Department of Wildlife, Fish, and Environmental Studies

Fire effects in a landscape of fear

 food availability and perceived predation risk as potential determinants of patch utilization by herbivore prey

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Master's thesis • 30 credits Management of Fish and Wildlife Populations Examensarbete/Master's thesis, 2019:10 Umeå 2019

Fire effects in a landscape of fear – food availability and perceived predation risk as potential determinants of patch utilization by herbivore prey

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Credits: 30 credits

Level: Second cycle, A2E

Course title: Master thesis in Biology - Management of Fish and Wildlife

Populations - Master's Programme

Course code: EX0934

Course coordinating department: Department of Wildlife, Fish, and Environmental Studies

Place of publication: Umeå
Year of publication: 2019

Cover picture: from camera traps

Title of series: Examensarbete/Master's thesis

Part number: 2019:10

Online publication: https://stud.epsilon.slu.se

Keywords: landscape of fear, forest fire effects, herbivore prey, camera

trapping

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Abstract

Context: A major effect of climatic change is the global increase in forest fires, which potentially creates an increase in food availability for herbivorous species. Also vegetation density and the numbers of tree logs increase in burned sites, and this is thought to influence the *perceived risk* of herbivore prey species, which affects their anti-predator behaviour and thereby the patch utilization. This cascading effect of forest fires might have implications on future ecosystem functioning in the burned area, and more knowledge about the effects of landscape features on predator-prey interactions is needed to adapt conservation and wildlife management policies, to the changing climate.

Aim: This study aims to gain insight into how varying food availability, visibility and escape impediments in burned and unburned forest sites, influence patch utilization by two herbivore species, mountain hare (*Lepus timidus*) and moose (*Alces alces*). I predicted that i) animals that are under high predation pressure will have a higher utilization of 'save' patches in the control sites where perceived risk is lower, and that ii) animals that experience no or low predation pressure will have a higher patch utilization in the burned areas where food availability is high.

Methods: I tested these predictions by conducting a correlative cross-sectional study in three different boreal forests in the north of Sweden, each with a burned site that burned in 2006 and an equal sized unburned control site. The herbivore community there is predominantly comprised of moose and mountain hare. Measurements on species passage rates and the time they spend in front of the camera are derived from footage obtained from remotely triggered cameras with a PIR sensor. Data on food availability, visibility and number of tree logs and other plot characteristics are collected by taking field measurements around each camera trap. I tested the relations between these variables using a multiple regression analysis with zero-inflated generalized linear models.

Results & discussion: In two of the three areas I did not find a difference in patch utilization between the burned and the control site for mountain hare. In one area there even was a significantly higher patch utilization in the burned site instead of the control, and this made sense since mountain hare utilization was positively correlated to the number of tree logs in two of the three areas. The positive correlation of tree logs could be explained by the fact that birds of prey are a dominant predator for mountain hare, in which case tree logs provide cover for the hares instead of increasing their perceived predation risk. For moose there was no significant difference in utilization between the burned and control site per area. However, in the areas with the highest number of moose passages the difference was almost significant. In this area the multiple regression model also showed the predicted positive correlation of patch utilization and food availability.

Conclusions: I conclude from the reflections on the results for mountain hare, that depending on the composition of the predator community, the landscape features will have a different effect on the patch utilization of the prey species. In a study area with many different predator types present, it is difficult to find strong correlations between the landscape features and patch utilization, since these features are ambiguous in their effect on perceived predation risk. Therefore, on the basis this study, it remains difficult to draw clear conclusions about the actual effects of forest fires on predator-prey interactions, since they are very predator specific. For moose it seems plausible that their patch utilization is indeed predicted by food availability, but that this correlation was not found two of the three areas because of the lack of data points there and/or the possible inaccurate proxy for food availability that was used in this study.

Keywords: *landscape of fear, forest fire effects, herbivore prey, camera trapping.*

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1. Introduction

Human activity has an increasing impact on ecosystems worldwide, either in the form of direct habitat degradation or transformation, or through human-induced climate change, resulting for example in an increase in forest-fire frequency (Flannigan et al., 1991; Gillet et al., 2004). These impacts continuously alter species interactions across systems (Dale et al., 2001; Gaynor et al., 2018; Hodson et al., 2010), which can lead to unforeseen and unwanted cascading effects that degrade or change an ecosystem or landscape (Hebblewhite et al., 2005; Wilmers et al., 2006). In order to be able to prevent or anticipate on the cascading effects of these changes in a way to either conserve ecosystems or to prevent crisis, a thorough understanding of the indirect and long term effects of ecosystem disturbances is needed. In this study, I tested if and how the effects of forest fires in a landscape influence predator-prey interactions and the way that prey species utilize their habitat.

Forest fires play a very important role in many ecosystems, by redistributing nutrients, creating heterogeneity throughout a landscape and providing variability in landscape features (Reich et al., 2001; Cayford et al., 1983; Goldammer et al., 2013). Now that the effects of climate change are increasing the frequency and intensity of wild fires in many places (Flannigan et al., 2000 & 1999; Fried et al., 2004), it is important to know more about the long term and indirect effects of these fires. The direct effects of forest fires on landscape features are numerous and by that, a forest fire is directly structuring ecosystems through for example the redistribution of nutrients and opening up of the canopy (Kutiel et al., 1983; Reich et al., 2001). The short-term effect on forest vegetation is both an increase in tree regeneration as well as tree mortality (Swezy et al., 1991). This, on the one hand results in a higher food availability for herbivores (Fisher et al., 2005), but on the other hand likely decreases visibility (since vegetation density increases) and increases the amount tree logs that both affect a preys' risk perception (Laundré et al., 2010; Kuyper et al., 2015). Forest fires are therefore believed to create an energetic trade-off for herbivore prey species (Brown et al., 1999), which forces a prey that perceives the risk of being eaten to high, to accept a lower foraging efficiency in a safer patch (Lima & Dill, 1990; Verdolin et al., 2006; Benhaiem et al., 2008). Or the other way around, that the trade-off forces an animal to accept a higher level of predation risk when food availability is to low in the safe patches. Therefore, forest fires do not only directly influence ecosystem structuring, but potentially have a long-term indirect influence through their effect on predator-prey interactions and the way they utilize their habitat (Fortin et al., 2005).

The interaction between large carnivorous predators and their herbivore (mammal) prey species plays a central role in a top-down ecosystem structuring (Terborg and Estes, 2010; Ripple et al., 2001), while landscape features have a bottom-up effect on predator-prey interactions as well. They are linked through a mechanism that is described in the theory of 'the landscape of fear' (LOF) and the theory suggests that the behavioural response of herbivore prey species to a perceived predation risk, does affect prey foraging behaviour and the way they utilize their habitat (Creel et al., 2005; Valeix et al., 2009; Thaker et al., 2011). The LOF is based on the idea that prey animals navigate through a landscape basing their habitat selection on the availability of food and their perception of predation risk. This perceived predation risk by a prey, and the resulting anti-predator behaviour, depend on the combination of predator abundance and a varying amount of landscape features like vegetation density and the number of tree logs that could add to the hunting success of a predator and thus form risk factors for the prey (Kuyper et al., 2013; Kauffman et al., 2007; Gaynor et al., 2019). In the case that a prey is predated by an ambush predator in a forest landscape, a dense vegetation and the presence of escape impediments like tree logs pose risk factors for the prey since these features are linked to predator hunting success (Hopcraft et al., 2005; Podgórsky et al., 2008). This would make patches with relatively low numbers of tree logs and high visibility be perceived as relatively safe. The combined spatial gradient of food availability and the preys' perceived predation risk and the way they overlap, forms a landscape of fear consisting of high risk patches with high food availability and safer patches with lower food availability (Tolon et al., 2009; Gaynor et al., 2019).

Few studies investigate the effect of forest fires on the foraging behaviour of large herbivores in boreal forests and even fewer empirical research is done on the effect of forest fires on the predator-prey interactions that are shaping the landscape of fear. Therefore, this study aims to gain insight into how the effects of forest fires influence anti-predator behaviour in the form of habitat utilization by prey species, and furthermore which landscape features specifically determine this behaviour.

The above presented theory and the energetic trade-off that arises in fire sites lead me to three hypotheses. The first is that a prey that is under high predation pressure will have a higher utilization of the safer patches (despite lower food availability) and that the main related variables for this are visibility (positively related) and tree log numbers (negatively related). Secondly, I hypothesize that the patch utilization of herbivore species that are under no predation pressure, is higher in the riskier patches with higher food availability, and that the main predictor for this is food availability (measured as number of small trees). The third hypothesis is that for a prey under low predation pressure the utilization will show no clear difference in utilization between safe and risky patches. For a conceptual model of these hypotheses see figure 1.

I conducted a correlative cross-sectional camera trap study in three different boreal forests, Bodträskfors (B), Muddus (M) National Park and Lainio (L), in the north of Sweden. In each of these areas a large natural forest fire occurred in 2006, providing a burned site and adjacent to it I selected a control site of approximately the same size and distance to water. The herbivore mammal (prey) community in these forests is dominantly comprised of moose (*Alces alces*) and mountain hare (*Lepus timidus*) (Ball et al., 2000). These species provide a good system for testing the presented hypotheses since each species is under a different predation regime. Single adult moose are assumed to have no natural predators there while moose cows, that are mostly with calf in the summer period, are exposed to predation risk since the calves are predated by brown bear (*Ursus arctos arctos*) (Swenson et al., 1994; Swenson et al., 2007). The mountain hare is predated by multiple predators present in the study areas, such as the lynx (*Lynx lynx*), red fox (*Vulpes vulpes*), European pine marten (*Martes martes*) and bird of prey (Pulliainen et al., 1995; Thulin et al., 2003; Helldin et al., 2000).

All in all, based on this hypothesis I predict that 1a) mountain hare will have a higher utilization in the control site and that 1b) this has a significant and positive relation to visibility and a significant negative relation to the number of tree logs. Furthermore, I predict that 2a) moose will have a higher utilization in the fire sites and 2b) that this is significantly predicted by food availability, and finally that 3a) moose with calf will utilize the burned and unburned site more or less equally (figure 1).

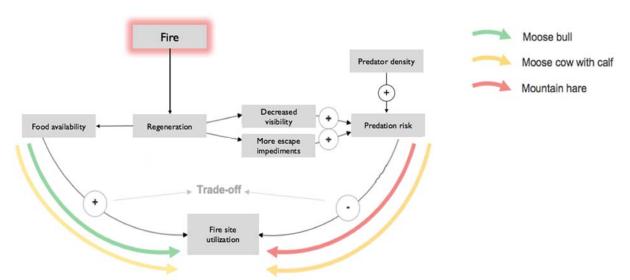


FIGURE 1. CONCEPTUAL MODEL OF ANTI-PREDATOR BEHAVIOUR HYPOTHESES: FIRE CREATES HETEROGENEITY IN A LANDSCAPE THROUGH INCREASED PLANT GROWTH AFTER FIRE, WHICH LOCALLY RESULTS IN DECREASED OPENNESS OF THE VEGETATION AND THUS DECREASED RANGE OF VISIBILITY. THE EFFECTS OF FIRE ALSO RESULT IN INCREASED NUMBERS OF TREE LOGS. BOTH THESE LANDSCAPE FEATURES POTENTIALLY INCREASE THE PREDATION RISK AT THE FIRE SITE IF PREDATORS ARE PRESENT. WHEN ANIMALS ARE UNDER HIGH PREDATION (MOUNTAIN HARE), THEIR HABITAT UTILIZATION WILL BE INCREASINGLY BE EXPLAINED BY RISK FACTORS (DECREASED VISIBILITY AND MORE TREE LOGS) THAT WILL CAUSE THEM TO AVOID FIRE SITES (PREDICTION 1). THE HABITAT UTILIZATION OF ANIMALS THAT ARE NOT UNDER PREDATION (SINGLE MOOSE) WILL MAINLY BE STEERED BY FOOD AVAILABILITY AND THUS WILL RESULT IN HIGH FIRE SITE UTILIZATION (PREDICTION 2). THE HABITAT UTILIZATION OF ANIMALS UNDER LOW PREDATION (MOOSE WITH CALF) WILL MOST LIKELY BE INFLUENCED MORE OR LESS EQUALLY BY FOOD AVAILABILITY AS WELL AS RISK FACTORS AND WILL RESULT IN A MORE OR LESS EQUAL UTILIZATION OF FIRE SITES AND CONTROL SITES (PREDICTION 3). THE HIGHER THE PERCEIVED RISK, THE SHORTER THE TIME A PREY ANIMAL WILL RESIDE THERE AND THE LESS OFTEN THE PREY WILL VISIT, RESULTING IN A LOWER UTILIZATION OF THAT LOCATION.

2. Methods

2.1 Study system

I have monitored species passage rates and the TIOC across the three study areas; Bodträskfors, Muddus NP and Lainio. These areas are located in the subarctic boreal forests in the province of Norrbotten, in the north of Sweden (figure 2), and have been chosen because they each contain a large site that has been naturally burned in the year 2006. Each area consisted therefore of two different forest treatments; a previously burned site and an unburned site of approximately the same size (~300ha) and distance to water. Between these two sites there is high heterogeneity in food availability and risk factors.

All three areas have comparable mammal species compositions with moose and mountain hare as the dominant mammalian herbivores, although reindeer where also abundant only in Lainio. The dominant carnivore and predator species associated with the mountain hare are the lynx, red fox and pine marten (Pulliainen et al., 1995; Thulin et al., 2003; Helldin et al., 2000). Birds of prey (raptors) are also potential predators for mountain hare (Pulliainen et al., 1995) but cannot be measured effectively with the use of the camera trap setup in this research. Therefore, I have not considered raptors in this research, however they could pase a confounding factor for my analysis. For moose only the calves are predated by the brown bear (Swenson et al., 2007), and therefore I have assumed that an adult moose with calf will consider a bear as predator as well and therefore most likely would adapt her behaviour to bear presence. Single adult moose are assumed not to be predated.

The three areas: Lainio, Muddus NP and Bodträskfors lie on a productivity gradient (north to south) that could have an influence on the regeneration speed after fire, and thus on the food availability and visibility in the three burned areas. This could have an influence on the occurrence of a trade-off in a post fire site.

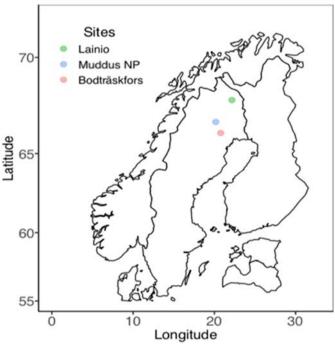


FIGURE 2: THE THREE AREAS CONSISTING OF HETEROGENEOUS BOREAL FORESTDEVIDED IN PREVIOUSLY BURNED AND UNBURNED FOREST.

2.2 Camera trapping

I have quantified patch utilization as the product of the amount of passages per camera trap location and the average time spend in front of that camera trap (TIOC) by a species. Resulting in a total amount of seconds that a certain species was detected by a camera trap, or in other words; the total time a species utilized that specific patch. The amount of passages and the TIOC were determined for every prey category (single moose, moose with calf and mountain hare) with the use of camera traps.

The cameras at each location (figure 3) were placed in the beginning of June 2018 and were picked up during September 2018. At all six sites (3 burned and 3 unburned sites), twelve PIR sensor-triggered remote cameras (Hyperfire HC500, Reconyx Inc., Holmen, WI, USA) were placed, making a total of 72 cameras. In each site, six cameras were placed randomly (small dots in figure 3) in northern direction and the other six were placed and oriented selectively (large dots in figure3) at locations where the chance of encountering elusive animals such as the lynx, was optimized. Before fieldwork, these positions were chosen based on a digital elevation map of the areas, the locations with the highest ruggedness index in the landscape were selected, as lynx is known to have a preference for sites with high ruggedness in this type of landscape (Rauset et al. 2013). These selectively placed camera positions were more exactly determined in the field on the basis of either the presence of clear animal tracks or traces or having a geographical characteristic (like a ridge or rock wall) that would likely lead animals in front of the camera (Kolowski et al., 2017).

All cameras were attached to a tree in such a way that ground level at 3 meters in front of the camera was ~30cm lower than the lens, to increase the possibility of capturing smaller animal species, while circumventing problems of small scale topography blocking the camera view. The camera traps were set to high sensitivity of the PIR-sensor and took a series of 10 images with no delay, when the camera got triggered. The cameras were also set to take an image at noon every day to test camera functioning.

The data generated by these cameras was organized with the use of the open source web-based application *TRAPPER* (Bubnicki et al., 2016). From each sequence of images related to one passage of one or more individuals, information was gathered on; time and date, species, number of individuals, time spent in front of camera (TIOC), and for moose, if they were with a calf. The TIOC was determined by the time difference between the first and the last picture of a sequence in which the animal (or a pair) triggering the camera is visible on the image.

The amount of registered passages of a certain species is influenced by the camera effort (the number of days the camera has been functionally active) as well as the average body size of a species and the specific matrix of a camera trap location (dense or open vegetation). To correct for these effects, I determined the camera effort for each camera and the *Effective Detection Distance* (EDD) (Hofmeester et al., 2017) for each camera-species combination, in order to correct for this influence. The amount of passages of every species at a certain camera trap location can then be corrected first off all for the camera *effort*, resulting in a *Passage Rate* (PR), the amount of passages per 100 days. Secondly this passage rate should then be corrected for the EDD of that camera for a specific animal species, resulting in the *Adjusted Passage Rate* (APR = Passage per 100 days per 10 meter of effective detection distance in front of the camera), which can then be multiplied by the total TIOC of a species to determine patch utilization.

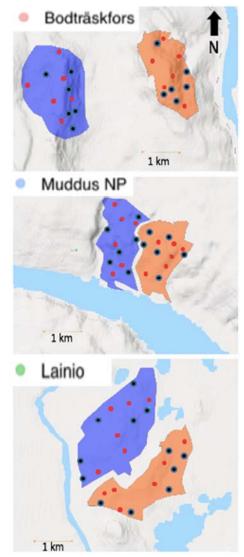


FIGURE 3: THE THREE LOCATIONS WITH BURNED SITE (RED) AND UNBURNED CONTROL SITE (BLUE) AND RANDOMLY SELECTED CAMERA TRAP POSITIONS (RED DOTS) AND NOT RANDOM PLACED CAMERA TRAPS (BLACK DOTS) THAT AIM TO CAPTURE MORE ELUSIVE ANIMALS LIKE THE LYNX. THE RED LINE AT THE BOTTOM OF EVERY AREA IS 1KM AND THE NORTH IS AT THE TOP.

2.3 Field procedures

In order to determine the EDD, right after the installation of each camera, pictures were taken with distance markers (at 2 meter intervals) in the middle of the camera view (Hofmeester et al., 2017). These markers were used during data organization to estimate the distance of an animal passing the centre line of the image. Furthermore, to determine the EDD I also measured the camera visibility range for each camera, defined as the average distance until first sight obstruction from three measurements in an angle of -45 degrees, 0 degrees and 45 degrees from the centre line of the camera view. Both these measurements allow a calculation of the EDD per species per camera trap, once all data was collected and categorized.

When collecting the cameras, at every camera location I quantified food availability, visibility, the amount of tree logs and the presence of animal trails. Mediating between time budget and realistic representation of these variables I used different plot sizes for each variable. Food availability was measured in a 5-meter radius plot around the camera. And for mountain hare I noted the number of young broadleaved and scots pine trees, ranging from 0 to 80 cm in height. For moose I noted the number of broadleaved and pine trees ranging from 0 to 300 cm. Visibility I quantified for mountain hare and for moose at respectively 30 cm and 200 cm above the ground, using a range finder (Nikon, Callaway LR550) to measure the average distance to first sight obstruction in 8 directions (all cardinal and semi cardinal), with the vertical axis of camera lens as centre point. Escape impediments I measured in a 10-meter radius plot where I counted the number of tree logs. For the logs to count as an impediment for both mountain hare as well as moose with calf, a log had to be at least 1 meter in length, 30 cm in diameter and have >20% of their length touching the ground. Otherwise, the logs had to be at least 1 meter in length, have no minimum diameter but be at least 30 cm of the ground at one point. Meaning that they were either more than 30 cm in diameter and laying on the ground or that they were thinner than 30 cm but raised above the ground. Finally, I noted the presence (as 0/1) of animal trails in a 10-meter radius within a 90-degree angle right in front of the camera.

2.4 Analysis

To test, per area, for differences between the burned and the control site in patch utilization I ran a zero-inflated model with a negative binomial error distribution and a log-link function in R (version 1.1.456). With the model I did a simple linear regression with only 'Site' as independent variable. The 'logit' part of this zero-inflated model (the part that considers the odds whether a zero count is a zero because there are no animals present or because it was coincidentally not detected) consisted of the both the log transformation of the 'EDD' and the 'camera effort', and further contained 'placement' and 'trail'. This are the main variables influencing the chance of whether any animal is detected yes or not. In both parts of the model I have entered the log functions of 'camera effort' and the 'EDD' as an offset variable. The use of a zero-inflated model was appropriate since the utilization data had excess zero counts, meaning that many camera traps detected zero passages for either moose or mountain hare. The negative binomial error distribution was justified by the fact that the data showed high over-dispersion (Gelman et al., 2006).

To test the difference in the number of small trees and the number of tree logs, I did a simple linear regression with a Poisson distributed generalized linear model with 'Site' as independent variable. To test the difference in visibility I did a simple linear regression with a linear model. To test if the differences were significant, I did a post-hoc Tukey test.

To test the relation of patch utilization to food availability, visibility and the amount of tree logs, I did a multiple linear regression and I also used a zero-inflated generalized linear model (GLM) with a log link function and with a negative binomial error distribution.

I did the utilization analysis separate for each area since the areas showed contrasting patterns of how patch utilization is related to the explanatory variables (see results). This made the assumption of comparability of the areas invalid, which meant that if I put the data of all the areas into one model this would likely blur any potential pattern or relation. This approach was justified since I was only interested in finding a correlation between the explanatory variables and the patch utilization, not in differences of utilization between the three areas.

For the analysis the dependent variable 'utilization' was calculated as the product of the raw passage counts and the TIOC (Passages*TIOC) instead of the product of the adjusted passage rates and the TIOC (APR*TIOC), since a GLM only allows integers as dependant variable. I corrected for camera effort and the EDD in the models by adding them as offset variables. I further corrected the model for trail presence which influences both capture frequency as well as excess zero's. Then I corrected for the placement of the camera since this was based on terrain ruggedness, and terrain ruggedness could also potentially influence both capture probability frequency as well as excess zero's because of relative predator abundance can vary with terrain ruggedness (Kolowski et al., 2017).

The 'counts' part of the zero-inflated model (the utilization analysis part) contained the log-transformed explanatory variables (food availability, visibility and the number of tree logs), the log transformed control variables 'EDD', 'camera effort' with an offset function, and optionally the variables 'placement' and/or 'trails'. When there was a correlation between two or more of the explanatory variables I excluded them from one and the same model. From these different models per area I chose the best fitting one based on the lowest AIC value (Spiegelhalter et al., 2002).

The 'logit' part of the zero-inflated models (the part that considers the odds whether a zero count is a zero because there are no animals present or because it was coincidentally not detected) contained only the 'EDD', 'camera effort', 'placement' and 'trails' since I reasoned that these are the main variables influencing the chance of whether any animal is detected yes or no. In both parts of the model I have entered the 'camera effort' and the 'EDD' as an offset variable.

3. Results

68 of the 72 cameras worked effectively and were considered in the analysis. Four cameras had only taken pictures of moving vegetation in the first couple of weeks, which resulted in depleted batteries before any animals were captured on the camera. The average effort per camera, not including the removed ones, was 99 days. They captured a total of 71 single-moose passages, 25 paired-moose, 66 mountain hare passages, 13 bear and 55 hare predator (red fox, pine marten, lynx) passages (appendix A). The passage rate of mountain hare predators was remarkably low in Muddus compared to the other areas (Table 1). The reason that there is no column for 'moose with calf' is that I had excluded them from the analysis because the models for the 'moose-pairs' analysis did not run. This was likely due to the overload of zero's in the 'moose with calf' data (only 8 of the 68 data points).

Table 1. Total raw passage rates of the focus species (group) and their potential predator captured in each area (B = Bodträskfors, M = Muddus, L = Lainio). The 'Moose' collumn represents only the single moose captures.

	Total raw passage rates per area						
Area	Hare	Moose	Bear	Hare predators			
В	26.1	18.1	3.4	19.5			
М	27.0	14.6	1.0	9.4			
L	10.0	35.8	8.0	26.0			

3.1 Simple linear regression

3.1.1 Mountain hare

In Bodträskfors and in Lainio there was no significant difference in patch utilization between the burned site and the control site although it appears so in the figure (figure 4). In Muddus the mountain hare had a significant higher patch utilization (p = 0.01) in the burned site (figure 4). Meaning that prediction 1a was not only not supported but even contradicted.

In Bodträskfors the explanatory variables for mountain hare patch utilization were in line with the theory about the effects of fire on the landscape features, namely that food availability and tree logs increase and that visibility decrease (figure 5) (although the difference in visibility between the two sites was not significant). This however did not appear to make the mountain hare utilize the control site significantly more as I had hypothesized. In Muddus and Lainio the food availability was also significantly higher in the burned sites but within each area the number of tree logs and the visibility were not significantly different between the two sites. This means that the assumptions I made about the change in landscape features after forest fire appear to be partly wrong.

The test summaries of the zero inflated models testing the differences in patch utilization can be found in Appendix B1 B2 and B3, and the post hoc test results of the differences in explanatory variables between the sites can be found in appendix B4, B5 and B6.

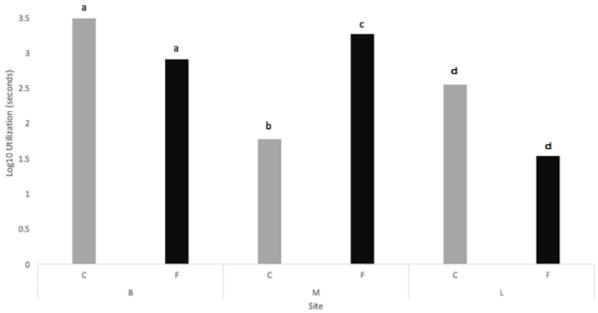


Figure 4. For each site (Bodträskfors = B, Muddus = M, Lainio = L and C stands for control site and F stands for fire site) an overview of the $\log 10$ patch utilization of mountain hare. In the areas Bodträskfors and Lainio there was no significant difference between the two sites, in Bodträskfors both sites belong to the same group a and in Lainio both sites belong to group d. In Muddus the patch utilization in the fire site was significantly higher (p = <0.01), then in the control site, the opposite of prediction 1a. The raw (non transformed) data is displayed in appendix D table D1. The test results of the zero-inflated models can be found in appendix B1, B2 and B3.

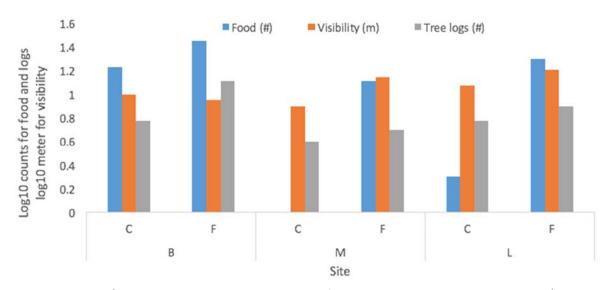


FIGURE 5. FOR EACH SITE (BODTRÄSKFORS = B, MUDDUS = M, LAINIO = L AND C STANDS FOR CONTROL SITE AND F STANDS FOR FIRE SITE) AN OVERVIEW OF THE LOG10 TRANSFORMED EXPLANATORY VARIABLES FOR MOUNTAIN HARE. IN EACH AREA THE FOOD AVAILABILITY WAS SIGNIFICANTLY LOWER IN THE CONTROL SITES, VISIBILITY WAS STATISTICALLY EQUAL BETWEEN THE SITES IN EACH AREA AND THE NUMBER OF TREE LOGS WERE ONLY SIGNIFICANTLY LOWER IN BODTRÄSKFORS IN THE CONTROL SITE. THE RAW (NON TRANSFORMED) DATA IS DISPLAYED IN APPENDIX D TABLE D1, AND THE TUKEY TEST RESULTS OF THE GLMS FOR 'FOOD' AND 'TREE LOGS', AND THE LM FOR 'VISIBILITY' ARE IN APPENDIX B4, B5 AND B6.

3.1.2 *Moose*

In all areas the patch utilization by moose was not significantly different between the burned and the control site (figure 5). This means that prediction 2a was not supported by the results, even though food availability was significantly higher in each of the burned sites compared to the adjacent control site (appendix C4). However, in Lainio the utilization was almost significantly higher in the burned site (p = 0.055).

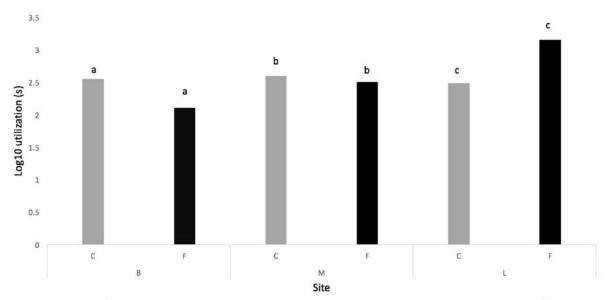


FIGURE 5. FOR EACH SITE (BODTRÄSKFORS = B, MUDDUS = M, LAINIO = L AND C STANDS FOR CONTROL SITE AND F STANDS FOR FIRE SITE) AN OVERVIEW OF THE LOG10 PATCH UTILIZATION OF MOOSE. IN NONE OF THE AREAS THERE IS A SIGNIFICANTLY HIGHER UTILIZATION OF THE FIRE SITE. THE RAW (NON TRANSFORMED) DATA IS DISPLAYED IN APPENDIX D TABLE D2, AND THE TEST RESULTS OF THE ZERO-INFLATED MODELS PER AREA CAN BE FOUND IN APPENDIX C1, C2 AND C3.

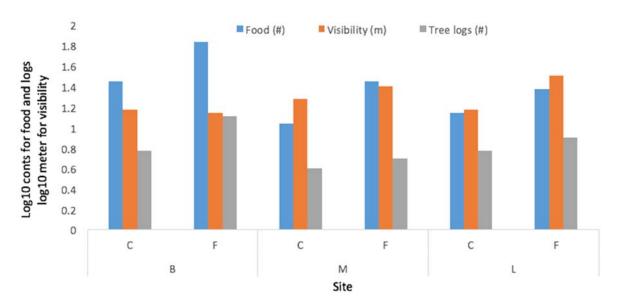


FIGURE 7. FOR EACH SITE (BODTRÄSKFORS = B, LAINIO = L, MUDDUS = M AND C STANDS FOR CONTROL SITE AND F STANDS FOR FIRE SITE) AN OVERVIEW OF THE LOG10 TRANSFORMED EXPLANATORY VARIABLES FOR MOOSE. THE RAW (NON TRANSFORMED) DATA IS DISPLAYED IN APPENDIX D TABLE D2, AND THE TUKEY TEST RESULTS OF THE GLMS AND THE LM CAN BE FOUNT IN APPENDIX A4, A6 AND A7.

3.2 Multiple linear regression per area

3.2.1 Mountain hare

For mountain hare, in Lainio the explanatory variable 'small trees' (<80 cm) was significantly correlated with 'visibility' (appendix E1) and therefore these two variables could not be put into one and the same model. From all the different models that I ran for analysing the relations between the mountain hares' patch utilization and the explanatory variables (appendix F1), I have presented those with the lowest AIC per area in table 2.

In none of the models the explanatory variables were related to patch utilization as proposed in prediction 1b (predicting that utilization is positively related to visibility and negatively to the number of tree logs). In every area the models had a very different outcome suggesting that the areas were indeed very different from each other (table 3). In Bodträskfors the utilization by mountain hare increased significantly with the number of small trees (food) (beta = 5.40, p = <0.001) and decreased significantly with visibility (beta = -6.94, p= <0.05). Furthermore, the number of tree logs was positively related with patch utilization in both Muddus (beta = 8.31, p = <0.001) and Lainio (beta = 5.81, p = <0.001).

Table 2. Best fitting models per area for mountain hare, a selection from all models (appendix F2). Part 1 is the counts part of the model that calculates the correlation between the dependent and the independent variables. Part 2 of the model is the 'logit' part that calculates if a detected zero was indeed a real zero (meaning that there were no mountain hares present) or an excess zero (meaning that there were mountain hare present but just not detected by the camera). The abbreviation 'Off.' stand for 'offset function'.

Area	Model part 1	Model part 2
Bodträskfors	Visibility*(-) + Food***(+) + Logs + Off. EDD + Off. Effort	Off. EDD + Off. Effort + Placement + Trail
Muddus	Visibility***(+) + Food^ + Logs***(+) + Off. EDD + Off. Effort	Off. EDD + Off. Effort + Placement + Trail
Lainio	Food***(+) + Logs***(+) + Off. EDD + Off. Effort + Placement***(+)	Off. EDD + Off. Effort + Placement + Trail

TABLE 3. SIGNIFICANT VARIABLES FROM THE COUNTS PART OF THE BEST FITTING MOUNTAIN HARE PATCH UTILIZATION MODELS FOR EACH AREA (TABLE 2). IN BODTRÄSKFORS THE FOOD AVAILABILITY WAS POSITIVELY CORRELATED AND VISIBILITY WAS NEGATIVELY CORRELATED TO PATCH UTILIZATION. IN MUDDUS BOTH VISIBILITY AND TREE LOGS WERE POSITIVELY CORRELATED AND IN LAINIO THE FOOD AVAILABILITY, TREE LOGS AND THE PLACEMENT WERE POSITIVELY CORRELATED TO PATCH UTILIZATION. FOR PLACEMENT THIS SUGGESTS THAT MOUNTAIN HARE PATCH UTILIZATION IS POSITIVELY CORRELATED TERRAIN WITH RELATIVELY LOW RUGGEDNESS. THE ESTIMATE IS THE COEFFICIENT OF THE RELATION BETWEEN THE INDEPENDENT VARIABLE AND THE DEPENDENT (PATCH UTILIZATION). THE MODEL SUMARIES CAN BE SEEN IN APPENDIX G1, G2 AND G3.

Area	Model AIC	Part 1 variables	P-value	Estimate
		Visibility	<0.05	-6,94
Bodträskfors	124.65	Food	<0.001	5,4
		Visibility	<0.001	7,04
Muddus	114.09	Logs	<0.001	8,31
		Food	<0.001	13,77
l		Logs	<0.001	5,81
Lainio	63.79	Placement	<0.001	5,13

3.2.2 *Moose*

For the moose analysis, there was a negative correlation between visibility (at 200 cm) and the number of small trees (<300 cm) in Muddus (appendix E2). Another limitation on the models was that I did not take into consideration the EDD for moose, since there was no relation between the distance at which a moose was captured on camera and the total number of captures on each camera, resulting in an equal EDD for all cameras which made the correction for EDD useless. From all the different models that I ran for analysing the relations between the patch utilization by moose and the explanatory variables (appendix F2), I have presented those with the lowest AIC per area in table 4.

In Bodträskfors as well as in Muddus there appeared to be no correlation between any of the explanatory variables and the patch utilization of moose. In Lainio the food availability was however indeed positively related to patch utilization (table 5), and this advocates for prediction 2b (that predicted a positive correlation between food availability and utilization, and no correlation with visibility and the number of tree logs). Yet, these results do not provide enough proof to suspect that prediction 2b is supported.

Table 4. Best fitting models per area for moose, a selection from all models (appendix F2). Part 1 is the 'counts' part of the model that calculates the correlation between the dependent and the independent variables. Part 2 of the model is the 'logit' part that calculates if a detected zero was indeed a real zero (meaning that there were no mountain hares present) or an excess zero (meaning that there were mountain hare present but just not detected by the camera). In Bodträskfors 'placement' was a significant predictor for if a zero would be an excessive zero, and in this case it means that random placement of a camera increased the odds of a zero value actually being a zero because there were no moose there. The abbreviation 'Off.' stand for 'offset function'.

Area	Model part 1	Model part 2	AIC
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort	Off. Effort + Placement* + Trail	123.06
Muddus	Food + Logs + Off. EDD + Off. Effort	Off. Effort + Placement + Trail	126.92
Lainio	Visibility + Food* + Logs + Off. EDD + Off. Effort + Placement***	Off. Effort + Placement + Trail	205.39

Table 5. Significant variables from the counts part of the best fitting moose patch utilization models for each area (table 4). Food availability is positively correlated, and placement is negatively correlated in Lainio. The estimate is the coefficient of the relation between the independent variable and the dependent (patch utilization). The model sumaries can be seen in appendix G1, G2 and G3.

Area	Model AIC	Part 1 variables	P-value	Estimate
Bodträskfors	123.06	-	-	-
Muddus	126.92	-	-	-
		Placement	<0.001	-2,1
Lainio	205.39	Food	<0.05	1,11

4. Discussion

In this correlative study I have aimed to test if the patch utilization in herbivore prey species is influenced by previous forest fires, and more specifically if patch utilization is correlated to the presence of risk factors such as low visibility and escape impediments that are thought to increase perceived increase predation risk. In order to test this, I have done a cross-sectional camera trap study throughout three different forests that each contained two forest treatments; a burned and an unburned (control) site. In these sites I collected data on the patch utilization of mountain hare and moose with the use of camera traps, and around each camera trap I collected data on food availability, visibility and the number of tree logs. I predicted that patch utilization of the mountain hare, that is assumed to have a high predation pressure, would be higher in the control sites then in the burned site (prediction 1a), and that this utilization would be positively predicted by visibility and negatively predicted by tree logs (prediction 1b). Furthermore, I predicted that patch utilization of moose, that is assumed to not be predated, would be higher in the burned sites (prediction 2a) and that this would be positively predicted by food availability (prediction 2b).

With the collected data I therefore first tested, with a simple linear regression, if there were any significant differences in patch utilization between the burned and the control site in each area. I also tested for differences in the explanatory variables between the burned and the control site, that could possibly help me to explain the patterns (or the lack of) in patch utilization better, and to see if indeed my assumptions about the effect of forest fires on the landscape features (food availability, visibility and tree logs) were accurate. Then secondly I tested, with a multiple regression analysis per species and per area, which of the explanatory variables were significant predictors for patch utilization. However, none of my predictions were supported by the results of this study.

4.1 Mountain hare

The patch utilization of mountain hare was not significantly higher in the control sites then in the burned sites in two of the three areas (Bodträskfors and Lainio), meaning that there was no support for prediction 1a. Moreover, in Muddus the patch utilization was even significantly higher in the burned site and thereby even contradicts this prediction. The fact that in this area the patch utilization was significantly higher in the burned site, can be explained by the results from the simple linear regression of the explanatory variables, which show that food availability in Muddus was almost zero in the control plot (figure 5). This might have forced the mountain hare to utilize other patches that did provided more foraging possibilities (Benhaiem et al., 2008). Furthermore, the difference in perceived predation risk between the two sites in Muddus might have been very small since perceived predation risk is increased by the immanent presence of predators (Périquet et al., 2012) and the predator passage rate in Muddus was relatively low (table 1), which possibly indicates a low predator presence. As such, the importance of risk factors is affected by predator presence, suggesting that the risk factors are perceived as less fearful when there is a low (or no) immanent threat of predators (Kuyper et al., 2015). This in combination with the low food availability in the control site, could explain the observed pattern in Muddus that patch utilization is higher in the burned site.

Furthermore; in two of the three areas (in Muddus and Lainio) there was no significant difference in the visibility nor in the number of tree logs between the two sites (appendix B5 and B6). Suggesting that at these latitudes forest fires do not necessarily have the assumed influence on these landscape features (namely, increased number of tree logs and decreased visibility) within the time since fire (~12 years). For visibility (which is related to vegetation density) this could be explained by the fact that in these higher latitude areas (Muddus and Lainio) the plant growths rates and succession speed of vegetation are lower than in the lower latitude area Bodträskfors (Svoboda et al., 1987). For the number of tree logs the lack of a significant difference between the two sites in the higher latitude areas (Muddus and Lainio), could be explained by the fact that at these latitudes fungus infections and other

pathogens, that are commonly the cause of death in fire scarred trees (Lombardero et al., 2006), do proceed at a lower speed as well. The actual difference in the number of tree logs between the burned and the control site in each area (figure 4), was indeed much bigger in Bodtraskfors then in Muddus and Lainio. Suggesting that my assumptions on the physical differences in landscape features between the burned and the control sites were inaccurate or un fulfilled still, and that this difference in successional stage (since fire) between the areas is a possible reason for not finding my predicted results. However, this does not explain why I did not find any significant difference in the lower latitude area Bodträskfors.

Not finding the predicted results for mountain hare, could also be explained by the possibility that my hypothesis about the effects of the landscape features on the mountain hare patch utilization, were fundamentally wrong for this specific species in this specific habitat. This becomes clearer in the light of the results from the multiple regression analyses, which tested the correlation of patch utilization with the explanatory variables. The fact that in both Muddus and in Lainio the path utilization was positively correlated to the number of tree logs (table 3) instead of negatively correlated as I had predicted, might suggest that for mountain hares the presence of tree logs is a positive contribution to their habitat. A possible explanation for this reversed effect of tree logs on the perceived predation risk, is the influence of birds of prey (raptors), who are known to be a dominant predator for mountain hares (Nyström, 2004; Nyström et al., 2006) but who's influence could not be measured in this study. As such, for a prey like the mountain hare, tree logs will likely be a form of protection against raptors, since they can hide under the logs when a raptor is signalled. This then could also provide an explanation for the negative correlation of visibility with patch utilization in Bodträskfors since a decreased visibility (indicating a denser vegetation that provides more cover) would benefit the mountain hare in the case of being predated by raptors (Moreno et al., 1996). This then would implicate that, if raptors would be the only predators for mountain hare, the mountain hare does not experience an energetic trade-off in the burned sites, but rather experiences a win-win situation when indeed food availability, vegetation density and tree logs all increase after fire. Providing a habitat that both offers abundant food as well as cover and safety from predation.

The different traits and hunting strategies within the predator community associated with mountain hares, make it difficult to interpret the effects of landscape features on prey species' patch utilization. Since the way certain landscape features influence perceived predation risk in prey is determined by the predator (and its hunting strategy) onto which the prey anticipates its behaviour (Kaufmann et al., 2007; Bergman et al., 2006; Hopcraft et al., 2005; Podgórsky et al., 2008).

Another plausible explanation for the results of this study could be that the mountain hare does not anticipate on predation risk by adapting its spatial distribution, but rather by adapting its temporal distribution patterns (Jacob & Brown, 2000; Ross et al., 2013). Meaning that the mountain hare would avoid utilizing 'risky' patches at the time of day where predator activity is peaking, but would utilize the risky patches at a time where predator activity is low, and thus the perceived predation risk as well (Périquet et al., 2012).

4.2 Moose

For moose there seems to be no clear preference for utilizing burned sites over control sites as suggested by MacCracken & Viereck (1990). Even though food availability was significantly higher in all burned sites (figure 6), the patch utilization of moose was not significantly higher in the burned sites compared to the control sites in any of the three areas (figure 5). In Lainio though, patch utilization was almost significantly higher in the burned site (p = 0.055) (appendix C3), which possibly suggest that an increase in data points might result in a significant difference. This however means that these results do not support prediction 2a, and suggests already that prediction 2b (that moose patch utilization is significantly predicted by food availability) is also not supported. The multiple regression analysis

indeed showed that prediction 2b was not convincingly supported, since in two of the three areas (Bodträskfors and Muddus) there was no significant predictor for patch utilization. In Lainio however, there was a significant positive relation between food availability and patch utilization and this makes more sense considering the fact that - as mentioned above - in that area the patch utilization of moose was almost significantly higher in the burned site and food availability was significantly higher as well.

A plausible explanation for not finding significant results that support my prediction, is that implicitly in my method I assumed that utilization would always be in the form of foraging. Considering the large home range of moose (Cederlund & Sand, 1994), which is many times larger than the study sites, it could be that patch utilization in my data, actually was a high number of individuals that did not forage but were just passing through very quickly. In this case it would be logical not to find a correlation between food availability and patch utilization.

Furthermore, the fact that food availability was not a significant predictor for patch utilization by moose could also have a methodological explanation, namely that the number of small trees might not be an accurate proxy for food availability in the summer (when the cameras where active). In the summer season the herb layer, that mainly consists of heather, (mostly blueberry (*Vaccinium Myrtillus*)) is very rich and provides a large part (~42%) of the moose's diet (Wam et al., 2010) and also a large part of the mountain hares diet (Wolfe et al., 1996). Taking this into consideration after having seen the abundant herb layer in all three areas, it seems more likely that food is abundant almost everywhere and that small trees alone might not be a good proxy for food availability for these herbivore species during the summer season.

4.3 General discussion

The data I collected on patch utilization of mountain hare and moose consisted of a very high amount of zero values (resulting from the low number of passages). This imposed some restrictions on my analysis, since it limited the power of my analysis and the number of variables I could include in my models. Combining the low number of observations with the fact that there was a variation among the different camera trap plots within an area, and a high variation among the areas as well, provides an explanation for not finding significant correlations since the models based their outcomes mainly on outliers (not on bundled data). To overcome this problem in future research I would suggest three changes to the study design. Firstly, I would try to conduct the study in areas with a higher density of the focus species in order to have a higher capture rate. Secondly I would increase the number of replicates per data point so that each data point is an average of these replicates. This would decrease the variation between the camera traps. Thirdly, I would try to find areas that are more similar, in order to be able to use all data in one model.

4.4 Conclusions

However, all in all I would conclude from my reflections on the results for mountain hare that depending on the composition (species types and densities) of the predator community and their hunting strategies, the landscape features will have a different effect on the perceived predation risk and the way prey species anticipate their behaviour to it (utilizing safer patches or utilizing them at safer times of the day). And that in a study area with different predator types present, it is difficult to find strong correlations between the landscape features and patch utilization, since these features are ambiguous in their effect on perceived predation risk. Therefore, on the basis this study, it remains difficult to draw clear conclusions about the actual effect forest fires on predator-prey interactions. For moose it seems plausible that their patch utilization is indeed predicted by food availability as was the case in Lainio, but that this correlation was not found in the other areas because of the lack of data points and/or an inaccurate proxy for food availability.

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Appendix

Appendix A

TABLE A1. TOTAL RAW PASSAGES OF THE FOCUS SPECIES IN EACH AREA (B= BODTRÄSKFORS, M = MUDDUS, L = LAINIO). THE 'MOOSE' COLLUMN REPRESENTS ONLY THE SINGLE MOOSE CAPTURES AND 'MOOSE WITH CALF' WAS EXCLUDED FROM THE ANALYSIS BECAUSE OF TOO FEW DATA POINTS.

Total raw passages per area					
Area	Hare	Moose	Bear	Hare predators	
В	30	21	4	21	
M	26	14	1	8	
L	10	36	8	26	
Total	66	71	13	55	

Appendix B

TABLE B1.

ZERO-INFLATED SIMPLE LINEAR REGRESSION FOR BODTRÄSKFORS. TESTING IF MOUNTAIN HARE PATCH UTILIZATION IS SIGNIFICANTLY DIFFERENT BETWEEN SITES WITHIN THE SAME AREA. THERE IS NO SIGNIFICANT DIFFERENCE IN MOUNTAIN HARE PATCH UTILIZATION BETWEEN THE BURNED/FIRE SITE IN BODTRÄSKFORS (BF) AND THE CONTROL SITE IN BODTRÄSKFORS. THIS TABLE ALSO SHOWS THAT THERE WAS ALSO NO SIGNIFICANT VARIABLE AFFECTING THE EXCESS ZERO'S.

```
Call:
```

```
zeroinfl(formula = Hare_Uti ~ Site | offset(log(EDDHare)) + offset(log(cam.days)) +
   Placement + Trail, data = Sub.Bod.Data, dist = "negbin")
Pearson residuals:
            1Q Median
                             3Q
-0.3284 -0.3252 -0.2041 -0.1411 2.5941
Count model coefficients (negbin with log link):
            Estimate Std. Error z value Pr(>|z|)
                         1.0168 4.515 6.34e-06 ***
(Intercept)
            4.5908
                         1.5524 -0.637 0.524
0.4538 -4.905 9.34e-07 ***
SiteBF
             -0.9887
Log(theta)
            -2.2259
Zero-inflation model coefficients (binomial with logit link):
           Estimate Std. Error z value Pr(>|z|)
                        1.328 -3.262 0.00111 **
105.156 -0.105 0.91607
(Intercept) -4.333
PlacementR -11.082
Trail1
              -4.728
                         22.916 -0.206 0.83655
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 0.108
Number of iterations in BFGS optimization: 131
Log-likelihood: -55.37 on 6 Df
```

TABLE B2.

Zero-inflated simple linear regression for Muddus. Testing if mountain hare patch utilization is significantly different between sites within the same area. There is a significant difference in mountain hare patch utilization between the burned/fire site in Muddus (MF) and the control site in Muddus (p = <0.01). This table also shows that there was no significant variable affecting the excess zero's.

```
zeroinfl(formula = Hare_Uti ~ Site | offset(log(EDDHare)) + offset(log(cam.days)) +
   Placement + Trail, data = Sub.Mud.Data, dist = "negbin")
Pearson residuals:
    Min
             10 Median
                                30
                                        Max
-0.41176 -0.39280 -0.36247 -0.06329 1.69027
Count model coefficients (negbin with log link):
           Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.5883
                        1.7528 0.336 0.73715
                        1.2063 2.966 0.00302 **
             3.5779
SiteMF
                        2.6839 -0.630 0.52875
Log(theta) -1.6906
Zero-inflation model coefficients (binomial with logit link):
           Estimate Std. Error z value Pr(>|z|)
                        2.811 -1.691
20.916 -0.165
(Intercept)
             -4.754
                                         0.0908 .
PlacementR
             -3.459
                                         0.8687
Trail1
             -2.326
                         6.687 -0.348 0.7279
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 0.1844
Number of iterations in BFGS optimization: 34
```

TABLE B3.

Log-likelihood: -46.88 on 6 Df

Zero-inflated simple linear regression for Lainio. Testing if mountain hare patch utilization is significantly different between sites within the same area. There is no significant difference in mountain hare patch utilization between the burned/fire site in Lainio (LF) and the control site in Lainio. This table also shows that there was no significant variable affecting the excess zero's either.

```
Call:
zeroinfl(formula = Hare_Uti ~ Site | offset(log(EDDHare)) + offset(log(cam.days)) +
   Placement + Trail, data = Sub.Lai.Data, dist = "negbin")
Pearson residuals:
   Min
           1Q Median
                           3Q
                                  Max
-0.2642 -0.2642 -0.2416 -0.0538 2.8384
Count model coefficients (negbin with log link):
           Estimate Std. Error z value Pr(>|z|)
(Intercept)
           2.0586
                        1.0933 1.883 0.0597
SiteLF
             -1.7381
                        1.9719 -0.881
                                        0.3781
            -2.6529
                        0.5707 -4.649 3.34e-06 ***
Log(theta)
Zero-inflation model coefficients (binomial with logit link):
           Estimate Std. Error z value Pr(>|z|)
(Intercept)
             3.582
                      115.030 0.031
                                         0.975
PlacementR
            -11.202
                       115.353 -0.097
                                          0.923
                      198.898 -0.085
Trail1
            -16.908
                                         0.932
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Number of iterations in BFGS optimization: 661
Log-likelihood: -26.46 on 6 Df
```

TABLE B4.

MULTIPLE COMPARISONS TEST: TUKEY CONTRASTS TEST. TESTING IF THE NUMBER OF SMALL TREES (FOOD AVAILABILITY) IS SIGNIFICANTLY DIFFERENT BETWEEN THE TWO SITES WITHIN THE SAME AREAS. IN THIS TABLE WE SEE THAT IN EACH AREA THE TWO SITES ARE SIGNIFICANTLY DIFFERENT FROM EACH OTHER.

Simultaneous Tests for General Linear Hypotheses

```
Multiple Comparisons of Means: Tukey Contrasts
```

```
Fit: glm(formula = TreeHare ~ Site, family = poisson(link = "log"),
    data = Plot_Data)
```

Linear Hypotheses:

```
Estimate Std. Error z value Pr(>|z|)
BF - BC == 0 0.49739 0.09052 5.495 <0.001 ***
LC - BC == 0 -1.91201 0.19560 -9.775 <0.001 ***
LF - BC == 0 0.14638 0.09582 1.528
                                           0.611
                                          <0.001 ***
MC - BC == 0 -2.64598 0.29708 -8.906
MF - BC == 0 - 0.29172
                        0.11009 -2.650
                                           0.072 .
                                           <0.001 ***
LC - BF == 0 -2.40940
                       0.19131 -12.594
LF - BF == 0 -0.35101 0.08674 -4.047 <0.001 ***
MC - BF == 0 -3.14337
                        0.29428 -10.682 <0.001 ***
MF - BF == 0 - 0.78911
                         0.10228 -7.715
                                           <0.001 ***
                                          <0.001 ***
LF - LC == 0 2.05839
                       0.19388 10.617
MC - LC == 0 - 0.73397 \quad 0.34157 \quad -2.149
                                           0.232
                       0.20131 8.049
0.29595 -9.435
MF - LC == 0 1.62029
                                          <0.001 ***
MC - LF == 0 -2.79236
                                          <0.001 ***
                        0.10700 -4.094 <0.001 ***
MF - LF == 0 -0.43810
MF - MC == 0 2.35426 0.30088 7.825 <0.001 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Adjusted p values reported -- single-step method)
```

TABLE B5.

MULTIPLE COMPARISONS TEST: TUKEY CONTRASTS TEST. TESTING IF VISIBILITY AT 30 CM ABOVE THE GROUND IS SIGNIFICANTLY DIFFERENT BETWEEN THE TWO SITES WITHIN THE SAME AREAS. IN THIS TABLE WE SEE THAT ONLY MF AND LF, AND LF AND BF ARE SIGNIFICANTLY DIFFERENT FROM EACH OTHER AND THUS THAT THERE ARE NO SIGNIFICANT DIFFERENCES BETWEEN THE SITES IN THE SAME AREA.

```
Simultaneous Tests for General Linear Hypotheses
```

Multiple Comparisons of Means: Tukey Contrasts

```
Fit: lm(formula = Vis.30 ~ Site, data = Plot_Data)
 Linear Hypotheses:
                                           BF - BC -- 0
LC - BC -- 0
MF - BF -- 0
MF - BF -- 0
MF - LC -- 0
                                                                                          2.061
2.016
2.016
2.114
2.061
2.061
2.157
2.105
2.016
2.114
2.061
2.114
2.061
2.157
                                                 -2.250
3.386
2.833
6.583
-1.000
4.636
3.750
-3.833
1.803
-7.583
-1.947
5.636
                                                                                                                                           0.89341
0.57355
0.74158
0.02564
0.99720
0.25153
0.43563
0.46477
                                                                                                              1.643
1.375
3.194
-0.464
2.202
1.860
-1.813
0.875
-3.587
-0.945
2.613
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (Adjusted p values reported -- single-step method)
```

TABLE B6.

MULTIPLE COMPARISONS TEST: TUKEY CONTRASTS TEST. TESTING IF THE TOTAL NUMBER OF TREE LOGS IS SIGNIFICANTLY DIFFERENT BETWEEN SITES. ONLY IN BODTRÄSKFORS THERE IS A SIGNIFICANT DIFFERENCE BETWEEN THE BURNED SITE AND THE CONTROL SITE (P = <0.001).

Simultaneous Tests for General Linear Hypotheses

Multiple Comparisons of Means: Tukey Contrasts

Fit: glm(formula = DeadTot ~ Site, family = poisson(link = "log"),
 data = Plot_Data)

Linear Hypotheses:

```
Estimate Std. Error z value Pr(>|z|)
                          0.1458 5.832 < 0.001 ****
0.1653 0.742 0.97576
0.1565 2.371 0.16128
BF - BC == 0 0.8501
               0.1226
0.3711
LC - BC == 0
LF - BC == 0
MC - BC == 0 -0.4683
                            0.2056 -2.278 0.19717
MF - BC == 0
               -0.1959
                            0.1836 -1.066 0.89122
LC - BF == 0
               -0.7275
                            0.1399 -5.200 < 0.001 ***
LF - BF == 0
                                     -3.701 0.00291 **
               -0.4791
                            0.1294
MC - BF == 0
                           0.1858 -7.094 < 0.001 ***
               -1.3184
                           0.1612 -6.488 < 0.001 ***
0.1511 1.645 0.56020
MF - BF == 0
               -1.0460
LF - LC == 0
               0.2485
MC - LC == 0
               -0.5909
                            0.2015 -2.932 0.03789 *
MF - LC == 0
               -0.3185
                            0.1790
                                     -1.779 0.47092
MC - LF == 0 -0.8393
                            0.1944 -4.318 < 0.001 ***
                            0.1710 -3.316 0.01129 * 0.2168 1.256 0.80315
MF - LF == 0 -0.5669
               0.2724
MF - MC == 0
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (Adjusted p values reported -- single-step method)

TABLE C1.

ZERO-INFLATED SIMPLE LINEAR REGRESSION FOR BODTRÄSKFORS. TESTING IF MOOSE PATCH UTILIZATION IS SIGNIFICANTLY DIFFERENT BETWEEN SITES WITHIN THE SAME AREA. THERE IS NO SIGNIFICANT DIFFERENCE IN MOUNTAIN HARE PATCH UTILIZATION BETWEEN THE BURNED/FIRE SITE IN BODTRÄSKFORS (BF) AND THE CONTROL SITE IN BODTRÄSKFORS. THIS TABLE ALSO SHOWS THAT THERE WAS ALSO NO SIGNIFICANT VARIABLES AFFECTING THE EXCESS ZERO'S.

```
zeroinfl(formula = MoS_Uti ~ Site | offset(log(cam.days)) + Placement + Trail, data = Sub.Bod.Data, dist = "neabin")
Pearson residuals:
Min 1Q Median 3Q Max
-0.9037 -0.5536 -0.2097 -0.1851 4.2003
Count model coefficients (negbin with log link):
Estimate Std. Error z value Pr(>IzI)
                        0.33361 13.126
0.62487 -0.092
0.52880 1.152
(Intercept) 4.37909
SiteBF -0.05772
Log(theta) 0.60927
                                              0.926
                                             0.249
Zero-inflation model coefficients (binomial with logit link):
0.0413
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 1.8391
Number of iterations in BFGS optimization: 22
Log-likelihood: -49.22 on 6 Df
```

TABLE C2.

ZERO-INFLATED SIMPLE LINEAR REGRESSION FOR MUDDUS. TESTING IF MOOSE PATCH UTILIZATION IS SIGNIFICANTLY DIFFERENT BETWEEN SITES WITHIN THE SAME AREA. THIS TABLE SHOWS THAT THERE IS NO SIGNIFICANT DIFFERENCE IN MOUNTAIN HARE PATCH UTILIZATION BETWEEN THE BURNED/FIRE SITE IN MUDDUS (MF) AND THE CONTROL SITE IN MUDDUS. THIS TABLE ALSO SHOWS THAT THERE WAS ALSO NO SIGNIFICANT VARIABLE AFFECTING THE EXCESS ZERO'S.

```
zeroinfl(formula = MoS_Uti ~ Site | offset(log(cam.days)) + Placement + Trail, data = Sub.Mud.Data,
    dist = "neabin")
Pearson residuals:
       Min
                     10
                              Median
                                               30
-4.671e-01 -4.001e-01 -2.281e-01 -4.955e-05 2.459e+00
Count model coefficients (negbin with log link):
Estimate Std. Error z value Pr(>|z|)
(Intercept) 4.5625 0.9959 4.581 4.62e-06
SiteMF -0.5405 1.1967 -0.452 0.652
Log(theta) -1.0638
                             0.8639 -1.231
                                                  0.218
Zero-inflation model coefficients (binomial with logit link):
Estimate Std. Error z value Pr(>|z|)
(Intercept) 13.90 4554.13 0.003 0.998
PlacementR -18.62 4554.13 -0.004 0.997
Trail1
                -19.31
                          4554.13 -0.004
                                                 0.997
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 0.3451
Number of iterations in BFGS optimization: 26
Log-likelihood: -52.3 on 6 Df
```

TABLE C3.

ZERO-INFLATED SIMPLE LINEAR REGRESSION FOR LAINIO. TESTING IF MOOSE PATCH UTILIZATION IS SIGNIFICANTLY DIFFERENT BETWEEN SITES WITHIN THE SAME AREA. THIS TABLE SHOWS THAT THERE IS ALMOST A SIGNIFICANT DIFFERENCE IN MOUNTAIN HARE PATCH UTILIZATION BETWEEN THE BURNED/FIRE SITE IN MUDDUS (MF) AND THE CONTROL SITE IN MUDDUS. THIS TABLE ALSO SHOWS THAT THERE WAS ALSO NO SIGNIFICANT VARIABLE AFFECTING THE EXCESS ZERO'S.

```
zeroinfl(formula = MoS_Uti ~ Site | offset(log(cam.days)) + Placement + Trail, data = Sub.Lai.Data,
    dist = "negbin")
Pearson residuals:
             1Q Median
    Min
                              30
-0.5374 -0.4884 -0.4317 -0.1584 3.2697
Count model coefficients (negbin with log link):
            Estimate Std. Error z value Pr(>IzI)
3.5226 0.6572 5.360 8.32e-08
(Intercept) 3.5226
              1.5977
                          0.8316
                                   1.921 0.0547
SiteLF
Log(theta) -0.9178
                          0.6248 -1.469 0.1419
Zero-inflation model coefficients (binomial with logit link):
           Estimate Std. Error z value Pr(>|z|)

-4.7657 1.0005 -4.763 1.9e-06 ***
(Intercept) -4.7657
PlacementR
           -0.8955
                          1.1708 -0.765
                                            0.444
Trail1
             -0.2683
                          1.1820 -0.227
                                            0.820
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 0.3994
Number of iterations in BFGS optimization: 11
Log-likelihood: -92.16 on 6 Df
```

Table C4. Multiple comparisons test: Tukey contrasts test. Testing if the number of small trees (<300 cm) is significantly different between sites. For the analysis in this study I am only interested the differences between sites in the same area.

```
Simultaneous Tests for General Linear Hypotheses
Multiple Comparisons of Means: Tukey Contrasts
Fit: glm(formula = TreeMoose ~ Site, family = poisson(link = "log"),
     data = Plot_Data)
Linear Hypotheses:
                Estimate Std. Error z value Pr(>|z|)
0.86558 0.06532 13.252 <0.001
-0.74106 0.09518 -7.786 <0.001
BF - BC == 0 0.86558
                                                        <0.001 ***
LC - BC == 0 -0.74106
                                                         <0.001 ***
LC - BC == 0 -0.74106

LF - BC == 0 -0.18232

MC - BC == 0 -0.98905

MF - BC == 0 -0.01123

LC - BF == 0 -1.60665
                                 0.08020
                                            -2.273
                                                          0.195
                                 0.11117
0.07842
                                            -8.897
                                                        <0.001
                                                          1.000
                                            -0.143
                                                         <0.001 ***
                                 0.08647 -18.580
                                                        <0.001 ***
   - BF == 0 -1.04791
                                 0.06965 -15.045
MC - BF == 0 -1.85463
MF - BF == 0 -0.87681
                                 0.10381 -17.866
0.06759 -12.973
                                                         <0.001 ***
LF - LC == 0 0.55874
MC - LC == 0 -0.24799
                                 0.09820
                                             5.690
                                                         <0.001 ***
                                            -1.987
7.543
-7.091
                                 0.12478
                                                          0.336
      LC == 0 0.72983
                                 0.09675
                                                         <0.001 ***
                                                         <0.001 ***
MC - LF == 0 - 0.80673
                                 0.11377
      LF == 0
                  0.17109
MF
                                 0.08206
                                             2.085
                                                          0.283
MF - MC == 0
                  0.97782
                                 0.11252
                                             8.691
                                                         <0.001 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Adjusted p values reported -- single-step method)

Table C5. Multiple comparisons test: Tukey contrasts test. Testing if visibility at 200 cm above the ground is significantly different between sites. For the analysis in this study I am only interested the differences between sites in the same area.

Appendix D

TABLE D1. RAW HARE DATA PER SITE.

	Hare data per Site						
Site	Adjusted Passage rate	Utilization by APR (sec.)	Food	Visibility	Tree logs		
ВС	53	3034	17	10	6		
BF	45	794	28	9	13		
LC	25	347	2	12	6		
LF	10	34	20	16	8		
МС	12	59	1	8	4		
MF	85	1825	13	14	5		

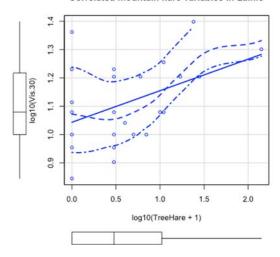
TABLE D2. RAW MOOSE DATA PER SITE.

	Moose data per site						
Site	Passage rate	Utilization by PR (sec.)	Food	Visibility	Tree logs		
ВС	5	357	28	15	6		
BF	13	128	68	14	13		
LC	12	305	14	15	6		
LF	24	1426	24	32	8		
МС	5	397	11	19	4		
MF	9	320	28	25	5		

Appendix E

E1. VISUALISATION AND TEST RESULTS OF CORRELATED EXPLANATORY VARIABLES IN THE MOUNTAIN HARE ANALYSES. I TESTED CORRELATIONS BETWEEN ALL VARIABLES WITH A LINEAR MODEL. ONLY VISIBILITY AT 30 CM HEIGHT WAS SIGNIFICANTLY POSITIVELY AFFECTED BY THE AMOUNT OF YOUNG TREES UNDER 80cm (BETA=0.11, P =<0.05).

Correlated mountain hare variables in Lainio



Call:

lm(formula = log10(Vis.30) ~ log10(TreeHare + 1), data = Sub.Lai.Data)

Residuals:

Min 1Q Median 3Q Max -0.19831 -0.09102 -0.00899 0.07944 0.31832

Coefficients:

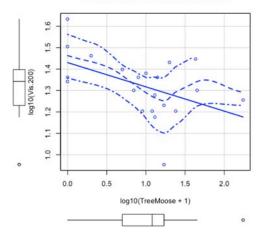
Estimate Std. Error t value Pr(>|t|) (Intercept) 1.04340 0.04135 25.234 <2e-16 *** log10(TreeHare + 1) 0.11145 0.04937 2.258 0.0342 * Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.134 on 22 degrees of freedom Multiple R-squared: 0.1881, Adjusted R-squared: 0.1512

F-statistic: 5.097 on 1 and 22 DF, p-value: 0.03423

E2. VISUALISATION AND TEST RESULTS OF CORRELATED EXPLANATORY VARIABLES IN THE MOOSE ANALYSES. I TESTED CORRELATIONS BETWEEN ALL VARIABLES WITH A LINEAR MODEL. ONLY VISIBILITY AT 200 cm Height was significantly negatively affected by the amount of young trees under 300 cm (beta= -0.11, p =<0.05).

Correlated moose variable in Muddus



Call:

lm(formula = log10(Vis.200) ~ log10(TreeMoose + 1), data = Sub.Mud.Data)

Residuals:

Min 1Q Median 3Q Max -0.33682 -0.06996 0.03353 0.06592 0.20285

Coefficients:

Estimate Std. Error t value Pr(>ltl)
(Intercept) 1.43062 0.05275 27.119 <2e-16 ***
log10(TreeMoose + 1) -0.11342 0.04739 -2.393 0.0272 *
--Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1281 on 19 degrees of freedom Multiple R-squared: 0.2317, Adjusted R-squared: 0.1912 F-statistic: 5.728 on 1 and 19 DF, p-value: 0.02717

Appendix F

Table F1. Different tested models for mountain hare. In Lainio there was a correlation between the amount of young trees (<80cm) and the visibility for hare. Therefore, they could not be in the same model. The best models (most parsimonous) are indicated in bold.

	Mountain hare					
Area	Model part 1	Model part 2	AIC			
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. EDD + Off. Effort + Placement + Trail	133.03			
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement	Off. EDD + Off. Effort + Placement + Trail	118.65			
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort + Trail	Off. EDD + Off. Effort + Placement + Trail	130.62			
Bodträskfors	Visibility*(-) + Food***(+) + Logs + Off. EDD + Off. Effort	Off. EDD + Off. Effort + Placement + Trail	124.65			
Muddus	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. EDD + Off. Effort + Placement + Trail	125.53			
Muddus	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement	Off. EDD + Off. Effort + Placement + Trail	119.03			
Muddus	Visibility + Food + Logs + Off. EDD + Off. Effort + Trail	Off. EDD + Off. Effort + Placement + Trail	119.96			
Muddus	Visibility***(+) + Food^ + Logs***(+) + Off. EDD + Off. Effort	Off. EDD + Off. Effort + Placement + Trail	114.09			
Lainio	Visibility + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. EDD + Off. Effort + Placement + Trail	64.15			
Lainio	Visibility + Logs + Off. EDD + Off. Effort + Placement	Off. EDD + Off. Effort + Placement + Trail	73.37			
Lainio	Visibility + Logs + Off. EDD + Off. Effort + Trail	Off. EDD + Off. Effort + Placement + Trail	71.31			
Lainio	Visibility + Logs + Off. EDD + Off. Effort	Off. EDD + Off. Effort + Placement + Trail	69.03			
Lainio	Food + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. EDD + Off. Effort + Placement + Trail	64.55			
Lainio	Food***(+) + Logs***(+) + Off. EDD + Off. Effort + Placement***(+)	Off. EDD + Off. Effort + Placement + Trail	63.79			
Lainio	Food + Logs + Off. EDD + Off. Effort + Trail	Off. EDD + Off. Effort + Placement + Trail	71.09			
Lainio	Food + Logs + Off. EDD + Off. Effort	Off. EDD + Off. Effort + Placement + Trail	66.49			

Table F2. Different tested models for moose. In Muddus there was a correlation between the amount of young trees (<300cm) and the visibility for moose. Therefore, they could not be in the same model. The best models (most parsimonous) are indicated in bold.

Moose single			
Area	Model part 1	Model part 2	AIC
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. Effort + Placement + Trail	-
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement	Off. Effort + Placement + Trail	129.73
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort + Trail	Off. Effort + Placement + Trail	127.36
Bodträskfors	Visibility + Food + Logs + Off. EDD + Off. Effort	Off. Effort + Placement* + Trail	123.06
Muddus	Food + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. Effort + Placement + Trail	143.31
Muddus	Food + Logs + Off. EDD + Off. Effort + Placement	Off. Effort + Placement + Trail	132.29
Muddus	Food + Logs + Off. EDD + Off. Effort + Trail	Off. Effort + Placement + Trail	132.29
Muddus	Food + Logs + Off. EDD + Off. Effort	Off. Effort + Placement + Trail	126.92
Muddus	Visibility + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. Effort + Placement + Trail	-
Muddus	Visibility + Logs + Off. EDD + Off. Effort + Placement	Off. Effort + Placement + Trail	132.39
Muddus	Visibility + Logs + Off. EDD + Off. Effort + Trail	Off. Effort + Placement + Trail	132.39
Muddus	Visibility + Logs + Off. EDD + Off. Effort	Off. Effort + Placement + Trail	127.28
Lainio	Visibility + Food + Logs + Off. EDD + Off. Effort + Placement + Trail	Off. Effort + Placement + Trail	211.42
Lainio	Visibility + Food* + Logs + Off. EDD + Off. Effort + Placement***	Off. Effort + Placement + Trail	205.39
Lainio	Visibility + Food + Logs + Off. EDD + Off. Effort + Trail	Off. Effort + Placement + Trail	213.71
Lainio	Visibility + Food + Logs + Off. EDD + Off. Effort	Off. Effort + Placement + Trail	208.84

Appendix G

```
G1. SUMMARY OF BEST FITTING ZERO-INFLATED MULTI LINEAR REGRESSION MODEL FOR MOUNTAIN HARE UTILIZATION IN
BODTRÄSKFORS.
zeroinfl(formula = Hare_Uti ~ log10(Vis.30) + log10(TreeHare + 1) + log10(DeadTot +
    1) + offset(log(EDDHare)) + offset(log(cam.days)) | offset(log(EDDHare)) + offset(log(cam.days)) +
    Placement + Trail, data = Sub.Bod.Data, dist = "negbin")
Pearson residuals:
    Min
           10 Median
                            30
                                   Max
-0.8155 -0.4570 -0.2155 0.1198 2.9869
Count model coefficients (negbin with log link):
                   Estimate Std. Error z value Pr(>|z|)
                               2.6187 -1.677 0.0935 .
(Intercept)
                    -4.3919
log10(Vis.30)
                    -6.9384
                               2.9817 -2.327 0.0200 *
                               1.2727 4.238 2.26e-05 ***
log10(TreeHare + 1) 5.3936
log10(DeadTot + 1)
                     1.8605
                               2.1097 0.882 0.3778
                    -0.3444
                               1.3374 -0.257
Log(theta)
                                                0.7968
Zero-inflation model coefficients (binomial with logit link):
           Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.549
                       1.098 -3.231 0.00123 **
            -3.340
PlacementR
                         2.092 -1.596 0.11042
Trail1
            -12.039
                     243.286 -0.049 0.96053
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 0.7087
Number of iterations in BFGS optimization: 122
Log-likelihood: -49.18 on 8 Df
G2. SUMMARY OF BEST FITTING ZERO-INFLATED MULTI LINEAR REGRESSION MODEL FOR MOUNTAIN HARE UTILIZATION IN MUDDUS.
zeroinfl(formula = Hare_Uti ~ log10(Vis.30) + log10(TreeHare + 1) + log10(DeadTot +
    1) + offset(log(EDDHare)) + offset(log(cam.days)) | offset(log(EDDHare)) + offset(log(cam.days)) +
    Placement + Trail, data = Sub.Mud.Data, dist = "negbin")
Pearson residuals:
    Min
            1Q Median
                            30
                                   Max
-0.5515 -0.4609 -0.2878 0.1311 2.3192
Count model coefficients (negbin with log link):
                    Estimate Std. Error z value Pr(>|z|)
                   -15.9408 2.8559 -5.582 2.38e-08 ***
(Intercept)
                                1.6480 4.271 1.94e-05 ***
log10(Vis.30)
                     7.0388
log10(TreeHare + 1) -1.8765
                                1.0008 -1.875 0.060810 .
                                2.3994 3.462 0.000535 ***
log10(DeadTot + 1)
                    8.3080
Log(theta)
                     -0.7683
                                0.8764 -0.877 0.380683
Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.8090
                        1.7726 -3.277 0.00105 **
                        2.0272 -0.402 0.68785
PlacementR -0.8145
Trail1
            -0.8845
                        2.7116 -0.326 0.74429
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 0.4638
```

Number of iterations in BFGS optimization: 62

Log-likelihood: -43.05 on 8 Df

```
G3. SUMMARY OF BEST FITTING ZERO-INFLATED MULTI LINEAR REGRESSION MODEL FOR MOUNTAIN HARE UTILIZATION IN LAINIO.
zeroinfl(formula = Hare_Uti ~ log10(TreeHare + 1) + log10(DeadTot + 1) + offset(log(EDDHare)) +
    offset(log(cam.days)) + Placement | offset(log(EDDHare)) + offset(log(cam.days)) +
    Placement + Trail, data = Sub.Lai.Data, dist = "negbin")
Pearson residuals:
       Min
                   10
                          Median
                                          30
-1.161e+00 -4.993e-01 -1.683e-02 -4.033e-05 1.807e+01
Count model coefficients (negbin with log link):
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)
                                 2.7692 -8.100 5.52e-16 ***
                     -22.4292
log10(TreeHare + 1) 13.7699
                                  1.8028
                                          7.638 2.21e-14 ***
                                          3.752 0.000176 ***
log10(DeadTot + 1)
                     5.8078
                                 1.5480
                                  0.8089
                                          5.926 3.10e-09 ***
PlacementR
                      4.7939
                     14.5651
                              215.8170 0.067 0.946193
Log(theta)
Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
(Intercept)
               3.917
                        154.084 0.025
                                            0.980
                        154.107 -0.053
              -8.186
                                            0.958
PlacementR
Trail1
              -9.919
                        154.104 -0.064
                                            0.949
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 2116127.2523
Number of iterations in BFGS optimization: 95
Log-likelihood: -19.1 on 8 Df
G4. SUMMARY OF BEST FITTING ZERO-INFLATED MULTI LINEAR REGRESSION MODEL FOR MOOSE PATCH UTILIZATION IN
BODTRÄSKFORS.
Call:
zeroinfl(formula = MoS_Uti ~ log10(Vis.200) + log10(TreeMoose + 1) + log10(DeadTot +
    1) + offset(log(cam.days)) | offset(log(cam.days)) + Placement + Trail, data = Sub.Bod.Data,
    dist = "negbin")
Pearson residuals:
            10 Median
                            30
-0.9425 -0.5948 -0.2181 0.0106 5.0828
Count model coefficients (negbin with log link):
                    Estimate Std. Error z value Pr(>|z|)
(Intercept)
                     -0.9499
                              1.9410 -0.489
                                                   0.625
                                 1.1882 0.605
0.7835 1.023
log10(Vis.200)
                      0.7192
                                                   0.545
log10(TreeMoose + 1) 0.8013
                                                   0.306
                                 1.6706 -0.728
log10(DeadTot + 1)
                     -1.2165
                                                   0.467
                                 0.5424 1.517
Log(theta)
                      0.8227
                                                   0.129
Zero-inflation model coefficients (binomial with logit link):
           Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.0066
                        1.1569 -1.734
                        1.2602 -2.042
PlacementR -2.5733
                                        0.0411 *
                        1.6277 -0.613 0.5400
Trail1
            -0.9976
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 2.2766
Number of iterations in BFGS optimization: 24
Log-likelihood: -48.39 on 8 Df
```

```
Call:
zeroinfl(formula = MoS_Uti ~ log10(TreeMoose + 1) + log10(DeadTot + 1) + offset(log(cam.days)) |
    offset(log(cam.days)) + Placement + Trail, data = Sub.Mud.Data, dist = "negbin")
Pearson residuals:
       Min
                   10
                         Median
                                        30
-0.4609086 -0.3932096 -0.3460549 -0.0000502 2.3980810
Count model coefficients (negbin with log link):
                    Estimate Std. Error z value Pr(>|z|)
                                 4.2876 -0.700
(Intercept)
                      -2.9995
                                                   0.484
log10(TreeMoose + 1)
                      0.8309
                                 1.1854
                                          0.701
                                                   0.483
                                                   0.642
log10(DeadTot + 1)
                      2.5763
                                 5.5444
                                          0.465
Log(theta)
                      -1.1779
                                 0.9377 -1.256
                                                   0.209
Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
               13.78
                      4476.67
                               0.003
                                          0.998
(Intercept)
                       4476.67 -0.004
PlacementR
              -18.63
                                          0.997
                       4476.67 -0.004
Trail1
              -19.42
                                          0.997
Theta = 0.3079
Number of iterations in BFGS optimization: 27
Log-likelihood: -52.15 on 7 Df
G6. SUMMARY OF BEST FITTING ZERO-INFLATED MULTI LINEAR REGRESSION MODEL FOR MOOSE PATCH UTILIZATION IN LAINIO
Call:
zeroinfl(formula = MoS_Uti ~ log10(Vis.200) + log10(TreeMoose + 1) + log10(DeadTot +

    + offset(log(cam.days)) + Placement | offset(log(cam.days)) + Placement + Trail,

    data = Sub.Lai.Data, dist = "negbin")
Pearson residuals:
    Min
             10 Median
                              30
                                     Max
-0.7394 -0.5918 -0.4908 0.2293 2.7323
Count model coefficients (negbin with log link):
                     Estimate Std. Error z value Pr(>|z|)
                                  2.94518 0.261 0.794034
(Intercept)
                      0.76891
log10(Vis.200)
                     -0.95699
                                  1.55158 -0.617 0.537379
log10(TreeMoose + 1) 1.10507
                                  0.46175
                                           2.393 0.016702 *
                      0.09146
                                  1.43989
                                           0.064 0.949351
log10(DeadTot + 1)
                                  0.59034 -3.562 0.000368 ***
PlacementR
                     -2.10290
                      0.08943
                                  0.40710
                                           0.220 0.826130
Log(theta)
Zero-inflation model coefficients (binomial with logit link):
            Estimate Std. Error z value Pr(>|z|)
                        0.83291 -5.529 3.22e-08 ***
(Intercept) -4.60513
PlacementR -0.79429
                        0.88598 -0.897
                                            0.370
Trail1
             0.03957
                        0.89338 0.044
                                            0.965
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Theta = 1.0935
Number of iterations in BFGS optimization: 16
Log-likelihood: -87.26 on 9 Df
```

G5. SUMMARY OF BEST FITTING ZERO-INFLATED MULTI LINEAR REGRESSION MODEL FOR MOOSE PATCH UTILIZATION IN MUDDUS.

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