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Estimation of Probability of Habitat Use of Roosevelt Elk on the Olympic Peninsula

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ABSTRACT

Estimating the probability of habitat use for a particular species is crucial to the direct management and conservation of that species. Without knowledge of habitat preferences, managers cannot effectively focus efforts on vital resources or landscape types. However, modelling probability of habitat use can be done in several ways which leaves room for variation and uncertainty in the estimates produced by each method. This study is an examination of the variation between two estimates of probability of habitat use while focusing on a particular subspecies of elk that inhabits a unique ecosystem relative to other elk subspecies. I modeled elk resource selection using both an occupancy framework and a zero-inflated Poisson regression. This project is essentially a comparison between using logistic regression to model habitat use and generalized linear regression. Occupancy modelling gives the same weight to every location where the target species is detected, no matter the frequency of use. Whereas a generalized linear model is a count-based approach that determines the relationship between the number of sightings at particular survey sites and associated habitat variables. Understanding the

differences in estimates that are produced by each method can help future researchers decide to implement one over the other for their particular application.

KEY WORDS: Occupancy modeling, Zero-Inflated Poisson, Logistic regression, Linear regression, Remote camera trap, *Cervus canadensis roosevelti*

INTRODUCTION

A critical component of ecological study is the examination of patterns of habitat use and landscape characteristics selected by wild animals. Identification of these patterns can provide insight into the environmental preferences of a target species. Wild animals most often prefer to occupy habitat that is of high quality and can therefore provide the basis for the prioritization of management initiatives (Regolin et al. 2021). Wildlife managers must know how animals use different patches of habitat within the landscape to direct management initiatives that will have a significant impact on the health of the population.

One way to identify patterns of habitat use is through occupancy modeling using camera trap data. Camera trapping protocols are well suited for identifying patterns of habitat use. The relatively low cost of operation of a camera trap grid allows for a large area to be surveyed for long periods of time, if necessary, with limited requirements for human presence (MacKenzie et al. 2002). The use of remote camera traps has proven reliable and accurate for many different surveying applications in the field of ecology and conservation (O'Connell et al. 2011).

While this method of survey is incredibly useful, it does have limitations. One of these limitations is that camera trap studies produce a large dataset, with only a portion of the captures representing the intended target species. Camera trapping consistently produces more data representing species that are not the intended target species, sometimes termed by-catch data

(Edwards et al. 2018). By-catch data, while not ideal for most analyses, can be used to produce simple models for occupancy. Additionally, since the independent closure assumption of a study site in an occupancy model is violated in observational camera trap studies, the model produces the relative probability of use rather than true occupancy. Relative probability of use, when defined by environmental variables, can be interpreted similarly to a resource selection function (MacKenzie & Bailey 2004). However, the relative probability of use produced by an occupancy model does not consider multiple repeated detections at a single site. Once a cell has been identified as being occupied, it holds the same weight in the model as every other occupied site no matter the frequency of use of each respective site. A direct measure of probability of use can be produced using a generalized linear model to represent resource selection (Manly et al. 2002). However, generalized linear regression is not able to predict relationships between animal presence and landscape variables when there is an excess of zeroes in the data set, as there often is in camera trap studies. Therefore, a second function must be used to account for the excess zeroes in the data set. Similar to an occupancy model, which models detection as well as occupancy, a Zero-Inflated Poisson (ZIP) model is a mixed effect model that uses a binary logistic regression to predict the probability of getting zero detections at a site as a result of some known or unknown process (probability of detection for example), but also incorporates a generalized linear model to predict count data (Böhning et al. 1999, Zeileis et al. 2008). The similarity between models allows for the direct comparison of differences between occupancy modeling for habitat use and resource selection for habitat use. In other words, this is a comparison of using logistic regression modeling for habitat use and generalized linear modeling for habitat use.

Standard resource selection models are often built with global positioning system (GPS) collar data points but can also be built using camera trap data (Lara-Diaz et al. 2018). A resource selection model, or resource selection function (RSF), compares used locations and available locations. GPS points, or sites where the target species was detected by a camera, act as used locations and are compared against unused locations which, in a GPS collar study, are random points placed on the landscape or, in a camera study, sites where the target species was not detected by a camera (Manly et al. 2002). RSFs are valuable because they inform managers of the different landscape variables that a species select for and associate with. Whereas occupancy models were originally designed to identify what locations a target species is found at and what characteristics may be associated with their habitation (MacKenzie et al. 2002). The question becomes what difference does it make to model animal preference with a direct measure of landscape use as opposed to the identification of presence? Does the difference between these methods change the predictions of animal-landscape variable associations that are made by each?

The Olympic Cougar Project is a large, collaborative, multi-national effort to map cougar connectivity, dispersal, and analyze movement data. The project's ultimate goal is to identify dispersal bottlenecks and work with Washington State developers to strategically place wildlife corridors and interstate crossings to increase connectivity between the isolated Olympic cougar population and the rest of North America (Elbroch 2018). The project has been working in collaboration with local tribes to collect camera trap data for species on the peninsula and have accrued detections of Roosevelt Elk (*Cervus canadensis roosevelti)* that were provided for this analysis.

I used camera trap by-catch data from the Olympic Cougar Project to model the probability of resource use of elk on the Olympic Peninsula in Washington through both occupancy modeling and resource selection modeling. Conservation of elk has been an important ecological goal for decades. Healthy elk populations contribute great ecological, economic, and social benefits in areas where they are present, and they are culturally significant (Gordon et al. 2004; Lopez-Hoffman et al. 2017; Pascual-Rico et al. 2021). Elk are also a critical component of the diets of North America's largest and most charismatic carnivores: bears *(Ursus sp.)*, wolves *(Canis lupus)*, and mountain lions *(Puma concolor)* (Griffin et al. 2011). In fact, one potential use of the results from this study could be to help inform the Olympic Cougar Project of the habitat preferences of a vital prey source for cougars. When considering these characteristics of elk, it makes sense that they have attracted so much attention and have been at the forefront of emerging wildlife research and management projects. Additionally, the use of occupancy modeling and RSFs to identify patterns of habitat and resource use for elk has mostly been performed on subspecies of elk that inhabit environments which are often dry or only moderately wet (Barbknecht et al. 2011, Rumble & Gamo 2011, Tolliver & Weckerly 2018). There is no recent research that has identified habitat use patterns of Roosevelt Elk in ecosystems with uniquely high averages of annual precipitation, such as those present on the Olympic Peninsula (Jenkins & Starkey 1984). Elk on the Olympic Peninsula have access to a greater diversity of ecosystems as well. Many types of ecosystems which range from alpine grasslands to marine shoreline are present within a relatively small area when compared to the typical home ranges of mainland elk (Chappell et al. 2001). In addition to inhabiting drastically different environments, it has also been seen that Roosevelt and Rocky Mountain elk differ in average body size and body fat percentage (Cook et al. 2010). These differences indicate a potential for differing physiological needs and therefore potentially differing habitat use patterns in their respective ecosystems. Thus, to better understand the habitat use patterns of Roosevelt elk on the Olympic

Peninsula, a resource selection model, and a model for the probability of habitat use with ecologically significant covariates must be developed.

STUDY AREA

My study area was the entire Olympic Peninsula of Washington state, bounded to the southeast by the I-5 corridor and to the south by the Columbia River (Figure 1). The peninsula ranges in elevation from sea level to 2432 meters at the peak of Mount Olympus in Olympic National Park. The peninsula's drastically varying elevation paired with its proximity to marine shoreline gives rise to many kinds of ecosystems within a relatively small area. The most ecologically significant ecosystems are generally described as: lowlands conifer-hardwood forest, montane mixed conifer forest, subalpine parkland, alpine grasslands and shrublands, and riparian-wetlands (Chappell et al. 2001). All of these ecosystems are prevalent on the landscape and receive a wide range of annual rainfall that can be anywhere from 50-360 centimeters on average (Chappell et al. 2001). In addition to elk, other large mammals on the peninsula include cougars *(Puma concolor)*, black bears *(Ursus americanus)*, black-tailed deer *(Odocoileus hemionus)*, and non-native mountain goats *(Oreamnos americanus)*. Outside of the confines of Olympic National Park, elk are subject to hunting with the proper permissions in every game management region on the peninsula, including with special permits on tribal reservations (Washington Department of Fish and Wildlife).

METHODS

Survey Design

The data I used for this study was collected by the Lower Elwha Klallam Tribe on the northern Olympic Peninsula from April to November of 2021 (Figure 2). A total of 97 camera stations were placed within 67, 4x4-kilometer grid cells. The cameras are located on national forest lands and tribal lands, but not within Olympic National Park itself (Figure 2). For the occupancy model, I defined a sampling event as a seven-day period and any sightings of elk within a particular grid cell during the survey period were recorded as a single sighting for that sampling event. For the resource selection function, I compiled the detection data to determine the total number of detections per grid cell over the entire survey period and then proceeded to build the model.

Candidate Variable for Detection

Imperfect detection of species during a camera trap survey introduces bias into models of habitat use. MacKenzie et al. (2002) developed their equation for occupancy to account for imperfect detection. Explaining probability of detection as a function of covariates helps the model deal with the uncertainty of missed captures at sites that are in fact occupied by the target species. Likewise, the ZIP model can use covariate effects to explain the prevalence of excess zeroes in a data set. I tested the effect of camera effort on detection in both the occupancy and ZIP models. I define camera effort in this study as the number of camera traps per 4x4 km grid cell which can range from 1-3. The number of cameras in a particular cell can influence the number and frequency of sightings at a site and therefore I analyzed it as a potential covariate on detection (Hofmeester et al. 2021).

Candidate Variables for Occupancy and Resource Selection

Elk are a highly charismatic species and there has been a plethora of prior work performed to examine their ecology and life history. Many of the environmental factors that influence elk occupancy have already been identified and implemented into various models. The potential covariates for elk occupancy I use in this study were mostly inspired by the work done by Rowland et al. (2018) which involved modeling the relationship between nutrition and habitat use of elk in western Oregon and Washington (Table 1).

I used the average Enhanced Vegetation Index (EVI) per cell for this study as a proxy for dietary digestible energy (DDE) (Villamuelas et al. 2016). Often, the Normalized Difference Vegetation Index (NDVI) is used as a proxy for DDE in elk studies because the study areas do not have a dense overstory. NDVI and EVI are very similar and measure the same wavelengths of light reflected from plants, but NDVI is more suited to detecting differing amounts of red and green light. This means that it is very good at finding variation in grasslands where healthy and productive vegetation is green and less productive vegetation will be less so to the point that it may even look yellowish to the human eye. When trying to use NDVI on a very green and very dense canopy like in the rainforests of the Olympic Peninsula, the NDVI values would plateau because NDVI cannot very well differentiate between different wavelengths of reflected green light. However, EVI is very effective at distinguishing differences in the greenness of a very green environment like rainforest canopy (Huete et al. 2002). While EVI is not directly measuring greenness of the forest's understory and therefore forage, it is able to detect general composition of the forest which can indicate the composition of the understory (Villamuelas et al. 2016). This method may not be able to directly identify the exact understory conditions elk prefer on the peninsula but, for the goals of this project, an indirect indicator of understory forage will suffice. EVI data for the study area was acquired from the MODIS Vegetation Index Data products.

Various anthropogenic disturbances have been shown to influence the occupancy and habitat use patterns for elk. One of those disturbances is roads and highways open to public use therefore distance to open roads is one of the covariates being analyzed for an effect on occupancy and use in this study. Evidence can also be found supporting the effect of vegetative cover on elk occupancy, often measured as cover-forage edge distances (Rowland et al. 2018). Due to the limited scope of this study, I used a remotely sensed surrogate variable for cover-forage edge. In the study area, various land cover types have been identified by MODIS Land Cover Type Data products. Each cell contains varying proportions of each land cover type and the influence of proportion of each land cover type on elk occupancy and habitat use was analyzed.

Slope and elevation were also evaluated as potential variables influencing occupancy of elk. Slope and elevation have been shown previously to have an influence on spatial distribution in other studies of elk and they have the potential to influence a model of occupancy or resource selection in the study area (Rowland et al. 2018, Cook et al. 2016). These variables were averaged across an entire sample cell producing a single value for the cell.

Covariate Analysis

I scaled all covariates [(value - mean value)/standard deviation] before analysis to aid comparison across variables (Menard 2011). I selected significant variables for the occupancy model by a univariate analysis performed in the 'unmarked' package in Program R (Kellner et al. 2023). For the occupancy model, I analyzed the effect of number of cameras per cell on detectability by assessing its explanation of the data while occupancy was null. If the variable had a p-value < 0.05 it was considered significant and served as the null for the analysis of variables relating to occupancy. For occupancy, any variable with a p-value < 0.25 was considered significant and selected for the multivariate analysis (Hosmer and Lemeshow 2000). I also tested the variables for multicollinearity among themselves using the 'cor' function in

Program R. Variables that were found to be colinear were evaluated against each other and the variable with the more significant p-value was selected for the multivariate analysis (Hosmer & Lemeshow 2000).

For the resource selection model, I performed the univariate analysis using the 'zeroinlf' function to fit a ZIP regression in the R package 'pscl' (Jackman 2024). Again, I evaluated the effect of number of cameras per cell on detection while the count regression was null. If the number of cameras had a p-value < 0.05 it was considered significant and served as the null for the analysis of variables in the count regression. For the count regression, any variable with a p-value < 0.25 was considered significant and selected for the multivariate analysis. Again, I used the 'cor' function in R to test the variables for multicollinearity and any variables found to be colinear were evaluated against each other, with the more significant variable being used in the multivariate analysis (Hosmer & Lemeshow 2000).

Model Building and Selection

I used a reverse-stepwise model building process as described in Hosmer and Lemeshow (2000) to select a model with statistically and ecologically significant covariates. For the occupancy model, I first built the model for detection while occupancy was null. If the number of cameras per cell was shown to have a significant effect on probability of detection (p-value < 0.05) then it was incorporated, if not, then detectability was be held constant across all cells. Then, the model for detectability acted as the null constant while I performed the reverse-stepwise process for the covariates for occupancy. I determined the top model for occupancy by comparing the difference in Akaike Information Criterion (AIC). The model building process for the ZIP regression was the same; the zero-inflation side of the ZIP model is comparable to the detection side of the model for occupancy and was evaluated for an effect of the number of cameras in the same way. I then used the zero-inflation model as a null model to perform the reverse-stepwise process for the covariates that may affect the number of detections per cell. I determined the top ZIP model by comparing differences in AIC values.

VALIDATION

To validate the main effects model produced by the model building process I used a Pearson Chi-Square goodness of fit test (Franke et al. 2012). For the ZIP model, I predicted a count value for each surveyed cell using the main effects model and also calculated a Pearson chi-square test statistic using the observed count values. I then determined if the two sets of data follow the same distribution, H_0, or if they followed different distributions, H_A, with a standard level of significance of $p < 0.05$. Rejection of the null indicates a poor fit of the model to the data. I performed the same test for the occupancy model but to properly interpret the test statistic I would generate random data using the probability of occupancy that I calculated from my sample and then fit a model with the same structure as the main effects model. I would then calculate a test statistic from the generated data. I would repeat this process many times to create a distribution of test statistics to compare against the test statistic produced by the sample and calculate a p-value (MacKenzie & Bailey 2004). Instead I only produced a test statistic from the sampled data which I compared against the degrees of freedom of the data to get an approximate guess of model fit.

RESULTS

Average survey duration per camera was 205 days. Eight cells detected elk at least once during the survey period with a total of 32 detections for the entire season. The data produced by the sampling design follows a Poisson distribution (Figure 3). The total estimated occupancy for the surveyed area was 12.600 percent ($\Psi = 0.126$). For occupancy, the number of cameras per cell was negatively related to detection and additionally was non-significant ($\beta_{cameras} = -0.851$, SE = 0.468, p-value = 0.069) so it was removed from the model building process (Table 2). The univariate analysis for the occupancy model only produced one significant covariate so there was only one model that could be produced by the model building procedure (Table 3). The occupancy model held detection constant across each cell and incorporated average annual EVI to predict occupancy (Occupancy (~1, ~EVI), $\beta_{EVI} = 1.520$, SE = 0.551, p-value = .006, Table 4). It should be noted that the Land cover class variable was removed from analysis for both models because the data was insufficient for calculating a potential effect of 10 different land cover classes in addition to the other variables.

The number of cameras per cell was not significantly related to the zero-inflation side of the ZIP model ($\beta_{cameras} = -0.171$, SE = 0.634, p-value = 0.787) and was removed from the model building process (Table 2). The univariate analysis produced three significant covariates, so I performed the reverse-stepwise model building procedure (Table 3). The procedure produced a lowest AIC model in which elevation was the only significant covariate and was negatively related to count (ZIP (Count ~ Elevation | 1), $\beta_{elevation} = -1.783$, SE = 0.521, p-value = .001, Table 4). A second model was produced with a Δ AIC < 2 which uses elevation and the distance to paved roads (ZIP (Count ~ Elevation + Distance to roads | 1), $\beta_{elevation} = -1.576$, SE = 0.618, p-value = 0.011; $\beta_{distance} = -0.276$, SE = 0.442, p-value = 0.532; Table 4).

The Pearson chi-square statistic for the occupancy model is high for the number of degrees of freedom ($\chi^2 = 7682.174$, df = 66). This is further explored in the discussion. The Pearson chi-square statistic for the ZIP model is also high for the number of degrees of freedom and the p-value produced is less than 0.05 (χ^2 = 180.196, df = 66, p-value = 2.580e-12). I plotted the relationship between probability of detecting a non-zero and elevation for the ZIP model (Figure 4). This relationship is further explored in the discussion and compared to the relationship between occupancy and EVI (Figure 5) and the regression component of the ZIP model (Figure 6).

I projected both main effect models to the entire Olympic Peninsula and each provided different estimates of probability of habitat use. The occupancy model was conservative of where it predicted higher probabilities of habitat use (Figure 7). The ZIP model projection shows the expected probability of returning a positive count, given the cell does not produce a zero as a result of the zero-inflation component of the model. The probability associated with each cell is therefore a probability of presence, which is directly comparable to the probability of occupancy produced by the occupancy model. With this in mind, we can see that the ZIP model predicted more of the peninsula to experience greater use by elk than the occupancy model (Figure 8).

DISCUSSION

The results of this study seem to indicate that there is a great difference in the probability of use estimates produced by using logistic regression and linear regression, specifically occupancy modeling and zero-inflated Poisson regression in this case. However, this initial exploratory analysis does not provide solid evidence that can justify the use of one model over the other, but it does provide food for thought to researchers who are trying to determine by which method they will estimate probability of habitat use.

When validated, both models performed poorly. The occupancy model was not properly validated using bootstrapped data but the large Pearson chi-square statistic in combination with a relatively small number of degrees of freedom provides some evidence that it may not fit the data well. The ZIP model also performed poorly when validated; the p-value produced is far below the significance level of 0.05, indicating that the null hypothesis of the Pearson chi-square test should be rejected and that the model does not properly fit the data. The ZIP also produced estimated probabilities of returning a non-zero that are greater than 1 (Figure 3); I attribute this to the poor fit of the model to the data. However, the occupancy model predicts probabilities between 1 and 0 despite also potentially being a poor fit to the data. I would like to further examine the nature of this discrepancy in future projects. Additionally, the linear relationship between count and elevation seems to be reasonable despite the model's overall lack of fit. I propose that the lack of fit of both models is the result of trying to build predictive models with insufficient data.

Some difficulties presented by the use of small data sets are that it is difficult to evaluate the assumptions of the associated analysis, the evaluation of the selected model is often ambiguous, and when the number of fitted parameters are a moderate proportion of the sample size, most model selection procedures will select variables that are not truly related to the response (Bissonette 1999). I think this study, while subject to all such issues, especially suffers from the selection of variables that are not truly related to the response. For instance, the ZIP model only uses elevation to explain elk habitat use, which appears to be inaccurate. Many of the places predicted to have the highest elk use are close to the coast and densely inhabited by humans. Whereas many places, such as montane mixed conifer forests above a certain elevation were predicted to be devoid of elk. This is unusual because other studies in this region have shown that elk do use this forest type and that elevation influences elk habitat use, but only within suitable patches of habitat (Rowland et al. 2018).

The data was too small to properly capture the true behavior of the elk to any reasonable degree with only 67 surveyed cells, 24 independent weekly detections over the entire survey period to make a total of 8 cells with actual detections of elk. Land cover class was not able to be evaluated with so little data and I was ultimately forced to remove it from the analysis. The occupancy model was unable to contend with the 10 different land classes presented and could not compute an effect. I deemed the removal of land cover acceptable due to the fact that the analysis is already incorporating a continuous habitat indicating variable, EVI (Coops & Wulder 2019). Another interesting result of the analysis was the negative correlation between detections and the number of cameras per cell. This result is unexpected but may be explained by the fact that relatively few cells had more than one camera, most cells that recorded detections only had one camera and others with more cameras did not record detections. Again, this is presumably a result of stochastic effects overriding true effects due to the small sample size.

There were many interesting developments in the univariate analyses as well. Firstly, when performing the univariate analysis for occupancy, the only significant variable found was EVI. This removed all other variables from consideration for the occupancy model. I would like to note that occupancy models were built with the other covariates and AIC values compared for the sake of redundancy and the model using EVI was found to have a significantly lower AIC than the other models (ΔAIC > 2). However, when performing the univariate analysis for the ZIP model, EVI was the only variable found to be non-significant. Elevation, slope, and distance to roads were all significant and were used in the reverse-stepwise model building process to determine a significant effect on elk habitat use. As mentioned in the results, the model using elevation performed the best.

Perhaps the most interesting and potentially indicative result from this analysis is the opposite predicted effect of EVI on habitat use between the two models. In the occupancy model it was the only variable that passed the univariate analysis, whereas it was the only one that was excluded from the multivariate analysis when building the ZIP model. My best explanation of this result is that several sample cells below average elevation had many detections of elk by comparison to other cells, which heavily swayed the ZIP model towards favoring sites at lower elevations while essentially overpowering the effect of EVI. While the occupancy model ignores multiple detections at one location, the ZIP model estimates importance of a location based on the number of detections. This discrepancy between the models comes from the difference in the purposes for which each were designed. To determine occupancy, only one animal needs to be found at a site. But, in resource selection, the number of animals found at a site is important because it may indicate a strong preference for a site-specific factor. In this application, both models served as proxies of probability of habitat use but the difference between probability of habitat use, occupancy, and resource selection are extremely nuanced. The nuance of these models becomes even greater when considering that all of the data was collected by camera traps, which changes little for the occupancy model, but is not how resource selection models were originally designed to be surveyed for (Manly et al. 2002). This creates problems for the resource selection model because multiple detections at a single site could indicate a high preference for that site, or it could indicate the presence of a single, highly consistent outlier. This problem is exacerbated by the fact that outliers will have stronger effects on models produced by small data sets, such as this one.

Unfortunately, this project has left many questions unanswered. The biggest and most glaring of which being whether or not the predictions of each model would converge with an appropriate amount of data. This is something that should be resolved in the future as more research on these methods is performed. If both methods are indeed effective at predicting elk habitat use with sufficient data, then the same variables should be found to be explanatory for each model and the resulting predictions of use would be similar. However, a common theme in ecological study is a lack of abundant or even sufficient data (Bissonette 1999). This study re-emphasizes the level of caution and consideration required when analyzing small data sets. In fact, it may even be reasonable to expect researchers to justify their use of a specific analysis rather than simply reporting it in the work they publish. This would force researchers to dive even deeper into the theory behind the methods they wish to use to describe relationships between ecological variables.

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Figure 1. *Olympic Peninsula Study Area, bounded to the south by the Columbia River, the southeast by interstate I-5, the northeast by the Puget Sound, to the north by the Strait of Juan de Fuca, and to the west by the Pacific Ocean.*

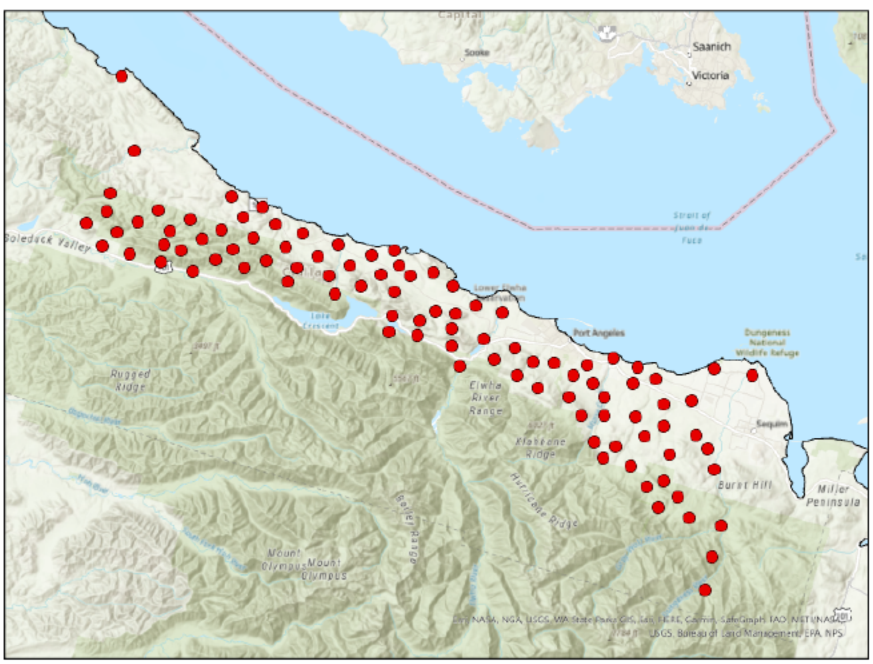

Figure 2. *Locations of all 97 camera stations on the northern edge of the Olympic Peninsula.*

Table 1. All potential covariates that were analyzed for univariate and multivariate significance, organized by model.

Model	Covariate	Predicted Effect	Justification
Detection/ Zero-inflation	Number of Cameras per Cell	+	The more cameras there are in a cell, the more likely it is that one of those cameras will detect an elk at some point during the survey period (Hofmeester et al., 2021).
Occupancy/ Zero-Inflated Poisson	Enhanced Vegetation Index (EVI)	+	EVI is able to detect differences in forage quality for ungulates, its predictive ability is strongest during times of increasing or decreasing greenness (spring and fall) (Villamuelas et al., 2016). The understory of the study area was not directly measured but canopy EVI values can act as a proxy variable.
	Land Cover	+	The distance to cover-forage edge affects elk use; elk prefer to stay close to cover if possible (Rowland et al. 2018). In this study, I used land cover type as a proxy for cover-forage edge and predict that elk select for forested areas.
	Elevation	+	Elevational gradients influence the forage composition of an area and elk selection for use. High elevation forests are better able to support lactating females in terms of available digestible energy (Cook et al. 2016).
	Distance to Roads	+	Elk prefer to avoid anthropogenic features and disturbances like roads and highways and are more likely to use habitat farther from those features (Rowland et al. 2018)
	Slope	-	The average slope of a cell can influence the quality of forage present and the ease at which elk can access the area. Flatter areas are more easily accessed by elk and may be selected for where available (Rowland et al. 2018).

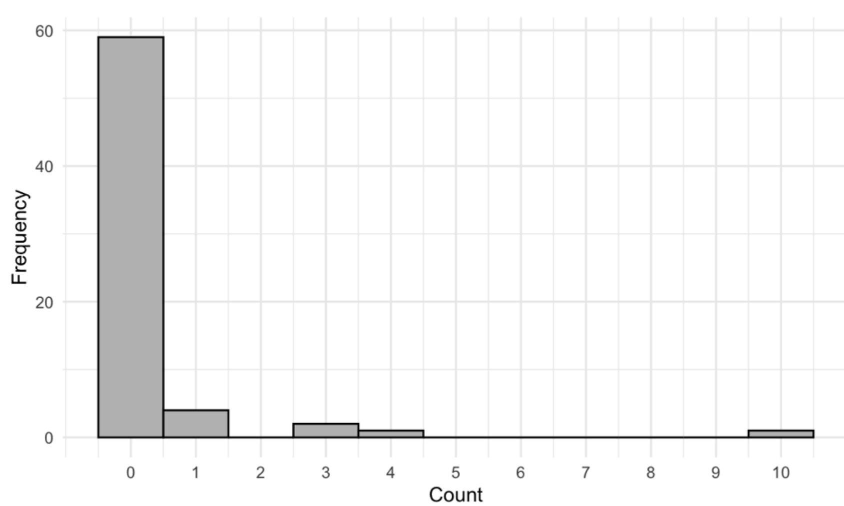

Figure 3. Visualization of count data collected by the camera trapping procedure.

Table 2. Results of univariate analysis for number of cameras per cell on detection.

Model	Covariate	β	*SE*	*P*
Occupancy (Detection)	Number of cameras per cell	-0.851	0.468	0.069
Zero-inflated Poisson (Zero-inflation)	Number of cameras per cell	-0.171	0.634	0.787

Table 3. Results of univariate analysis for potential covariates for presence/absence in the occupancy model and count in the Zero-Inflated Poisson model.

Model	Covariate	β	*SE*	*P*
Occupancy (Presence)	EVI	1.520	0.551	0.006
	Elevation	-0.461	0.457	0.313
	Distance to roads	0.116	0.366	0.752
	Slope	-0.081	0.388	0.834
Zero-inflated Poisson (Count)	EVI	0.244	0.260	0.347
	Elevation	-1.783	0.521	0.001
	Distance to Roads	-1.180	0.394	0.003
	Slope	-1.059	0.378	0.005

__Table 4.__ Comparison of models produced for each method. Note that detection is constant in the occupancy model and the zero-inflation term is constant in the ZIP models.

Model type	Model Rank	Model	Δ AIC
Occupancy	1	Occu (~ 1, ~ EVI)	0.00
Zero-Inflated Poisson	1	ZIP (Count ~ Elevation | 1)	0.00
	2	ZIP (Count ~ Elevation + Distance to roads | 1)	1.60
	3	ZIP (Count ~ Elevation + Distance to roads + Slope | 1)	3.55

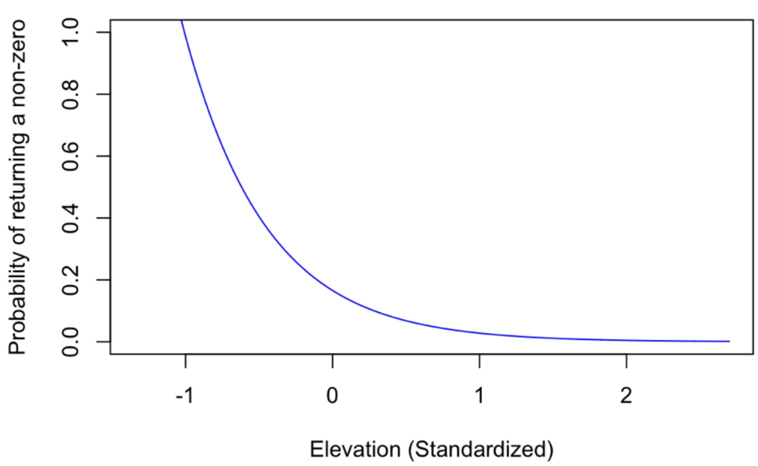

__Figure 4.__ Probability of returning a non-zero as related to change in elevation. Note: probability estimates exceed 1; I believe this to be a result of poor model fit.

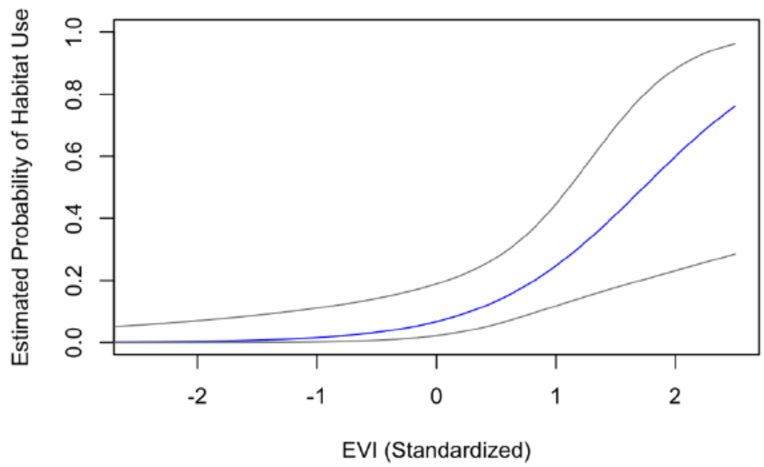

Figure 5. *Estimated probability of habitat use (occupancy) as a function of EVI values. Grey lines show standard error.*

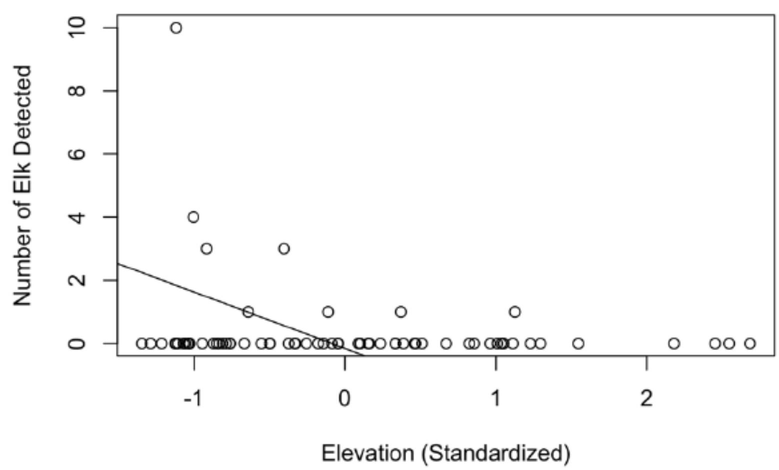

Figure 6. *ZIP count regression of the relationship between the number of elk detected at a site and elevation.*

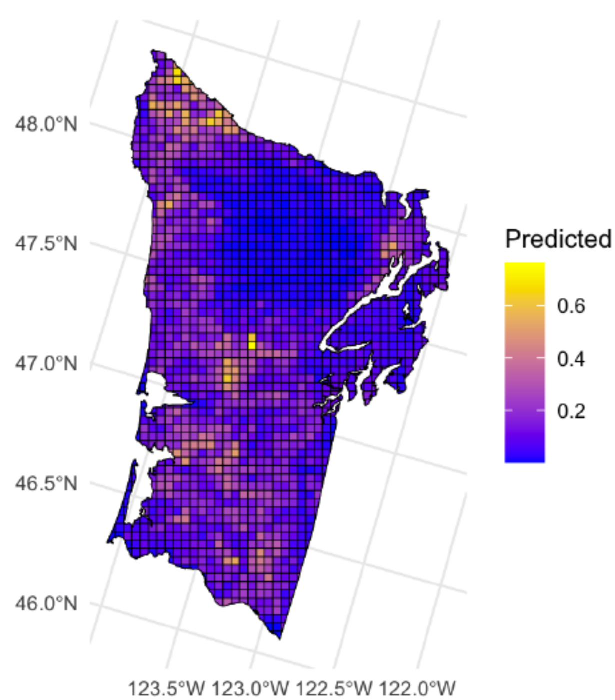

Figure 7. *Projection of predicted values for probability of habitat use (occupancy) based on average annual EVI per cell.*

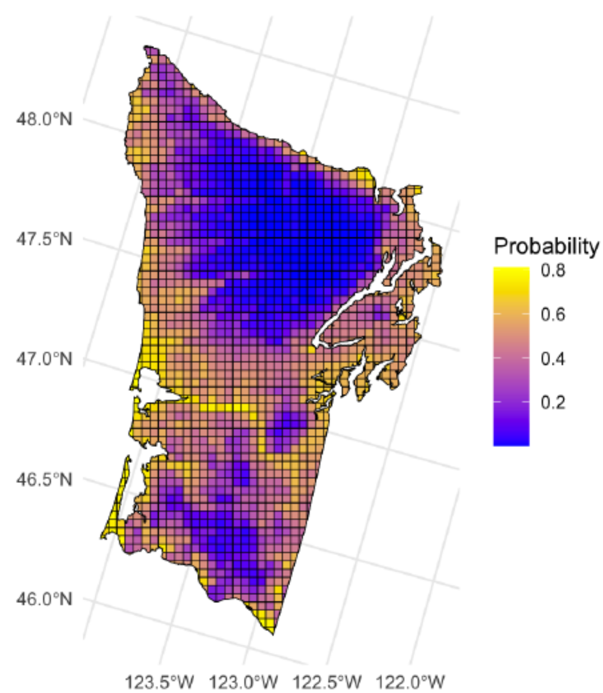

Figure 8. *Assuming non-zero-point mass zeroes, a projection of the probability of detecting a non-zero count in each cell based on average elevation using the ZIP model.*