Eyes in the Wild: Camera Traps and Hunter Counts give similar moose reproductive outcome estimates

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Abstract

In wildlife management, accurate monitoring of animal populations and estimation of population densities are essential for informed decision-making. In Sweden, traditional moose monitoring uses hunter observations during the hunting season, a system called Älgobs. While cost-effective, this method is constrained by the time lag between counting in autumn and implementing the management plans the next year. This study investigates the effectiveness of camera trap deployments, both systematic and targeted, in estimating moose reproductive outcome estimates, specifically the proportions of females without calves, females with one calf, and females with two calves in comparison to the proportions found in the counts of the Älgobs method. Using static multi-state occupancy models, I analysed data from systematically deployed cameras, alongside targeted cameras.

My results indicate that systematically deployed cameras provide reproductive outcome ratio estimates comparable to those of the proportions calculated with the Älgobs counts. The naïve occupancy estimates, despite not accounting for detection probabilities, yielded ratios similar to those from the multi-state occupancy models. This suggests that naïve occupancy can still be useful for detecting population differences. However, the heterogeneous data sources and deployment methods presented challenges, with two datasets showing large standard errors and wide confidence intervals, highlighting the need for enough cameras for sufficient data and consistent methodologies.

This study underscores the potential of camera traps in providing reliable data on moose population ratios, particularly when combined with occupancy modelling. It shows the possible solution for the limitation of traditional method Älgobs, the time lag between moose counts and the production of management plans. Future research should focus on optimizing camera placement strategies and providing clear guidelines for volunteers to enhance data quality and model robustness. The inclusion of AI tools like MegaDetector can further streamline the classification process and could improve the efficiency and accuracy of wildlife monitoring.

Keywords: Camera trap, Älgobs, Alces alces, Occupancy model, MegaDetector

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Abbreviations

SLU	Sveriges lantbruksuniversitet - Swedish University of Agricultural Sciences
CT	Camera Trap
BM	Beyond Moose
RefNM	Reference area Nordmaling
AI	Artificial intelligence
IPCC	Intergovernmental Panel on Climate Change
SJF	Svenska Jägareförbundet - Swedish Association of Hunting and Wildlife Management
TP	True positive
FP	False positive
TN	True negative
FN	False negative

1. Introduction

Human-wildlife conflicts, defined as interactions between wildlife and humans with a negative outcome for at least one of both (Madden 2004), have emerged as a significant contributor to biodiversity loss. As shown by the rise in studies on the topic of human-wildlife conflicts (Nyhus 2016; König et al. 2020), there is an increase in the frequency of cases globally. These conflicts are worsened by the growing competition for space and resources, a trend further impacted by climate change (Abrahms 2021). The moose population in Sweden serves as a compelling case study, given its economic, ecological and cultural importance (Mattsson et al. 2014). Conflicts involving moose range from browsing damage to forest stands to the risk of vehicle collisions (Lavsund et al. 2003; Seiler 2003; Månsson et al. 2011).

The situation in northern regions is worsened by the disproportionately large impacts of climate change (Intergovernmental Panel on Climate Change (IPCC) 2023), with a notable increase in temperatures. Moose populations, in particular, are vulnerable to climate-induced stressors (Holmes et al. 2021, 2023). A warm and dry May and June can lead to a lower number of calves per female in autumn, due to lower calf survival. This reproductive outcome is a crucial indicator of population health, as fit females are more likely to produce two calves. Extreme weather events, which have increased over the past 50 years and are expected to become more frequent (IPBES 2019), may further alter moose population dynamics. Since the moose population is managed through regulated hunting, where harvesting quotas are based on estimates of the population size (Månsson et al. 2011), a balance needs to be found between maintaining a viable population for an acceptably sized harvest and keeping the browsing-induced damage (human-wildlife conflict) sufficiently low (Appollonio et al. 2010). Additionally, it is essential to monitor population changes due to extreme weather and climate change to inform and adapt management plans effectively.

1.1 Monitoring methods

A good estimation of the population size and structure is crucial for a good management plan (Månsson et al. 2011). Right now, moose monitoring is done through hunter observations, however, this results in problems mentioned further on. This study will compare the use of these hunter observations with a newer technique, camera traps, to inform sustainable management practices amid the interplay of human-moose conflicts and the challenges posed by climate change in the northern regions.

1.1.1 Älgobs

Estimations of the moose population in Sweden are now based on hunter observations (Ericsson & Wallin 1999; Singh et al. 2014; Ericsson & Kindberg 2019). Since 1985 there has been a system where during the first seven hunting days of the first month of the hunting season hunters report the amount of moose seen and this number is divided by the number of hours spent looking by hunters (Älgobs) (Kindberg et al. 2009; Ericsson & Kindberg 2019). The moose observations per man-hour are critical for assessing population levels within each moose management area (älgförvaltningsområde) and hunting unit (älgskötselområde) (von Essen et al. 2023) and to see the reproductive status of the population by assessing the number of calves per female. A minimum of 5000 man-hours are needed per hunting team for the observational data to be considered reliable for trend analysis (Singh et al. 2014).

Multiple studies have shown that population estimates based on hunter observations are similar to densities based on other census methods (Fryxell et al. 1988; Ericsson & Wallin 1999; Solberg & Saether 1999; Rönnegård et al. 2008; Kindberg et al. 2009; Ericsson & Kindberg 2019). Next to that, Älgobs is a cost-effective method compared to for example aerial counts (Månsson et al. 2011; Singh et al. 2014), however, there are limitations. Since the moose counts are only performed once a year during the hunting season, the harvest quotas of a certain year are based on the observations of a year prior (Månsson et al. 2011). The sensitivity of the moose population to warm weather events in combination with climate change, as mentioned above, can have significant effects on the moose numbers between counting events. As a result, the population estimate from a year prior might not be accurate anymore, possibly leading to the overharvesting of the population during the hunting season.

1.1.2 Camera trapping

Another monitoring technique that in contrast could be used year-round is camera trapping. Camera traps (CTs) have become a more widely used census technique within the field of ecology and conservation (Rowcliffe & Carbone 2008). This increase in popularity can be attributed to the improvements in technology and subsequent reduction in costs (Tobler et al. 2008). The cameras, capturing either images or videos, are used for a variety of purposes, including the detection of rare species (O’brien & Kinnaird 2008; Tobler et al. 2008; Swann & Perkins 2014), estimation of population sizes, assessment of activity patterns (Frey et al. 2017), investigation of behaviour and population dynamics (Rovero et al. 2013).

Equipped with passive infrared (PIR) sensors, camera traps are activated by heat and motion (Rovero et al. 2013). The placement strategy and settings of the cameras depend on the target species (Hofmeester et al. 2021). The chance of capturing individuals from a given species, the trapping rate, is not only dependent on the abundance of the species, but, also on actors like movement rates (Rovero & Marshall 2009; Rowcliffe et al. 2011), body size (Tobler et al. 2008; Rowcliffe et al. 2011), vegetation density (Rowcliffe et al. 2011), preference of specific trails (Hofmeester et al. 2017), camera sensitivity (Rovero & Marshall 2009) and camera trap models(Rovero et al. 2013). The integration of CTs can offer a solution for the time gap between moose monitoring and the formulation of conservation strategies by increasing the sampling occasions (Rovero et al. 2013) as they can be deployed year-round.

Population estimations can be based on camera trap observations without identifying individuals (Steenweg et al. 2017). Occupancy models are a set of statistical methods used in ecology to estimate the probability that a given area is occupied by a species, based on detection and non-detection data collected from field surveys (Mackenzie 2005). Occupancy models separate the observation process, the detection of species given their presence or absence, from the state process, the true occupancy status of the sites (Mackenzie 2005). These models account for the fact that a species may not always be detected when it is present, by incorporating detection probabilities – the chance of observing an animal given it is present at a location. In this particular study, a multi-state occupancy model is used (Mackenzie et al. 2009), to be able to compare the reproductive status of the Älgobs counts with the outcomes of the occupancy models.

1.1.3 Citizen Science

A sufficient amount of CT data is needed for addressing scientific questions. Citizen science is the involvement of the public in scientific research and monitoring (Singh et al. 2014). The inclusion of citizens with privately owned CTs could offer a solution. The use of commercial CTs, particularly among hunters, has increased (Rovero et al. 2013). Integration of these privately used commercially available camera traps in science projects offers a substantial increase of data with large temporal and spatial scales. Citizen science has been shown to besides increasing the amount of data, improve people's confidence in science and stimulate their interest in research and natural sciences (Bryn et al. 2023). However, the utilization of data lacking a standardized protocol poses challenges in analysis and interpretation.

The Viltbild project, a collaboration between the Swedish Association of Hunting and Wildlife Management (SJF) and the Swedish University of

Agricultural Sciences (SLU), is developing a citizen-science platform for the collection of camera trap data from privately owned camera traps. Hunters are asked to upload pictures of their camera traps on the platform, and this data can be used to monitor the wildlife species populations in the country. The integration of an artificial intelligence (AI) model, MegaDetector, within the platform to identify vehicles, humans and animals, facilitates efficient analysis of large amounts of data (Pfeffer et al. 2018; Beery et al. 2019; Tabak et al. 2019; Carl et al. 2020; Mitterwallner et al. 2023). MegaDetector has demonstrated notable efficacy in discerning various levels and has resulted in an 8.4-fold reduction in time required for classification in the study of Fennell et al. (2022). Nevertheless, instances of systematic misidentification have been found (Mitterwallner et al. 2023).

1.2 Objectives

In this study, the primary objective is to assess the efficacy of camera traps for moose population evaluation in conservation efforts and hunting regulations, in comparison to the traditional Älgobs method and to address the time lag between hunter counts and the development of management plans by deploying cameras year-round. Traditionally, population estimates have relied on hunter observations, which are constrained by seasonal data collection and may not reflect rapid changes in moose populations and reproductive outcomes due to environmental stressors. This study proposes camera traps as an alternative monitoring method that could provide more timely and continuous data, thus overcoming the time-lag problem inherent in the traditional method.

Two distinct methodologies for camera deployment are used in this research. In the first approach, cameras are systematically placed in a grid pattern, while in the second approach, volunteer hunters are asked to place cameras within their hunting grounds, without location restrictions. It is expected that the CT data is as good as hunter observations when using the right analytical frameworks with corrections for imperfect detection (Gilbert et al. 2021). However, differences could be expected between the cameras placed in a grid and the cameras placed by volunteering hunters. The latter may be strategically positioned in areas favoured by moose due to the hunters' knowledge of the terrain, potentially resulting in an elevated frequency of moose detections.

Additionally, this thesis will review the performance of the AI model MegaDetector by manually checking all AI-made classifications, with a particular focus on the confidence levels of the AI model associated with these classifications. According to Mitterwallner et al. (2023), a confidence level threshold higher than 90% should be used for ecological studies, however for occupancy studies, a lower threshold might be better, to mitigate the risk of overlooking individuals. Balancing the risk of missing animals classified as blank when increasing the threshold level with the amount of time and effort required to classify the pictures is crucial. Fully trusting the AI to classify blank images could significantly reduce the time spent on classification, but it also carries the risk of losing observations.

2. Methods

2.1 Study site

The study was conducted in the Nordmaling municipality, in the Västerbotten province in northern Sweden, situated southwest of Umeå (Figure 1). The area is located between the highway E4 and the Baltic Sea, with a few cameras placed north of the E4 (Figure 1). The area has a combination of boreal forests, wetlands and agricultural land. A variety of ungulate species is found in the region, including moose, roe deer, fallow deer, and red deer (Widén 2023). Three moose hunting areas overlap with the study area (Hörneåns, Hörnefors, Järnäshalvöns älgskötselområde).

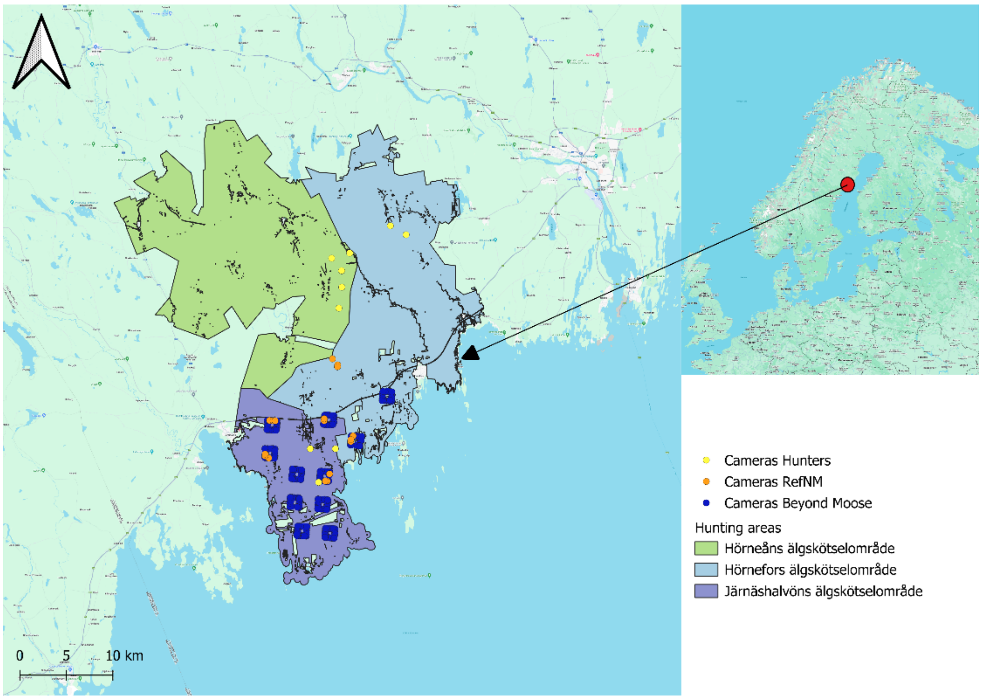


Figure 1: Distribution of camera traps in the Nordmaling municipality, showing systematic deployments (Cameras Beyond Moose, 2017; Cameras RefNM, 2023), and cameras placed by citizen scientists—hunters (Cameras Hunters, 2023). The polygons show the hunting areas (Hörneåns, Hörnefors, Järnäshalvöns älgskötselområde). The inset map indicates the location of the study area in northern Sweden.

2.2 Data collection

2.2.1 Camera deployments

Systematic deployments

In 2023, a total of 17 camera traps (RefNM project) were systematically deployed, supplementing data from 189 units deployed in 2017 (Beyond Moose project). Originally, the plan was to install three cameras within each of the same 1km^2 grid cells used in 2017, for a total of 33 cameras. However, due to constraints in time and communication with landowners, the project had contact with major landowner organizations such as Holmen. This partnership allowed us to strategically place 17 cameras in the restricted areas. The cameras were placed within 1km^2 grid cells, as described in more detail by Pfeffer et al. (2018), all positioned no more than 500 meters from a road to facilitate maintenance for multi-year operation. The cameras were mounted on wooden poles at a height of 1 meter above the ground and oriented horizontally. They were strategically positioned to avoid areas with high human activity and were operational from August to October 2023. The cameras from the Beyond Moose project used a similar methodology (Hofmeester et al. 2020) and were placed in the same region. Initially, the analysis of systematically placed cameras was intended to be conducted solely with the 2023 RefNM data. However, the sample size from 2023 alone was insufficient for robust statistical analysis. To address this limitation, the 2017 BM dataset was included (Hofmeester et al. 2020), thereby increasing the sample size and enhancing the reliability of the results.

We used the Reconyx camera models equipped with passive infrared (PIR) sensors to detect motion and heat. Additionally, the cameras were set up to take time-lapse pictures every day at noon, to make sure they were functioning properly and nothing was blocking the view. The 2017 cameras were active for periods varying between 8 to 80 days, spanning from January 2017 to February 2018. We refer to the 2017 initiative as the "Beyond Moose" or "BM" project and the 2023 undertaking as "RefNM".

Opportunistic deployments

Volunteer hunters within specified hunting areas (Figure 1) - Hörnefors, Hörneåns, Järnäshalvöns - participated in the study by placing cameras on their hunting grounds. Unlike the systematic deployment, this approach did not follow a predetermined schema for camera placement, although the same camera brands (Reconyx) were used. The 10 cameras were set up between July and September

2023, with SD cards collected and data uploaded to the data processing platform from August 2023 to April 2024 for classification. It consisted of 6 targeted cameras, 2 pointed at a wildlife trail, 4 at a licking stone, and 4 randomly placed by the hunters. The random placement by citizens is not comparable to the systematic placement of the RefNM and BM cameras.

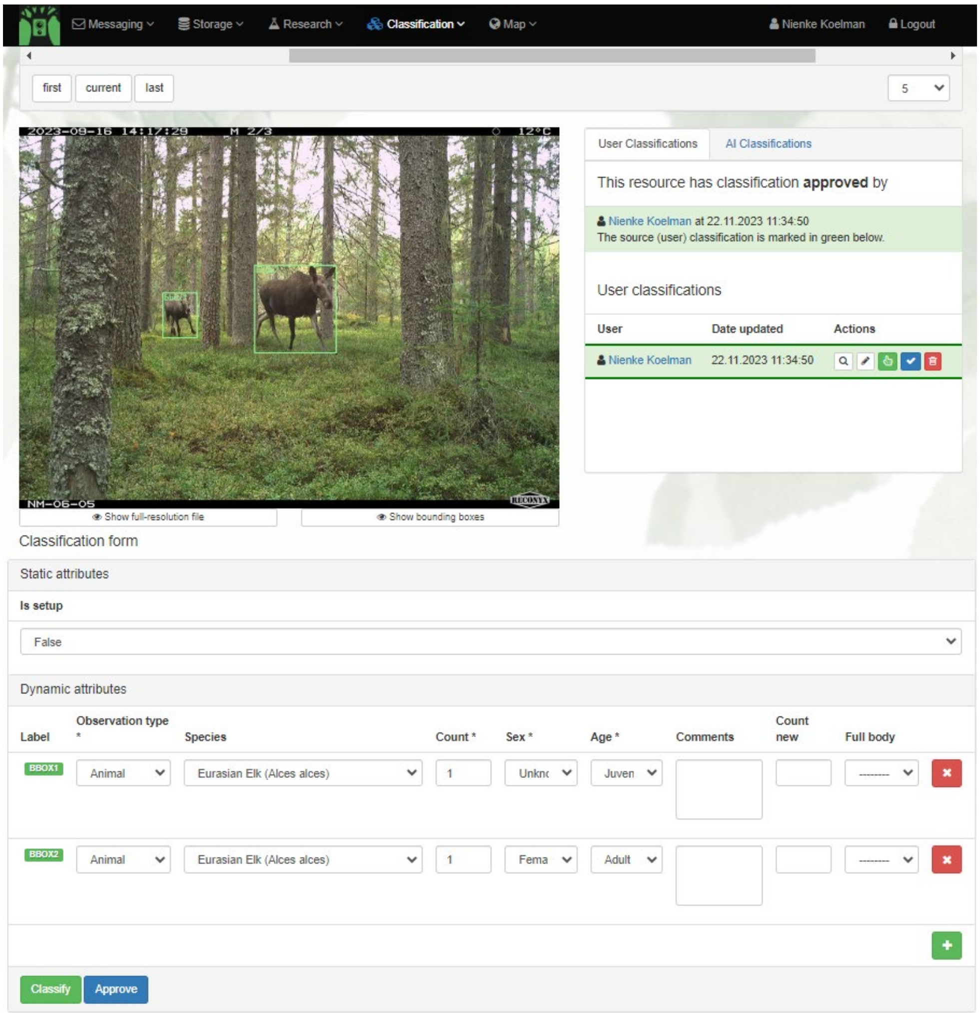
2.2.2 Älgobs

The Älgobs system requires hunters to record detailed observations during the first seven hunting days of the first month of the hunting season. This data collection includes the number of moose observed, categorized by sex (males, females), age (adults, calves) and number of offspring per female. These observations are then adjusted by the number of hunting hours to calculate observation ratios, providing an estimate of reproductive status and population structure.

For this study, count data was acquired from the Algdata.se website (https://www.algdata.se/) from Länsstyrelserna for the three hunting areas (Hörnefors, Hörneåns and Järnäshalvöns älgskötselområde; Figure 1), covering the years 2017 and 2023. Each of these areas reached the minimum threshold of 5000 man-hours, which is required to be able to detect population changes reliably (Singh et al. 2014; Ericsson & Kindberg 2019).

2.2.3 Camera trap image processing

I classified the pictures from the camera traps using two different platforms: Trapper for the ‘Beyond Moose’ and ‘RefNM’ data, and Viltbild.se for the data collected by hunters. The Vilbild.se server, owned by Jägareförbundet, did not have storage capacity for this project’s data, resulting in delays in accessing the platform. Consequently, the initial data available was classified in Trapper. Trapper (Figure 2) is a versatile and open-source web application designed for managing, classifying, integrating, sharing and repurposing data in camera trapping studies (Bubnicki et al. 2016). Viltbild.se (Figure 3) is designed to be a more user-friendly version, enabling hunters and other volunteers to directly upload their images, with the Trapper system in the backend. A table showing the exact classification scheme is located in Appendix 1.



This resource has classification **approved** by

Nienke Koelman at 22.11.2023 11:34:50
The source (user) classification is marked in green below.

User classifications

User	Date updated	Actions
Nienke Koelman	22.11.2023 11:34:50	

Classification form

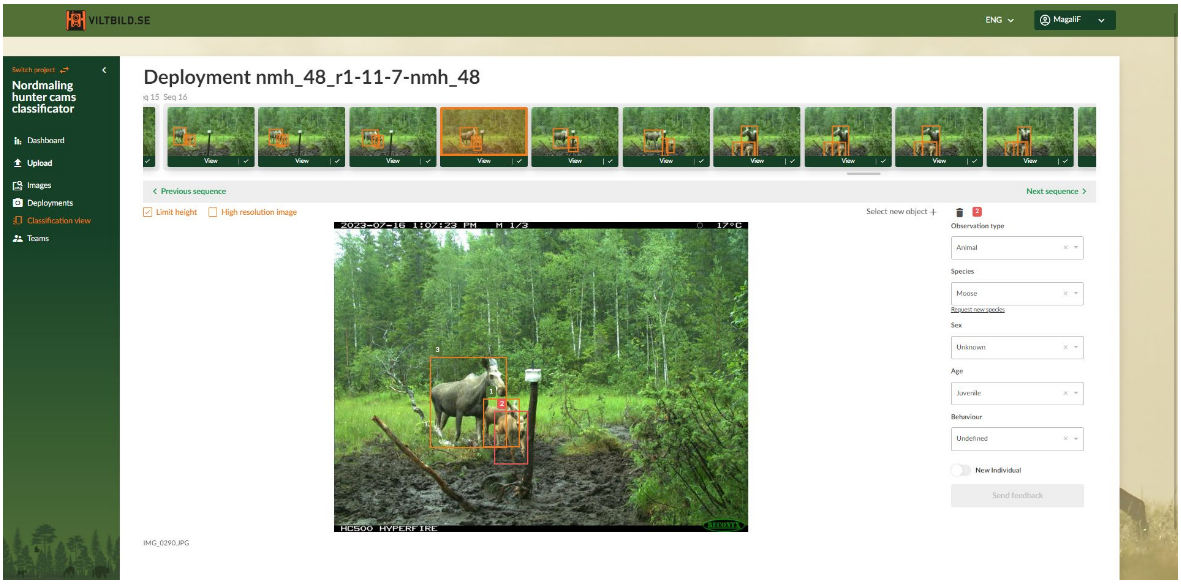
Static attributes

Is setup: False

Dynamic attributes

Label	Observation type *	Species	Count *	Sex *	Age *	Comments	Count new	Full body
BBOX1	Animal	Eurasian Elk (Alces alces)	1	Unknc	Juven			---------
BBOX2	Animal	Eurasian Elk (Alces alces)	1	Fema	Adult			---------

Figure 2: Example of Alces alces classification in Trapper, both a calf and a female adult



Deployment nmh_48_r1-11-7-nmh_48

☑ Limit height ☐ High resolution image

Observation type: Animal

Species: Moose

Sex: Unknown

Age: Juvenile

Behaviour: Undefined

New Individual

Figure 3: Example of Alces alces classification in Viltbild.se, two calves and a female adult

MegaDetector, an open-source AI object detection model developed by the Microsoft AI for Earth program (Beery et al. 2019), is integrated into both Trapper.se and Viltbild.se, and improved the efficiency of the camera-trap data processing. The model identifies and categorizes objects within images as animals, people, or vehicles and draws bounding boxes around the detected objects. A critical feature of MegaDetector is its confidence values for each detection, giving the user the possibility of selecting a confidence threshold fitting their project (Mitterwallner et al. 2023). For example, using a confidence threshold of 0.7, results in that images below this level are classified as "Blank." While automatically recognizing blank images can streamline the classification process considerably, it is important to carefully choose the threshold to minimize the risk of missing animals that might be incorrectly classified as blank (Beery et al. 2019). Different confidence level thresholds were used in this study. For the RefNM data, a confidence level of 0.1 was used to be able to compare the classification at different confidence levels (Mitterwallner et al. 2023), while for the Hunter data, a confidence level of 0.7 was chosen by my supervisor, since it seemed more suitable for this kind of dataset and for occupancy models you want to minimise the losses of false negatives by setting your threshold not too high.

Following the AI's preliminary classification, each observation was manually verified to ensure accuracy and to add characteristics, such as species, age, and sex. The performance of MegaDetector was compared to the manual classification to establish the optimal confidence threshold for the specific project. Confusion matrices were composed and compared between the datasets. I calculated the performance metrics (Table 1) based on true positive (TP), true negative (TN), false positive (FP) and false negative (FN). In line with Mitterwallner et al. (2023), I focused for the performance on the accuracy level only. The precision, recall and specificity outcomes are shown in Appendix 3. Also, the number of bounding boxes drawn by the AI model was compared with the number drawn manually.

Table 1. Formulas used for AI performance assessment. True positive (TP), true negative (TN), false positive (FP), false negative (FN)

	Formula
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Precision	(TP) / (TP + FP)
Recall	(TP) / (TP + FN)
Specificity	(TN) / (TN + FP)

2.3 Data analysis

2.3.1 Naïve occupancy

The naïve occupancy is the proportion of sites that are occupied by a state without considering detection probability. It is the fraction of sites where the state is observed at least once during the study period, relative to the number of surveyed sites (Ewing & Doll 2024). The naïve occupancy was calculated for all datasets.

2.3.2 Multi-state occupancy models

Occupancy models were applied to analyse moose reproductive outcomes from the camera trap data. The ‘Unmarked’ package (version: 4.3.2) (Fiske & Chandler 2011) in R (version: 4.3.1) was used to run the occupancy models. I used a multi-state framework (OccuMS), with four states (Table 2), to be able to compare the occupancy probabilities of the reproductive outcome states with similar states collected from the Älgobs observations. The static model was chosen over the dynamic model, focusing on single-season data. I assumed that when a calf was seen in an image that the mom was close by. The hunter dataset was split into the two placement methods for analysis, since it consists of 6 targeted and 4 randomly placed cameras.

Table 2. The states used in the multi-state occupancy models with the classes they represent

State	Class
0	No female moose
1	Female moose
2	Female moose + one calf
3	Female moose + two calves

Determination of survey length

In the preliminary analysis of the camera data, I assessed the influence of survey length on the fitting of the occupancy models. Increasing the survey length could increase model fit (Steenweg et al. 2019; Pautrel et al. 2024). Initially, the observations were aggregated daily. However, the first attempts to fit a simple model to daily aggregated data proved unsuccessful, indicating insufficient data within each interval to support robust model estimation. To resolve this, the aggregation interval was systematically increased from one to seven days in consecutive steps. These changes mostly influenced the count of state 0 and NA’s in the observations (Table 3). As the interval increased, the model's ability to fit improved.

After evaluating the model's performance across different survey lengths for the BM dataset, a 7-day interval was determined to produce converging models without losing too many observations. This interval balanced the need for sufficient data aggregation to support model stability and the desire to minimize the loss of state counts and decrease of certainty of the detection probability estimates.

Table 3. The counts of observations per state for different chosen survey lengths. The state NA is produced when the cameras are not deployed during surveys.

/ State	0	1	2	3	NA
Survey length					
1	11630	55	38	9	80762
2	5865	55	37	9	40384
3	3938	52	37	9	27070
4	2974	53	35	9	20207
5	2427	49	34	9	16227
6	2026	50	35	9	13356
7	1756	49	34	9	11542

Covariates

A range of covariates were included within the models to compare the model fit and correct for differences between camera timing and location. The covariates were effort, season, year, proportion of open land and proportion of forested land.

Effort was defined as the operational duration of each camera, utilized as an observation-level covariate. This was quantified in a matrix assigning a value between 0 and 1 per survey per site, representing the proportion of each survey period during which each camera was operational.

Temporal aspects were derived from the start and end dates of camera deployments and incorporated as site-level covariates. Year was designated as the deployment's starting year, resulting in the year 2017 for the BM data and 2023 for the RefNM as well as Hunter data. Season was determined by averaging the start and end dates, categorized as follows: Winter (December to February), Spring (March to May), Summer (June to August) and Autumn (September to November).

Land cover data from 2017 was sourced from Naturvårdsverket's land cover maps (https://www.naturvardsverket.se/en/services-and-permits/maps-and-map-services/national-land-cover-database/) and processed using GIS software (QGIS, version: 3.32.2). A buffer of 100 meters was drawn around each camera trap location to prevent excessive overlap. Within these buffers, the proportions of forested and open land were quantified by analysing pixel counts from each land cover type and calculating the proportion for both land cover types. For the 2023 datasets (RefNM and Hunter) a similar methodology was followed using satellite images from Sentinel (https://apps.sentinel-hub.com/eo-browser) since there was no updated 2023 data available for the region from Naturvårdsverket. In this case, the difference between open and forested land was drawn by hand. A comparison of the 2017 land cover maps with Sentinel satellite images from 2017 for 10 camera locations confirmed a high correlation in forested land proportions between both methods (Figure 4). This validated the simultaneous use of both methods to save time.

As expected, the correlation between open and forested land proportions was very high (-0.912). Consequently, only open land was used as a covariate in the models, as clear-cuts are a preferred habitat type (Widén 2023).

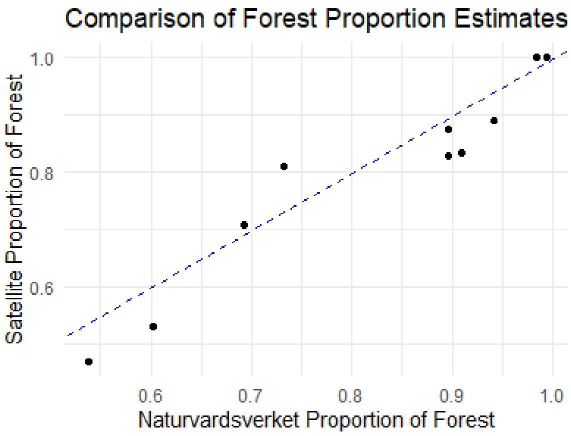


Figure 4: Comparison of proportion of forest acquired via Sentinel satellite images and Naturvardsverket landcover data

Models

To estimate the reproduction outcome proportions, I ran various models with all datasets using Unmarked in R and evaluated their performance. Table 6 in section 3.1.2 of the Results section provides a summary of all null models and the models with covariates that converged, including the detection and state covariates used and the AIC values.

The rationale for focusing on the four-state occupancy models in the main analysis is to allow for a more comprehensive comparison with the Älgobs values. Including the fourth state enables the comparison of multiple ratios, providing a more detailed understanding of how the methods align and improving the accuracy of the comparisons.

Detection probabilities

A multi-state occupancy model with four states provides six detection probabilities in the output. These detection probabilities are essential in understanding the likelihood of detecting a given occupancy state during surveys. Understanding these probabilities is important for accurately interpreting the results.

Interpretation of Detection Probabilities:

- $p11$: Probability of detecting state 1 when state 1 is actually present.
- $p12$: Probability of detecting state 1 when state 2 is actually present.
- $p13$: Probability of detecting state 1 when state 3 is actually present.
- $p22$: Probability of detecting state 2 when state 2 is actually present.
- $p23$: Probability of detecting state 2 when state 3 is actually present.
- $p33$: Probability of detecting state 3 when state 3 is actually present.

2.3.3 Comparison of methods

In this study, Älgobs counts from the regions where the cameras were situated (Älgskötselområde: Hörnefors, Hörneåns, Järnäshalvöns, Älgförvaltningsområde: Sydöstra, Västerbottens län) were compared with the occupancy probabilities derived from camera traps to evaluate whether these methodologies provide consistent and reliable estimates of moose population structure, specifically reproductive status. I chose to look at all three regions combined, and at the regions excluding Hörneåns, since only 5 of all cameras are situated in this region.

The different state counts for Älgobs were calculated from the counts per sex and age. Specifically:

- State 1: proportion of females out of the total adult population.
- State 2: proportion of females with one calf out of the total number of females.
- State 3: proportion of females with two calves out of the total number of females.

For the comparison, all state proportions were aggregated to form a total of 100%, allowing for the calculation of percentages per state. This demographic approach facilitated a direct comparison between the methods. Chi-squared tests were used to compare the specific camera trap datasets with the Älgobs ratios for each year.

3. Results

In this study, I collected data across three distinct datasets. A total of 1714 sampling weeks were recorded for the BM dataset across 189 sites, complemented by 139 sampling weeks from 17 sites for the RefNM dataset, and 136 sampling weeks from 10 sites for the Hunter dataset. Table 4 presents the weekly aggregated observations per state for each dataset, wherein state 0 indicates the absence of a female moose, state 1 the presence of a female moose, state 2 the presence of a female moose with one calf and state 3 the presence of a female moose with more than one calf. Notably, the number of observations is lower for the RefNM and Hunter datasets compared to the BM dataset, and the RefNM dataset recorded no observations of a female moose with two calves, while the Hunter data reported no sightings of a female with one calf.

Table 4. Observation counts per state per dataset, aggregated weekly

Dataset/State	0	1	2	3
BM	1628	45	32	9
RefNM	127	5	2	0
Hunter	119	14	0	3

3.1 Occupancy

3.1.1 Naïve occupancy

The naïve occupancy was calculated for all datasets with the detection data from the camera traps. Table 5 shows the probabilities for the different datasets per state. The more complex the state the lower the naïve occupancy probability, except for the Hunter dataset and the split Hunter dataset in targeted cameras only. A naïve occupancy of 0 was seen for RefNM state 3 and all Hunter state 2s and state 3 for the Hunter random, because these states were not observed in those datasets as seen in table 4.

Table 5. Naïve occupancy probabilities per state per dataset

Dataset / State	1	2	3
BM + RefNM	0.194	0.126	0.029
BM	0.190	0.127	0.032
RefNM	0.235	0.118	0.000
Hunter	0.700	0.000	0.200
Hunter targeted	0.667	0.000	0.333
Hunter random	0.750	0.000	0.000

3.1.2 Multi-state occupancy models

The following table summarizes all the models run during this thesis (Table 6). The four-state occupancy model results show three occupancy states (female moose, female moose with one calf and female moose with two calves) and one state unoccupied (no female moose). Models that produced NaNs were able to execute; however, their results are likely unreliable and should be interpreted with caution.

Table 6. Models run with OccuMS from Unmarked in R. Showing the dataset, number of states, covariates used and AIC values for each model.

Model	Dataset	# states	Covariates	AIC	Notes
M1	BM+RefNM	4	None	862.290	
M2	BM+RefNM	4	Effort (detection)	869.355	NaNs produced in detection
M3	BM+RefNM	4	Effort (detection) ProportionOpenLand(state)	854.162	
M4	BM+RefNM	4	ProportionOpenLand(state)	850.621	
M5	BM	4	None	805.6203	
M6	BM	4	Effort (detection)	806.768	
M7	BM	4	ProportionOpenLand(state)	792.691	
M8	BM	4	Effort (detection) ProportionOpenLand(state)	792.306	
M9	RefNM	4	None	68.167	No state 3 detections
M10	Hunter	4	None	116.494	NaNs produced in both occupancy and detection
M11	Hunter (targeted)	4	None	75.339	NaNs produced in both occupancy and detection

Null models

In my baseline analysis, the null model estimated the occupancy probabilities for the three moose states for the different datasets without considering covariates, with state 1 the observation of a female moose, state 2 the observation of a female moose with one calf and state 3 the observation of a female moose with two calves. Figures 5 to 9 illustrate the multi-state occupancy probability estimates and their confidence intervals for each dataset in blue and for comparison the naïve occupancy probabilities in red.

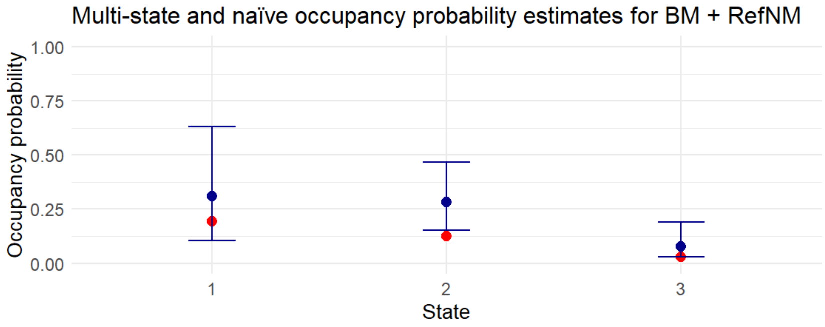


Figure 5. Graph showing the multi-state occupancy probabilities with confidence intervals in blue and the naïve occupancy probabilities in red for the combined datasets BM and RefNM.

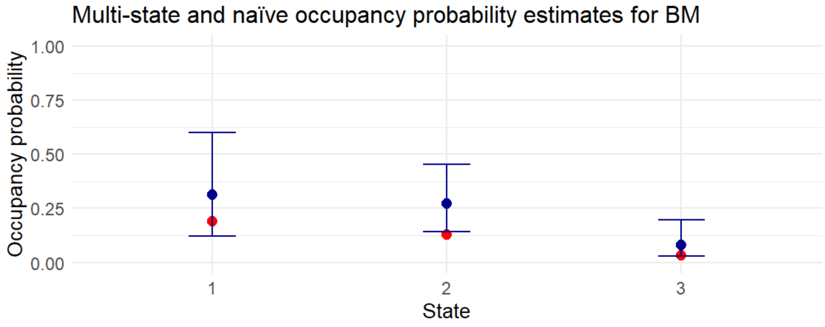


Figure 6. Graph showing the multi-state occupancy probabilities with confidence intervals in blue and the naïve occupancy probabilities in red for the BM dataset.

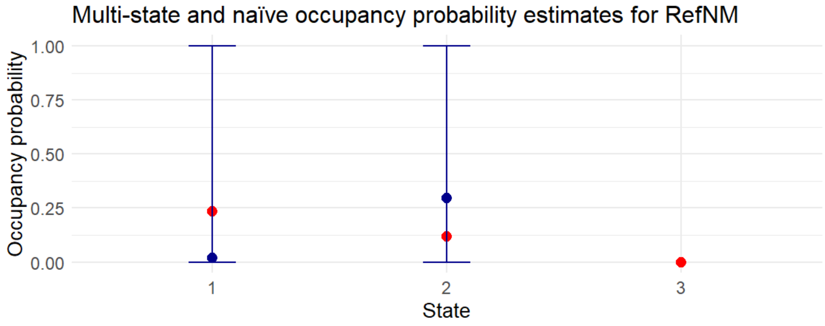


Figure 7. Graph showing the multi-state occupancy probabilities with confidence intervals in blue and the naïve occupancy probabilities in red for the RefNM dataset.

The occupancy probability estimates of the BM+RefNM dataset (Figure 5) and the BM dataset (Figure 6) show the same pattern as the naïve occupancy probabilities, with lower occupancy estimates for the higher states. Although, the naïve occupancy estimates are a bit lower than the multi-state occupancy estimates. The multi-state estimates for the RefNM dataset show a different pattern, with larger confidence intervals, while the naïve occupancy probabilities show a similar pattern with the other datasets. The similarity between the BM dataset and the combined dataset of BM and RefNM, while RefNM shows a lot of uncertainty, resulted in the decision not to combine BM and RefNM for the 2023 comparison with Älgobs.

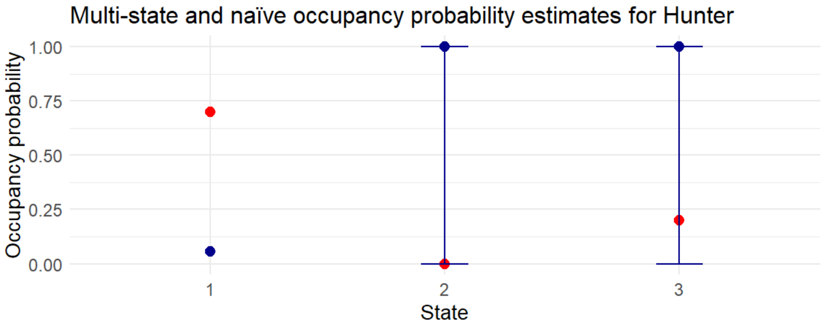


Figure 8. Graph showing the multi-state occupancy probabilities with confidence intervals in blue and the naïve occupancy probabilities in red for the Hunter dataset.

The confidence intervals for the estimates are generally large, with the widest intervals observed for the RefNM data (Figure 7) and the Hunter data (Figure 8). Notably, for state 1 in the Hunter dataset, the model was unable to get the standard error (SE) and produced NaN instead. The Hunter dataset is a combination of four randomly placed and six targeted cameras. The model was rerun excluding the randomly placed cameras, focusing solely on the six targeted cameras. This adjustment resulted in estimates with slightly smaller confidence intervals, as shown in Figure 9.

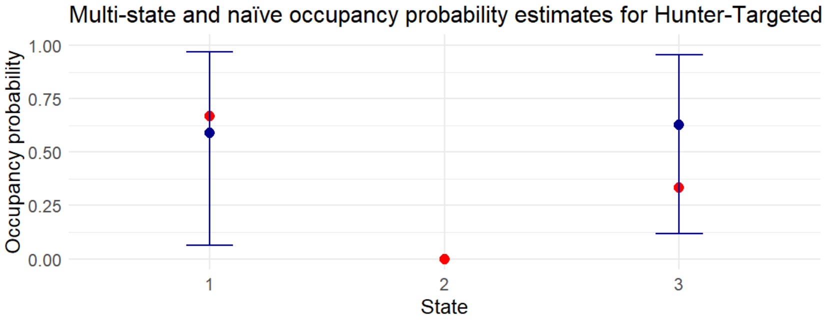


Figure 9. Graph showing the multi-state occupancy probabilities with confidence intervals in blue and the naïve occupancy probabilities in red for the targeted Hunter dataset

The targeted cameras captured seven observations of a female moose alone (state 1) and three observations of a female moose with two calves (state 3). There were no observations of a female moose with one calf (state 2), explaining the occupancy probability estimate of 0, which is similar to the naïve occupancy (table 4).

Occupancy models do take detection probabilities into account. The detection probabilities for the null models shown above are in Table 7. Table 7 presents the detection probabilities for each state, with their 95% confidence intervals in brackets, indicating the likelihood of detecting a given state when it is actually present or when a higher hierarchical state is present. The detection probability estimates are lower than 0.17, except for the Hunter and Hunter (targeted) datasets, although with large confidence intervals.

Table 7. The detection probabilities for the three occupied states for all the null models for the datasets with the 95% confidence intervals in brackets.

Detection probability	BM + RefNM	BM	RefNM	Hunter	Hunter (targeted)
p11	0.060 (0.022, 0.153)	0.065 (0.027, 0.149)	0.005 (0.000, 1.000)	0.035 (NaN, NaN)	0.086 (1.514e-02, 0.363)
p12	0.047 (0.022, 0.101)	0.037 (0.014, 0.092)	0.141 (0.044, 0.363)	0.038 (0.014, 0.103)	0.379 (7.148e-40, 1.000)
p13	0.147 (0.064, 0.301)	0.145 (0.063, 0.301)	-	0.405 (0.222, 0.619)	0.397 (1.513e-01, 0.709)
p22	0.079 (0.037, 0.163)	0.083 (0.039, 0.170)	0.062 (0.012, 0.264)	4.819e-06 (5.73e-44, 1.000)	0.075 (NaN, NaN)
p23	0.126 (0.049, 0.288)	0.126 (0.048, 0.289)	-	1.716e-05 (1.59e-59, 1.000)	3.588e-06 (5.100e-188, 1.000)
p33	0.168 (0.066, 0.366)	0.171 (0.068, 0.367)	-	0.172 (0.052, 0.439)	0.330 (7.480e-02, 0.749)

Model with covariates

Different covariates were fitted to the model to assess their impact on occupancy probabilities and detection probabilities. Of the covariates tested, only effort as a detection covariate and proportion of open land as a state covariate were found to be significant. The open land proportion has varying effects on the different states (Figure 10), with states 1 and 3 showing an increase with increased open land with a slope of 0.765 (p=0.0698) for state 1 and 1.7595 (p=0.000753) for state 3, and state 2 showing a slight increase with a slope of 0.0175, although not significant (p=0.968). The large confidence intervals indicate a high uncertainty in the predicted occupancy probabilities.

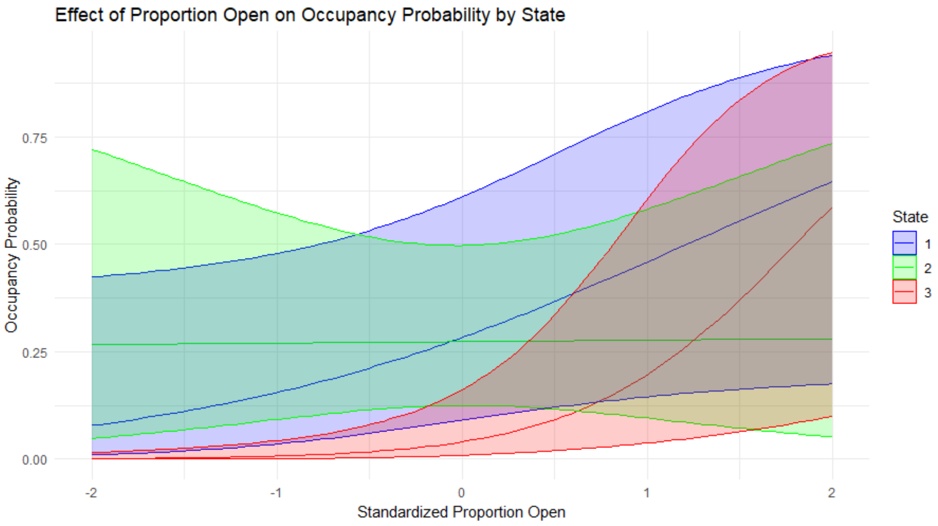


Figure 10. The effect of the covariate proportion open land on the occupancy probability per state with confidence intervals (BM dataset)

Effort was used as a detection level covariate in model M6 (Figure 11). The effects differ per detection probability. P33 shows a significant increase in detection probability with increasing effort, the other probabilities have no significant changes with effort. The confidence intervals (shaded areas) around the detection probability estimates indicate the uncertainty in these estimates.

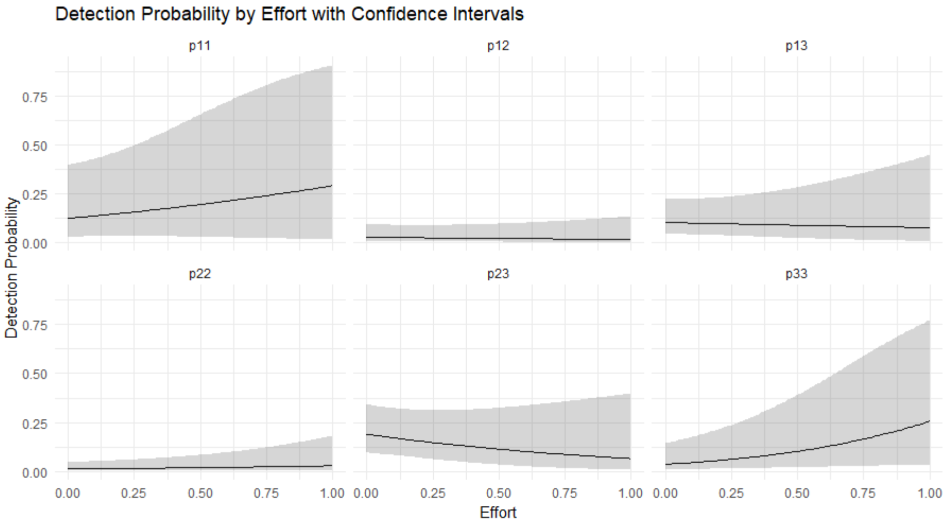


Figure 11. The effect of the covariate Effort on the detection probability per state with the confidence intervals (BM dataset)

3.2 Älgobs

For the comparison of the Älgobs method with the different camera trap methods, I took the Älgobs from 2017 and 2023 for all the hunting areas combined and for the regions excluding Hörneåns (Table 8).

Table 8. Ratios for each state per Älgobs dataset

Dataset/ State	1	2	3
Älgobs 2017 (all three)	0.610	0.349	0.110
Älgobs 2023 (all three)	0.610	0.376	0.089
Älgobs 2017 (Hörneåns excluded)	0.599	0.353	0.088
Älgobs 2023 (Hörneåns excluded)	0.559	0.400	0.093

3.3 Method comparison

The monitoring methods were compared by calculating the ratios for the different reproductive outcome states and comparing these side by side for both years 2017 and 2018. A comparison of the bars visually in combination with chi-squared tests revealed the following: the BM naïve occupancy and the BM multi-state occupancy estimates show no significant differences compared to the Älgobs method (Figure 12).

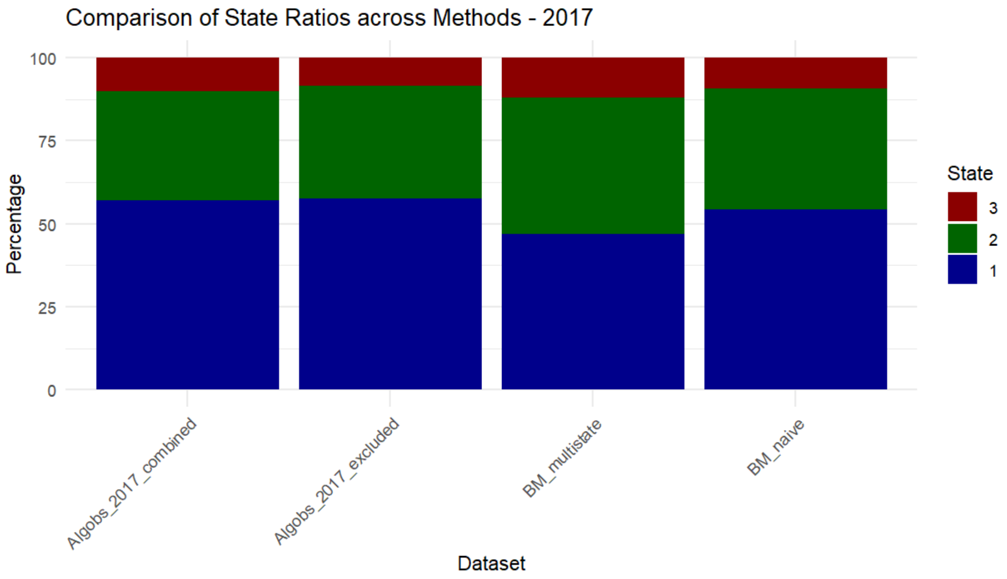


Figure 12. Stacked bar graph showing the reproductive outcome state ratios for each state per dataset for 2017

The Hunter and RefNM datasets show significant differences with the Älgobs ratios (Figure 13). For a table with all the calculated state ratios for both methods and years and a detailed list of p-values for all chi-squared comparisons for both 2017 and 2023, see Appendix 2.

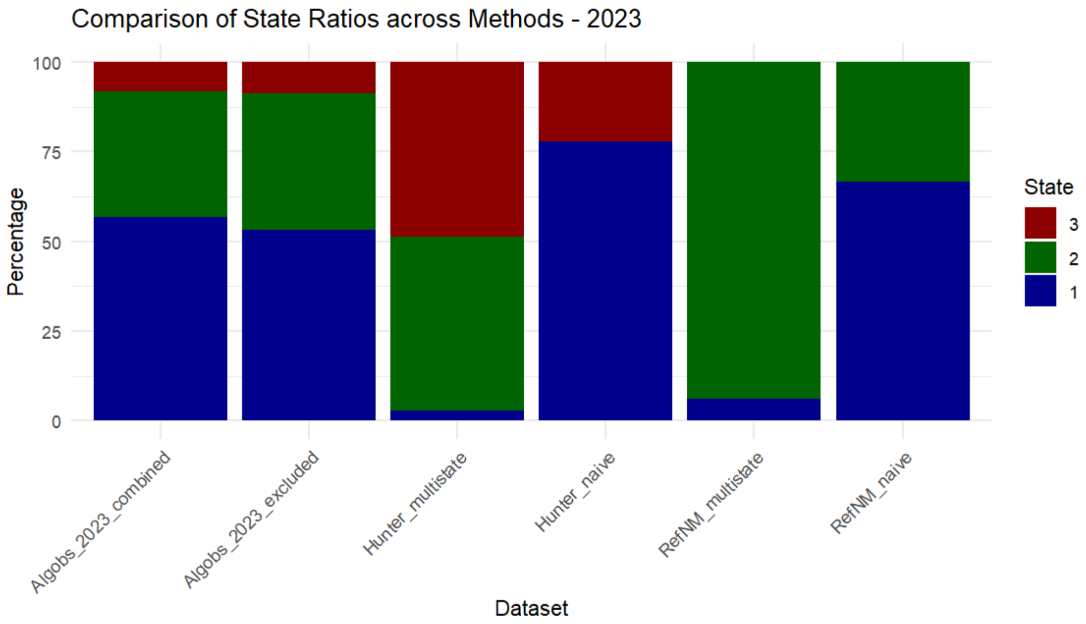


Figure 13. Stacked bar graph showing the reproductive outcome state ratios per state per dataset for 2023

3.4 MegaDetector performance

To assess the performance of MegaDetector I calculated the confusion matrices and the number of bounding boxes to be able to compare the effect of the AI confidence thresholds on its performance and the accuracy of the AI per confidence level to look at the overall performance.

3.4.1 Confusion matrices

The confusion matrices for the RefNM and Hunter datasets, across all confidence levels, show the matches and mismatches between the AI and manual classifications (Figure 14 and Figure 15 respectively). The RefNM dataset, with a confidence level threshold of 0.1, has more misclassifications than the Hunter dataset, with a confidence level threshold of 0.7, and a higher proportion of false negatives and false positives for the animal classification.

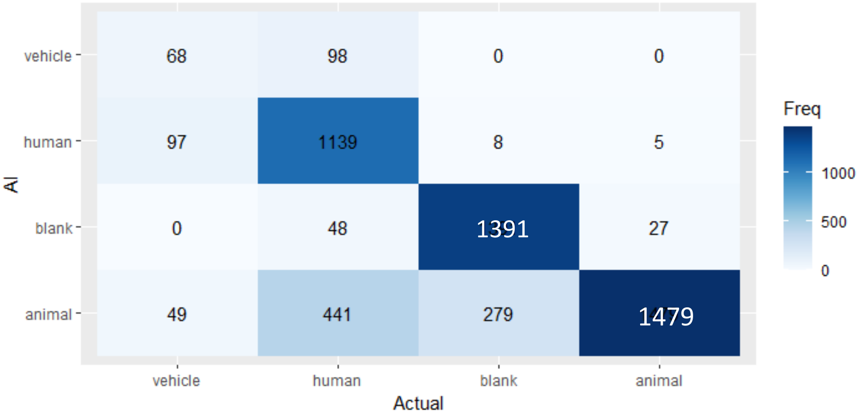


Figure 14. Confusion Matrix for the RefNM dataset, AI against manual classifications, confidence threshold = 0.1.

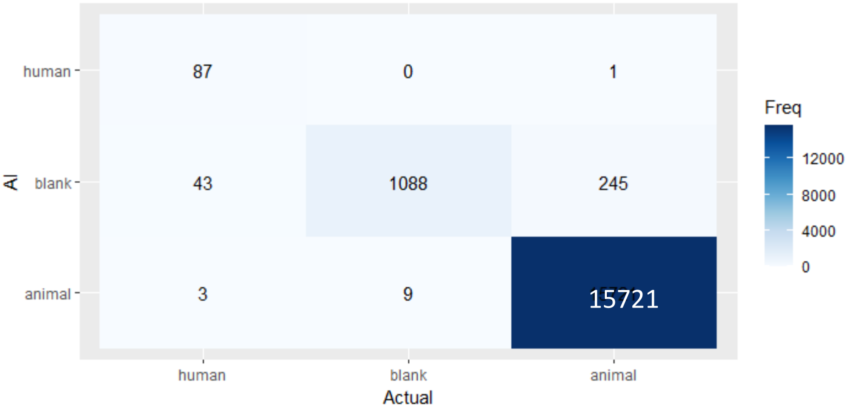


Figure 15. Confusion Matrix for the Hunter dataset, AI against manual classifications, confidence threshold = 0.7

3.4.2 Accuracy across confidence levels

The overall accuracy of MegaDetector was calculated per confidence level for both datasets. For the RefNM dataset, the accuracy for all confidence levels from 0.1 to 1.0 could be calculated and for the Hunter dataset from 0.7 to 1.0. The accuracy is higher with higher confidence levels for both datasets. At a 95% confidence level in the RefNM dataset, MegaDetector correctly classified 97.4% of the animals, 96% of the humans and 99.3% of the vehicles (Figure 16). At a 95% confidence level in the Hunter dataset, MegaDetector correctly classified 98.3% of the animals and 99.7% of the humans (Figure 17). In the hunter data, there were no sightings of vehicles. The exact values in combination with the precision, recall and specificity values are located in Appendix 3.

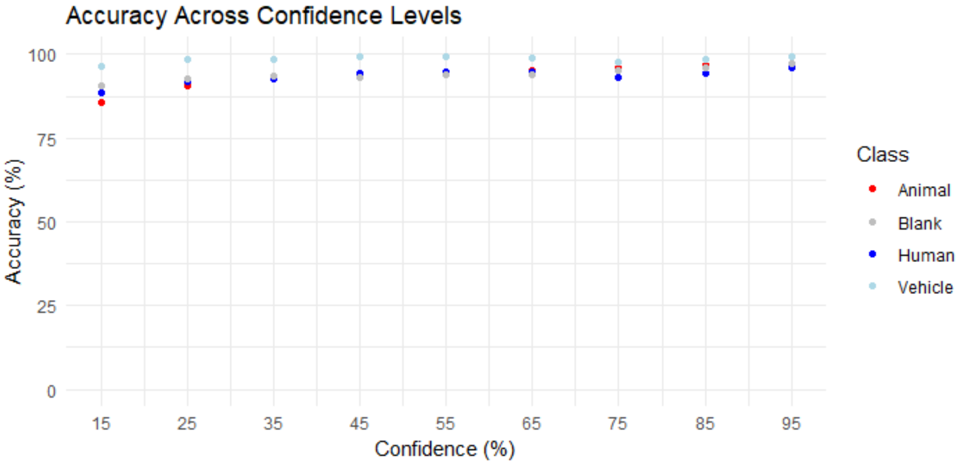


Figure 16. Accuracy across confidence levels for the three classes and blanks. RefNM dataset, confidence threshold = 0.1

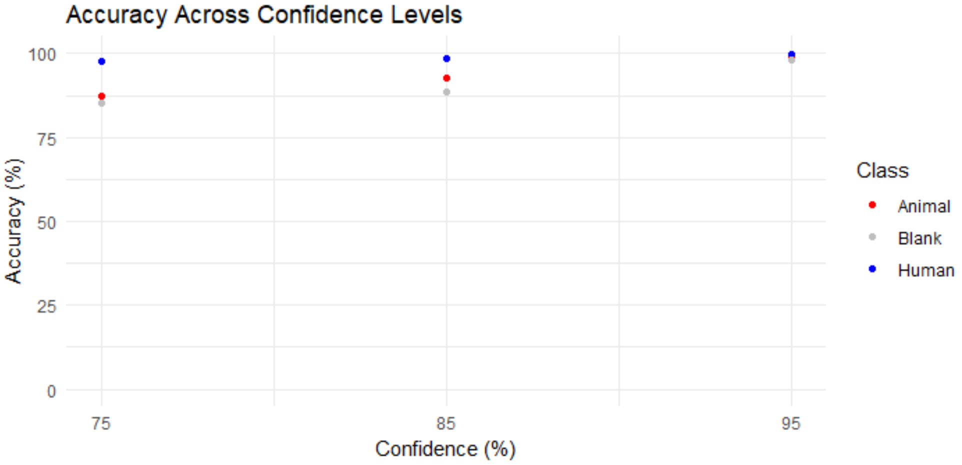


Figure 17. Accuracy across confidence levels for the two classes and blanks. Hunter dataset, confidence threshold = 0.7

3.4.3 Bounding boxes

The comparison of confidence levels was also assessed by comparing the number of bounding boxes it generated against manually corrected bounding boxes across the two 2023 datasets. The AI model's ability to detect the right amount of objects and draw bounding boxes around them varied across different deployments, as shown in the graphs (Figures 18 and 19). Higher proportions of misidentifications were prevalent in the dataset with the lower confidence threshold of 0.1 compared to the confidence threshold of 0.7. An example of a mismatch in bounding box numbers is in Figure 20 C and D.

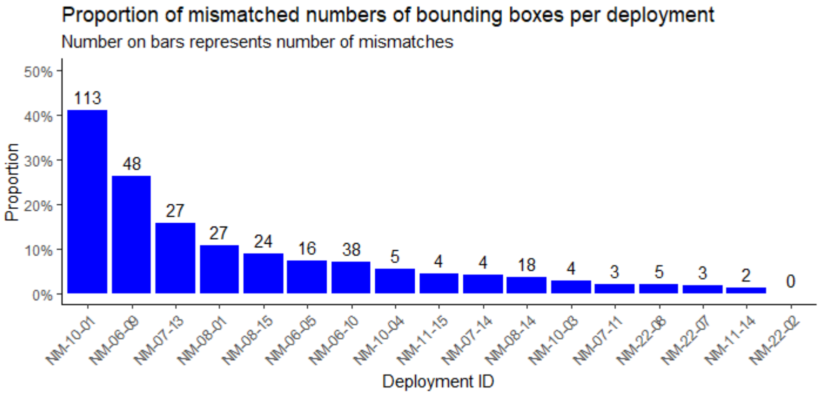


Figure 18. The proportion of mismatched numbers of bounding boxes between AI and manual classification per deployment for the RefNM dataset, confidence threshold = 0.1

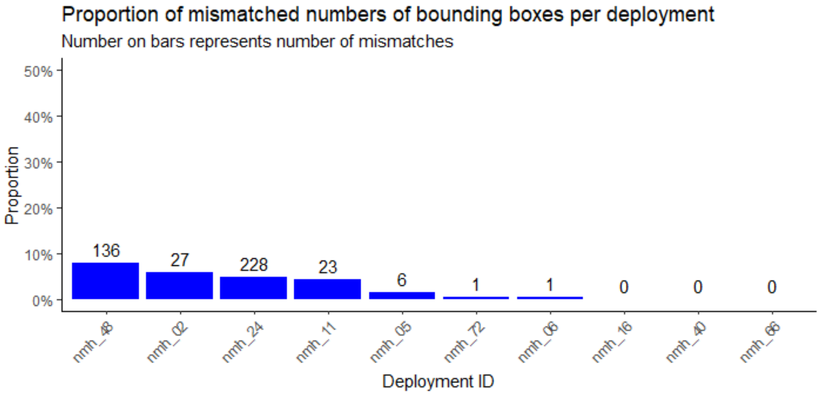


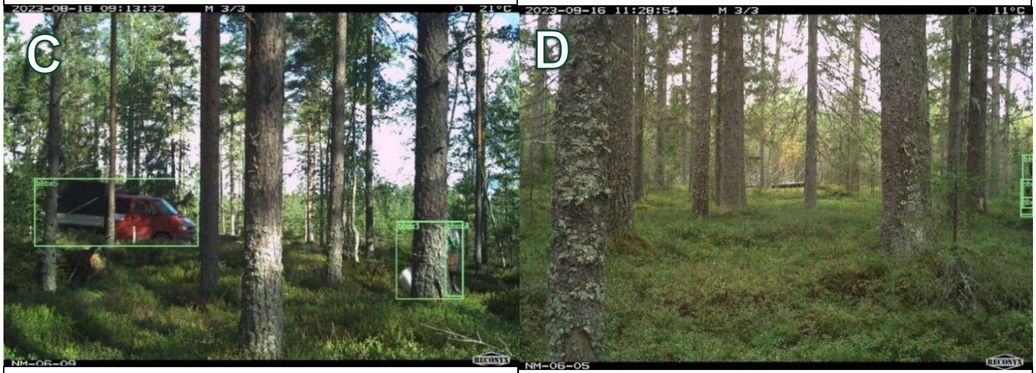
Figure 19. The proportion of mismatched numbers of bounding boxes between AI and manual classification per deployment for the Hunter dataset, confidence threshold = 0.7

3.4.4 Examples misclassifications

This section shows example images with misclassifications by MegaDetector from the RefNM dataset. The misclassifications in these examples have a confidence level lower than 0.378 and higher than 0.13.

Manual classification = empty
Model classification =animal (0.378)
Blank seen as animal.

Manual classification = empty
Model classification =animal (0.142)
Blank seen as animal.



Manual classification = vehicle, human
Model classification = animal x2 (0.18, 0.21), vehicle (0.75), human x2 (0.18, 0.41)
Wrong counts of objects and wrong classification.

Manual classification = animal
Model classification = animal x3 (0.13, 0.23, 0.33)
Wrong count of objects.

Figure 20. Examples of incorrectly classified pictures by MegaDetector showing the manual classification and the model classification with the confidence of the AI's classification within brackets and an explanation of the misclassification. All pictures are from the RefNM dataset. A: false positive detection, B: false positive detection. C: false class and false counts detected, D: false counts detected.

4. Discussion

This study compares the effectiveness of systematic and targeted camera trap deployments against the Älgobs method to assess their relative accuracy and reliability in estimating moose populations. By integrating occupancy models with camera trap data and comparing the results with Älgobs observations, I aimed to enhance the understanding of monitoring moose population reproductive outcomes and inform better management practices. The BM dataset showed similar state ratios with the Älgobs for 2017 indicating that systematically deployed cameras give similar reproductive status estimates, for the ratios of female moose without calves, female moose with one calf and female moose with two calves.

In wildlife management, monitoring animal populations and estimating population densities is essential. In Sweden, traditional moose monitoring has relied on hunter counts through the Älgobs system that give reproductive status and population estimates (Ericsson & Wallin 1999; Singh et al. 2014; Ericsson & Kindberg 2019). While cost-effective and long-established, this method has a significant limitation: the seasonal constraint of data collection during the hunting season (Månsson et al. 2011). Camera trapping could offer a solution to this limitation.

The naïve occupancy, which does not account for detection probability, showed a similar ratio to the Älgobs counts when compared with the BM dataset. This is comparable to the ratios calculated for the multi-state occupancy model. Initially, this might seem surprising, as naïve occupancy values are typically lower than those from the occupancy models due to false absences (MacKenzie et al. 2002; MacKenzie & Royle 2005; Ewing & Doll 2024). However, when these values are converted into percentages for each reproductive outcome state, the ratios are similar between the two occupancy methods. This suggests that despite the naïve occupancy values being lower, the proportionate differences between the states remain consistent. Therefore, naïve occupancy could still be useful for detecting differences within a population, even though the absolute occupancy values are underestimated and could be misleading for the exact population status (Mackenzie 2005). However, it is important to note that when detection probabilities differ significantly between states, this could influence the outcomes of the naïve occupancy ratios, leading to lower or higher estimates due to low or high detection of a state.

My findings showed that using a variety of deployment methods and heterogeneous data sources for camera trap data posed challenges in running occupancy models. The large standard errors and wide confidence intervals in the occupancy estimates of the RefNM and Hunter datasets highlight the need for a sufficient number of observations and the impact of mixed methods on model precision. Both datasets showed a low number of observations for the higher states, with no state 3 observations for the RefNM data and no state 2 for the Hunter data, leading to problems with the estimation of multi-state occupancy values and the generation of NaNs. Low detection probabilities can bias the occupancy model estimates (MacKenzie et al. 2002). Optimizing the methodology and placement of CTs (Hofmeester et al. 2021), as well as increasing the number of surveys and locations can help to improve detection probabilities (MacKenzie & Royle 2005; Kays et al. 2020). In this study, the lack of data resulted in not being able to compare the systematically and targeted placed cameras and made the comparison with the 2023 Älgobs counts also not justifiable.

The Hunter dataset particularly showed high uncertainty for the occupancy probability estimates. This was largely due to the small number of cameras, and the different placement strategies within the dataset. Although the targeted cameras, placed directed on either a salt stone or wildlife passage, increased the detection probability (although, with large confidence intervals), six targeted cameras were not enough to make the model estimates more precise. Since increasing the detection probability can increase the robustness of the model (MacKenzie et al. 2002; Pautrel et al. 2024), I ran the model while excluding the randomly placed cameras from the Hunter dataset. This led to more reliable estimates, although still with large confidence intervals. This finding underscores the importance of consistent data collection methodologies in ecological studies and enough camera trap locations. Future studies can look deeper into the effect of the targeted camera trap placement on the detection probabilities. Another way to mitigate problems would be to provide volunteers with clear guidelines on effective camera deployment to further improve data quality and reliability (Bryn et al. 2023), ensuring comparable placement methods for all cameras.

The hierarchical nature of the occupancy states (Mackenzie et al. 2009) in a multi-state occupancy model can cause problems (Evans et al. 2024). When state 3 (female moose with two calves) was observed at a location, subsequent observations of state 1 (female moose) or state 2 (female moose with one calf) were considered misclassified by the model. So it could be possible to see a female moose with two calves and the next day a female moose with one calf at the same location, which could either mean that it is different individuals or that the second calf is not seen. This was not taken into account in the model used in this study, but future research should consider this aspect.

When analyzing the RefNM and BM datasets separately using the multi-state occupancy models, the results for BM alone did not show significant changes compared to the combined datasets, however, the RefNM dataset had difficulties producing reliable estimates. Initially, the idea was to combine both datasets to be able to compare the RefNM dataset with the 2023 Älgobs data. However, this was not possible with the available data. Therefore, the BM data was used for the 2017 comparison and the RefNM dataset for the 2023 comparison.

When including covariates in the models, only the BM dataset converged with some of the covariates. The RefNM and Hunter datasets had fewer than 40 sites, which, according to Kays et al. (2020), is the minimum needed to be able to run an occupancy model with covariates. Only the proportion of open land at the occupancy level and effort at the detection level were found to be significant for the BM dataset. For State 1 and State 3, there was an increase in occupancy with an increase in open land, suggesting that open land is an important habitat feature for moose. This finding aligns with Widén (2023), who showed that clearcuts are a preferred habitat form for moose. Effort was included as a covariate at the detection level to account for variation in survey intensity across sites. The model revealed that effort has a positive effect on the detection probability for p33, although the results showed high uncertainty for other detection probabilities. Ultimately, I chose to use models without covariates for the method comparison to ensure a more straightforward comparison with the Älgobs counts, which do not account for covariates, thus making the comparison of occupancy estimates more fair.

The Älgobs data represent a single count per hunting area, which I assumed to be representative of the entire area. However, it is important to acknowledge that there could be regional differences within these hunting areas. As illustrated in Figure 1, the camera trap locations overlap with the Älgobs regions but do not perfectly align. There are portions of the hunting areas that do not have camera deployments. This discrepancy should be considered when looking at the results of the comparisons between the camera trap data and Älgobs values.

The placement of the camera traps for RefNM and BM at a maximum of 500 m from roads could have influenced the behaviour of moose, since moose adjust their distance to roads depending on the time of the day, keeping larger distances from roads during the daytime (Neumann et al. 2013). Next to that, they increase their speed within the proximity of roads (Neumann et al. 2013). This can have an influence on the detection probabilities of the species. The rutting period also seems to influence the movement rate of moose(Neumann et al. 2009), with increased movement to find mates, and an increase in road-crossings during the migration period of moose (Neumann et al. 2012) having the same influence on the detection probabilities as the avoidance of roads. Additionally, another methodological point to consider is the false positive classification of female moose in the period that male moose do not have their antlers. This misclassification can impact the accuracy of reproductive status estimates.

This study underscored the importance of having enough observations to be able to perform the occupancy models effectively. Large datasets, however, take a long time to classify. The inclusion of the AI model MegaDetector on the classification platform can speed up the process of classifying (Beery et al. 2019). In this study, I evaluated the performance of the MegaDetector AI model by examining the impact of different confidence level thresholds and the overall model performance. The RefNM data, classified with a lower confidence level of 0.1, showed a higher degree of misclassifications, false positives and false counts compared to the Hunter data, which used a threshold of 0.7. While a higher confidence threshold reduces false positives, it should be balanced with the need to minimize false negatives to ensure no important data is lost. This balance is crucial to keep the workload manageable while maintaining all observations in the dataset. Overall the accuracy of the AI model was quite high for both datasets, consistent with the findings of Mitterwallner et al. (2023). For future studies, comparing confidence levels using the same dataset can provide a clearer understanding of their effects. Next to that, the implementation of species-recognizing AI models can further streamline the classification process, however, these models still need learning and refinement (Norouzzadeh et al. 2018; Glover-Kapfer et al. 2019).

This study illustrates the potential of camera traps to provide reliable data on moose population structure in the form of reproductive outcomes, particularly when combined with occupancy modelling. One significant issue identified in the traditional method Älgobs is the time lag problem, where there is a year in between moose counts and management plan writing. During this period, environmental stressors can cause changes in the population structure, which camera traps could effectively mitigate by offering continuous, real-time data collection. This real-time data collection provides a more comprehensive understanding of moose population dynamics. This study showed that systematically placed camera traps give similar reproductive outcome estimates compared to the traditional Älgobs counts. However, applying this method on a large scale requires considerable time and resources. The use of citizen science could increase the amount of data without increasing the effort. Future studies could also investigate whether a larger pool of targeted cameras results in higher detection probabilities, which could increase the robustness of the occupancy models and reduce the number of cameras needed for the models to converge. Additionally, it may be beneficial to provide volunteers with clear guidelines and protocols on how to deploy the cameras effectively to create more standardized deployment methods for fairer comparisons.

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Popular science summary

Moose are an important part of Sweden's wildlife, and understanding their populations is crucial for effective wildlife management. Traditionally, moose populations have been monitored using the Älgobs system, where hunters record their observations during the hunting season. While this method is useful, it has some limitations, especially since data is only collected during a specific time of year.

In this study, I explored whether using camera traps could provide a better way to monitor moose populations. Camera traps are special cameras placed in the wild that automatically take pictures when they detect movement. We used two types of camera traps: systematically placed ones, which are set up in a grid-like pattern, and targeted ones, which are placed in specific locations like near salt stones or wildlife trails.

I compared the data from these camera traps with the data collected by the Älgobs system to see how well they matched. I specifically looked at the ratios of different groups of moose: females without calves, females with one calf, and females with two calves. This helps in understanding the reproductive status of the moose population.

My findings were promising. The systematically placed camera traps provided ratios that were similar to those from the Älgobs system, suggesting that camera traps can be a reliable method for monitoring moose. I also found that using more cameras and placing them strategically can improve the accuracy of the data. Additionally, I used an AI tool called MegaDetector to help classify the images more quickly and accurately.

Overall, my study shows that camera traps, combined with advanced data analysis methods, can provide continuous, real-time monitoring of moose populations. This could help overcome some of the limitations of traditional methods and offer a more detailed understanding of moose population dynamics. Future research should continue to refine these methods and explore how best to use camera traps to get the most accurate data.

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Appendix 1

Table 1. The classification scheme used for the camera trap data classification in Trapper and Viltbild.se. The observation types below 'Classes' were only assigned when the Class was 'Animal'

Observation Type	Classification
Classes	Animal
	Human
	Vehicle
	Unknown
	Unclassified
	Blank
Species (Animal)	American Mink, Arctic Fox, Asiatic Raccoon, Beech Marten, Birds, Black Grouse, Brown Bear, Cattle, Common Crane, Common Muskrat, Common Otter, Coypu, Crows, Deer, Domestic Cat, Ermine, Eurasian Beaver, Eurasian Lynx, Eurasian Red Squirrel, European Badger, European hare, European Pine Marten, European Polecat, European Rabbit, Falcons, Fallow Deer, Gray Partridge, Gray Wolf, Gulls, Hares, Hawks, Hazel Grouse, Least Weasel, Moose, Mountain hare, mustelids, Owls, Perching Brids, Pheasants, Pigeons, Raccoon, Red Deer, Red Fox, Reindeer, Roe deer, Shore birds, Unknown, Waterfowl, Western Capercaillie, West European Hedgehog, Wild Boar, Wolverine, Woodpeckers
Sex (Animal)	Female
	Male
	Unknown
Age (Animal)	Adult
	Subadult
	Juvenile
	Offspring
	Unknown
Behaviour (Animal)	Grazing
	Browsing
	Rooting
	Vigilance
	Running
	Walking

Appendix 2

The percentages for each state calculated for the comparison with Älgobs are visible in the table.

Table 2. Percentages calculated for the different states per dataset per method

/State Dataset	1	2	3
Naïve occupancy			
BM+RefNM	55.5	36.1	8.3
BM	54.4	36.4	9.2
RefNM	66.7	33.3	0.0
Hunter	77.8	0.0	22.2
Targeted	66.7	0.0	33.3
Random	100.0	0.0	0.0
Multi-state occupancy nullmodel			
BM+RefNM	46.1	42.5	11.4
BM	47.0	40.9	12.1
RefNM	6.1	93.9	0.0
Hunter	2.8	48.6	48.6
Älgobs			
Hörneåns+Järnäshalvöns+Hörnefors			
2017	57.1	32.7	10.3
2023	56.7	35.0	8.3
Järnäshalvöns+Hörnefors			
2017	57.6	34.0	8.5
2023	53.2	38.0	8.9

Chi-squared test outcomes for comparisons between ratios for the datasets with Älgobs for both 2017 (Table 3) and 2023 (Table 4). A p-value below 0.05 shows that the compared ratios are significantly different.

Table 3. Chi-squared test p-values for comparisons of camera trap ratios and Älgobs ratios for the year 2017

Comparison	p-value
BM_naive and Algobs_2017_combined	0.850
BM_naive vs. Algobs_2017_excluded	0.904
BM_multistate vs. Algobs_2017_combined	0.361
BM_multistate vs. Algobs_2017_excluded	0.311

Table 4. Chi-squared test p-values for comparisons of camera trap ratios and Älgobs ratios for the year 2023

Comparison	p-value
RefNM_multistate vs. Algobs_2023_combined	3.164e-17
RefNM_multistate vs. Algobs_2023_excluded	6.303e-16
RefNM_naive vs. Algobs_2023_combined	0.010
RefNM_naive vs. Algobs_2023_excluded	0.005
Hunter_multistate vs. Algobs_2023_combined	5.235e-18
Hunter_multistate vs. Algobs_2023_excluded	8.249e-17
Hunter_naive vs Algobs_2023_combined	2.021e-10
Hunter_naive vs Algobs_2023_excluded	3.237e-11

Appendix 3

Table 5. The Accuracy, Precision, Recall and Specificity per class (Animal, Human and Blank) for different confidence levels for the Hunter dataset

Confidence (%)	Class	Accuracy	Precision	Recall	Specificity
75	Animal	0.874	0.987	0.714	0.993
75	Human	0.978	1.000	0.151	1.000
75	Blank	0.853	0.791	0.995	0.684
85	Animal	0.926	0.999	0.887	0.998
85	Human	0.986	0.967	0.397	1.000
85	Blank	0.885	0.791	0.999	0.872
95	Animal	0.983	1.000	0.982	0.998
95	Human	0.997	0.983	0.578	1.000
95	Blank	0.981	0.791	0.998	0.979

Table 6. The Accuracy, Precision, Recall and Specificity per class (Animal, Human and Blank) for different confidence levels for the RefNM dataset

Confidence (%)	Class	Accuracy	Precision	Recall	Specificity
15	Animal	0.857	0.263	0.771	0.863
15	Human	0.887	0.799	0.352	0.984
15	Vehicle	0.967	0.333	0.179	0.990
15	Blank	0.908	0.949	0.929	0.843
25	Animal	0.907	0.295	0.667	0.919
25	Human	0.918	0.846	0.333	0.992
25	Vehicle	0.983	0.357	0.200	0.995
25	Blank	0.928	0.949	0.965	0.756
35	Animal	0.930	0.313	0.603	0.944
35	Human	0.929	0.827	0.283	0.994
35	Vehicle	0.987	0.417	0.250	0.996
35	Blank	0.937	0.949	0.979	0.688
45	Animal	0.937	0.497	0.724	0.951
45	Human	0.943	0.852	0.346	0.995
45	Vehicle	0.995	0.500	0.111	0.999
45	Blank	0.933	0.949	0.974	0.696
55	Animal	0.949	0.540	0.705	0.964
55	Human	0.948	0.925	0.431	0.997
55	Vehicle	0.995	0.375	0.429	0.997
55	Blank	0.938	0.949	0.980	0.695
65	Animal	0.953	0.528	0.679	0.968
65	Human	0.949	0.945	0.460	0.997
65	Vehicle	0.988	0.350	0.500	0.992
65	Blank	0.938	0.949	0.980	0.698
75	Animal	0.961	0.732	0.800	0.975
75	Human	0.932	0.857	0.424	0.992
75	Vehicle	0.976	0.440	0.595	0.984
75	Blank	0.953	0.949	0.994	0.792
85	Animal	0.970	0.892	0.910	0.980
85	Human	0.945	0.918	0.654	0.991
85	Vehicle	0.985	0.440	0.407	0.993
85	Blank	0.962	0.949	0.999	0.875
95	Animal	0.974	0.941	0.964	0.978
95	Human	0.960	0.967	0.841	0.992
95	Vehicle	0.993	0.800	0.190	1.000
95	Blank	0.973	0.949	1.000	0.945

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