species within the study was edge-tolerant and preferred roads while also having a higher chance of including these roads into their home range. Conversely, another species that was more forest dependent within the same study had the opposite result of occurring farther away from roads. This suggests that the squirrels present within the Whittell area are more edge-tolerant based on their preference to be closer to the road (Table 2 and Table 3). Another study’s most parsimonious models included a null model and a model with habitat ranking for occupancy with the rest of the variables null (Ford, et al., 2010). This suggests that habitat quality ranking could be a potential variable that is important for squirrel occupancy. These similarities and differences can assist in drawing conclusions as well as determining future management or research directions.

Limitations of this study include camera issues, human detection error, and site selection. Concerning the camera, it can malfunction especially when left outside for long periods of time. This could come in the form of data corruption where the memory card cannot be accessed or the files will not open. It is also common for the camera's memory card to fill up as well as for battery depletion to occur (Gerber et. al 2014). Human detection error can also occur within this process. Despite the best possible efforts, there is the chance that false positives and missed detections within the photo analysis occurred. This probability is also increased specifically with squirrels because of the smaller size and color that is matched with the surrounding environment. This error can have direct impacts on the occupancy and detection probabilities that were derived from the data. Site selection could also have been a factor within this study and is related to the previous two limitations. There could have been a better representation of all of the ecosystem types that are found within Whittell forest and the camera placement could have been improved for some of the sites. An example of this was camera placement within the meadow site. The movement of the vegetation resulted in the camera acquiring pictures when nothing was present which led to large file sizes, longer analysis times, and memory filling up faster. This leads to missing time points within the data due to collection not occurring after the memory fills up. For our distance to road parameter, there could be bias with the results. The two camera traps that were set far away did not pick up squirrels which could have led to the results that were derived from the data. It is suggested that steps be taken to reduce or mitigate these limitations.

Management Implications

Based on the findings within this study, distance to road should be prioritized for management purposes with elevation followed afterwards. If promotion of squirrel species within the area is desired, maintaining habitat quality near roads will be beneficial for the populations there. Maintaining habitat across an elevational will also promote the species. Within the west, climate change driven drought mortality of vegetation as well as uncharacteristic wildfire events because of historic fire exclusion have impacts not only of the vegetation and in turn, the wildlife within the area. Returning forest conditions to those closer to historic conditions (species composition, basal area, trees per acre, etc.) can help to alleviate these issues while also promoting wildlife species, such as squirrels, to continue to thrive.

Conclusion

The study was performed with the intent to discover which variables have an impact on squirrel occupancy and detection probabilities within the Whittell Forest area. This was accomplished by using camera traps in multiple sites. Occupancy modeling was also utilized with the purpose of providing accurate estimates of the squirrels. Using this, it was found that distance from roads had the most significant effect on occupancy with detection probability's variable being time. Competing models suggest that elevation should also be considered when squirrels are considered. These results can be used to inform land managers about the variables that affect this wildlife group as well as suggestions for how it can be managed. Future research should further investigate how roads play an impact on the life history of squirrels within this forest. While this future research is occurring, time of day should also be considered when performing the study and could be used to efficiently obtain results or optimize the study itself. Elevation is another variable that would merit investigation to determine whether it plays an important enough role to consider in management decisions.

Acknowledgements

Special thanks should be given to Dr. Perry Williams and MS Student Jillian Schuyler from the Department of Natural Resources of the University of Nevada, Reno for organizing the activities related to the execution of the methods performed in this study. Furthermore, acknowledgements should also be given to all the students from the Dynamics and Management of Wildlife Populations (NRES 488) course at the University of Nevada, Reno for successfully performing a collaborative role in data collection, entry, and analysis, which were essential in guiding the processes described in this study.

Ethics Statement

Ethical approval for this research was obtained from the University of Nevada, Reno Department of Natural Resources. No vertebrate subjects were harmed during handling processes. Every handling procedure complied with US federal laws safeguarding animal welfare as well as the guidelines set forth by the Institutional Animal Care and Use Committee (IACUC).

References

Chen, H. L. and Koprowski, J. L. 2016. Differential Effects of Roads and Traffic on Space Use and Movements of Native Forest-Dependent and Introduced Edge-Tolerant Species. PLOS ONE 11(1): e0148121. https://doi.org/10.1371/journal.pone.0148121. Accessed 17 Dec 2023.

Ford, W. Mark, et al. 2010. Area occupancy and detection probabilities of the Virginia northern flying squirrel (Glaucomys sabrinus fuscus) using nest-box surveys. Proceedings from the Conference on the Ecology and Management of High-Elevation Forests in the Central and Southern Appalachian Mountains. https://www.fs.usda.gov/research/treesearch/download/36047.pdf#page=48. Accessed 17 Dec 2023.

Gerber, B. D., P. J. Williams, and L. L. Bailey. 2014. Primates and cameras: noninvasive sampling to make population-level inferences while accounting for imperfect detection. International Journal of Primatology 35:841–858. <http://link.springer.com/10.1007/s10764-014-9761-9>. Accessed 17 Dec 2023.

Whittell Forest & Wildlife Area | Research & Innovation. n.d. University of Nevada, Reno. <https://www.unr.edu/whittell>. Accessed 17 Dec 2023.

Appendices

Squirrel Occupancy R-Studio Analysis

This appendix consists of all the R-Studio code used to conduct the squirrel occupancy modeling analysis. The process requires uploading the raw data from Excel into R-Studio and installing the package named “unmarked” to create the occupancy models. 16 occupancy models were created based on all combinations between the covariates of elevation, distance to road, vegetation type, and time using the occu () function. AIC values were determined for all models and the model with distance to road and time was the best performing model, which was delineated by model 12. The model was then transformed using the backTransform () function and further analyzed for interpretation and significances to squirrel population dynamics in Whittell Forest.