Version of Record: https://www.sciencedirect.com/science/article/pii/S0006320722003469
Manuscript_2e0254f97cd7e17dba3d346c348f2018

Developing cost-effective monitoring protocols for track-surveys: an empirical assessment using a Canada lynx *Lynx canadensis* dataset spanning 16 years

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Funding: This work was supported by the Maine Department of Inland Fisheries and Wildlife, Nongame and Endangered Species Fund and Maine Federal Aid in Wildlife Restoration Grant W-82-R, W-86-R, and W-87-R, Maine State Wildlife Grants T-1, T-2, and T-3, Maine Wildlife Conservation and Restoration Program Grant R-1, and Maine Section 6 Endangered Species Grant E-1, USDA National Institute of Food and Agriculture, McInitire-Stennis Project Number MEO-41602 and MEO-41913 through the Maine Agricultural and Forest Experiment Station. Additional funding was provided by the Dirigo Fund of the University of Maine.

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Abstract

Management agencies need statistically robust, cost-effective monitoring programs to effectively conserve and manage wildlife. However, this requires pilot studies to assess the monitoring protocol's ability to detect meaningful changes in the state variable of interest. This is more challenging for elusive mammals due to low detection rates and the costs associated with fieldwork. A key knowledge gap concerns how spatio-temporal dynamics in species occupancy and detection rates alter the cost-effectiveness of sampling protocols. To fill this gap we used a dataset spanning 16 years on Canada lynx (*Lynx canadensis*) track surveys conducted in Maine, USA, and developed optimal monitoring protocols that empirically assess the cost-effectiveness of these protocols under different scenarios. We surveyed 96 townships and detected 949 track intercepts, which were converted to detection histories under a spatially-replicated occupancy design. By combining occupancy modeling and power analyses, we estimated the sampling effort required to detect declines in occupancy from 10 to 50%. Calculating the monetary cost of these protocols indicated that detecting subtle changes in occupancy (<10%) is very expensive even within high suitability habitats and may often be unrealistic. However, protocols that detected medium (30%) to large (50%) declines required similar budgets and were consistent with the observed shifts in occupancy during our study period (34%), suggesting that a modest budget increase would pay large dividends in population assessment efficacy. Our results provide important guidance on how to implement robust and cost-effective monitoring programs with snow track surveys – a popular survey method used by many conservation agencies.

Key-words: Carnivores, Habitat suitability, Occupancy modeling, Optimal sampling allocation, Power analysis, Maine, USA

1 Introduction

Population monitoring (i.e., "collection of repeated observations or measurements to evaluate changes in conditions and progress towards a management objective" (Elzinga and Salzer 2007)) is crucial in wildlife conservation (Yoccoz et al., 2001; Wintle et al., 2010). Indeed, half of the resources available to conserve threatened species are allocated to research and monitoring (Buxton et al., 2020). Nevertheless, developing statistically robust, cost-effective monitoring programs is challenging as it requires clear management objectives and a combination of pilot field studies with power analyses and optimization algorithms (Legg and Nagy, 2006). Protocols for monitoring uncommon or elusive mammals are especially difficult to develop because of the low detection rates and the inherent costs associated with fieldwork (Kindberg et al., 2009; Boitani and Powell, 2012; Galvez et al., 2016).

Extensive work has been conducted to assess the optimal sampling effort allocation for mammals under an occupancy modeling framework (Ellis et al., 2012; Steenweg et al., 2016; Mortelliti et al., 2022). This approach typically entails the collection of detection/non-detection data to estimate species detection and occupancy probabilities (Mackenzie et al., 2003) followed by power analyses to estimate the sampling effort required to detect a specific change in occupancy (e.g. 10% decline) over time at different sites (Steidl et al., 1997). Power analysis ensures that a monitoring program has sufficient statistical power (i.e. detecting a change in the population when the change has occurred) to meet management objectives (e.g. detecting a 10% decrease in occupancy) (Guilleta-Arroita and Lahoz-Monfort, 2012). Previous work has mostly focused on developing optimal monitoring protocols using camera traps; however, many conservation agencies employ other survey techniques.

Track surveys (on snow, mud, or track plates) are a widely used method for surveying mammals, mainly because they are effective, relatively cheap, and easy to implement (Silveira et al., 2003). Many studies use track surveys to measure habitat selection (Hebblewhite et al., 2011), animal movement (Lomolino, 1990), and occupancy rates (Hines et al., 2010). Snow track surveys have been extensively used by conservation agencies to survey carnivores such as wolves (*Canis lupus*) (Liberg et al., 2012), wolverines (*Gulo gulo*) (Magoun et al., 2007), and lynx (*Lynx canadensis*) (Squires et al., 2004). Nevertheless, few studies have examined the most cost-effective way to monitor mammal populations through snow track surveys. Examples of key unanswered questions are: how does the feasibility and cost-effectiveness of a monitoring protocol vary with the habitat suitability for a given species? What are the conditions that make a monitoring protocol infeasible? Can we derive general rules about the cost-effectiveness of track-survey protocols despite specific details linked to a particular species, location, or conservation agency? Lack of knowledge on these topics is a significant concern because conservation budgets are limited and thus quality data must be gathered with minimal expense.

Though many snow track surveys have evaluated the sampling effort required to effectively detect changes in occupancy of carnivores (Aing et al., 2011; Liberg et al., 2012; Whittington et al., 2013), few have translated their results into a formal monitoring protocol. This is a major shortcoming because the optimal sampling effort is likely to change as a function of the spatial variation in detection probability, habitat quality, and temporal changes in species occupancy (Guilleta-Arroita and Lahoz-Monfort, 2012). For example, sites with different characteristics may require different efforts to detect the same magnitude of change. Similarly, a decline in occupancy between surveys may indicate the need for a more intense sampling effort (Mackenzie and Royle, 2005; Guilleta-Arroita and Lahoz-Monfort, 2012). Conservation agencies have no clear guidelines regarding the cost-effectiveness of snow track surveys and the conditions under which they will have the power to detect a given change in occupancy over time. More specifically, we do not fully understand yet how the spatio-temporal dynamics in species occupancy and detection rates alter the cost-effectiveness of snow track sampling protocols.

Here we performed an empirical assessment of the cost-effectiveness of monitoring protocols accounting for operational costs – a key consideration given limited budgets (Galvez et al., 2016). Our objectives were to **1)** identify the sampling effort required to detect a range of 10 to 50% change in occupancy; **2)** assess the feasibility of monitoring programs designed to detect these changes considering fieldwork costs; **3)** identify general rules that could guide practitioners in allocating survey effort. To answer these questions, we used a dataset for Canada lynx (*Lynx canadensis*) spanning 16 years in the state of Maine, USA to develop optimal monitoring protocols for snow track surveys that are widely relevant to monitoring carnivores in snowy environments.

2 Material and Methods

2.1 Study area and data collection

Our study was conducted in Maine, northeastern United States (Fig. 1). The average temperature ranges from -10°C to 19°C, with annual mean precipitation of 113 cm and annual mean snowfall of 120 cm in the central and northern parts of the state.

The detection history data were collected by the Maine Department of Inland and Fisheries Wildlife as part of their wintertime Canada lynx snow track survey. This project was conducted in two periods: 1) between 2003 – 2008 and 2) between 2015 – 2019 on extensive network of unplowed dirt roads by snowmobile. Trained observers recorded with a GPS all survey routes and the locations of Canada lynx track intercepts along those trails. Track intercepts (hereafter “track”) were defined as any trail made by a lynx encountered along the route that could not be connected to an adjacent lynx trail based on visual examination from the route.

Surveys were conducted at the township level (i.e. sites) within the Canada lynx distribution in Maine, encompassing the northern part of the state (Fig. 1). Townships were used to locate and stratify surveys to guarantee an even distribution across the state, but surveys in practice exceeded township boundaries (usually 100 km^2), thus we used a cell-based approach to create the detection history (see below). A total of 78 townships were surveyed during the first period (2003 - 2008) and 58 townships in the second (2015 - 2019), with 40 townships surveyed during both periods.

To ensure spatial replicates and independence among tracks, we subdivided each township into 5 km x 5 km grid cells, which corresponds to half the size of a male Canada lynx winter home range in Maine (Vashon et al., 2008) (Fig. 1). We considered these grid cells as visits within townships (i.e. a space-for-time substitution). On average, each township had 8 grid cells for both survey periods. The detection history refers to the cell scale, where we assigned to each cell a detection (1) or non-detection (0) based on whether at least one track was recorded within the cell. To confirm there was no spatial dependency among detections, we performed a spline correlogram analysis using the package ncf (Ottar 2020) in program R version 4.0.3 (R Development Core Team 2021) (Fig. A1).

Variables collected during the surveys and used as covariates in the analyses were the travel distance within each grid cell (in km) and the time since the last snowfall in each township (in hours). For both survey periods, the average travel distance per cell was approximately 9.5 km, and the time since the last snowfall varied from 12 to 84 h (average = 40 h, but two townships were surveyed 182 and 206 h after a snowfall).

We also collected GIS layers for the entire state of Maine that could affect Canada lynx detection and occupancy probabilities such as the proportion of conifer forest (GAP/LANDFIRE National Terrestrial Ecosystem, 2016), forest disturbance index, and terrain roughness index. The forest disturbance index was calculated using Landsat imagery processed by Kilbride (2018) in which we extracted the intensity and the year of the most recent forest loss event and combined them into a single variable (Mortelliti et al., 2022; Evans and Mortelliti, 2022) (Supplementary material Appendix B). The terrain roughness index was calculated using a Maine elevation map extracted from the R package elevatr (Hollister, 2020). We scaled all GIS layers (conifer forest, disturbance index, and terrain roughness index) to the township level (i.e. we calculated the average of all 30 m pixels within a township) and to an 8 km radius buffer around each township. We also extracted the centroid coordinates of each township to use as covariates as they are often associated with climatic (temperature) and anthropogenic (urbanization) variables in Maine. This data processing was performed in ArcGIS Pro 2.8.

2.2 Occupancy models

To estimate Canada lynx occupancy and detection probabilities, we fit single-season occupancy models using the unmarked (Fiske and Chandler 2011) package in R for each survey period separately. We used single-season models because only half (51%) of the townships surveyed in the first period were revisited in the second survey, thus precluding us from adopting a multi-season modeling approach (Mackenzie et al., 2003).

We included travel distance as an observation-level variable (i.e., grid cell) and time since snow, conifer forest, forest disturbance, terrain roughness, latitude, and longitude as site variables (i.e. township level). For conifer forest, forest disturbance, and terrain roughness, we also included an 8 km buffer around the township. In practice, no variables included in the same model had a correlation > 0.2.

We followed a forward stepwise approach to estimate detection and occupancy probabilities. First, we modeled detection probability (p) as a function of travel distance, time since snow, latitude, longitude, forest disturbance index, and conifer forest. We used the Akaike Information Criterion to rank competing models (Burnham and Anderson 2002), and inference was made using models within 2 ΔAIC of the top model. We first tested single variable models and then tested additive models if more than one model ranked within 2 ΔAIC and if it did not include the same feature at different scales (e.g. disturbance at township and buffer levels). Then, we retained the top model for the detection process and modeled occupancy probability (ψ) using the following predictors: latitude, longitude, forest disturbance, conifer forest, and terrain roughness. We quantified model fit using Nagelkerke's R-squared through R package unmarked (Fiske and Chandler, 2011).

2.3 Sampling effort

To estimate the sample size required to detect changes in Canada lynx occupancy in northern Maine, we used the algorithms developed by Guillera-Arroita and Lahoz-Monfort (2012). Specifically, Guillera-Arroita and Lahoz-Monfort (2012) provide a closed-formula that allows the calculation of the number of survey sites they need to survey to detect differences in occupancy under imperfect detection with a specific power. These algorithms determine the sample size (i.e. number of townships) needed to achieve a specific power as a function of the significance level (alpha) and effect size (percent decline to be detected) given occupancy probability ψ, detection probability p, and the number of visits (number of surveyed cells).

Alpha (the probability of a type I error, detecting a decline when it is not there) was set at 0.1 in all analyses. We chose this value because of the trade-off between type I and type II errors (not detecting a decline when it is there), and for conservation research, a type II error can have more severe negative consequences (Di Stefano, 2001; Legg and Nagy, 2006). The effect size corresponds to management objectives determined with stakeholders (Maine Department of Inland Fisheries Wildlife). We developed sampling protocols to detect declines in occupancy from 10 to 50% in 5% increments (i.e. 10%, 15%, 20%, up to 50%). Based on the change in the occupancy probability between the two survey periods (see Results), we focused our protocol on three degrees of decline: 10% (minor), 30% (moderate), and 50% (extreme). The power to detect this range of declines was set at 80% which is widely used for power analyses (power = 0.8; Elzinga and Salzer, 2007).

Initial occupancy probability was based on occupancy results and predicted for each township within the Canada lynx range in Maine (Fig. 1). The distribution of snow track surveys was such that the full distribution of certain important predictor variables were under-represented. Specifically, towns sampled during snow track surveys tended to be more recently disturbed than towns within the potential lynx range as a whole (Supplementary material Appendix B). As a result, model intercepts from snow track survey occupancy models tended to over-predict occupancy when applied to the full project area. To produce occupancy probability maps to establish state-wide monitoring protocols, we implemented an adjustment method to normalize the model intercept to make predictions for both survey periods. For this normalization, we used camera trapping data collected by Mortelliti et al. (2022) in the same study area and applied a uniform adjustment to model predictions (Supplementary material Appendix B). Based on the corrected values of occupancy, we calculated the difference in occupancy between both surveys (proportional temporal change in occupancy):

$$Temporal\ change\ in\ \Psi = \frac{(mean(\Psi_{2015-2019}) - mean(\Psi_{2003-2008}))}{mean(\Psi_{2003-2008})} \times 100$$

The initial detection probability was also based on the occupancy model results and was predicted for each township within the Canada lynx range in Maine. The top model for the detection process for both survey periods included time since snow and travel distance– two survey-level variables collected specifically for the towns we surveyed that cannot be extrapolated for the remaining townships. Including only these two would produce an unrealistically static detection probability throughout the state. Therefore, to account for the spatial heterogeneity in the detection process, we used model averaging of all models that were 2.0 ΔAIC above the null model to predict detection probability across the state. Thus, variables included were: time since snow, travel distance, latitude, disturbance, and conifer for the first period, and time since snow, travel distance, latitude, and disturbance for the second period. Model averaging was conducted using the R package MuMIn (Barton, 2020).

The number of visits was fixed at 13 cells for the first survey period and 7 cells for the second. Though the average number of cells per township was 8 cells, we chose these values because they allow for a high (0.98) cumulative probability (p*) of detecting lynx at least once (Fig. A3). The different number of cells for each survey period were due to differences in detection probabilities between surveys:

$$p^* = 1 - (1 - p)^{\,k}$$

where *k* is the number of cells required to achieve a given p* and p is the detection probability.

The sampling effort to detect a given change in Canada lynx occupancy was calculated at the township level. We categorized the sampling effort (i.e. the number of townships) into five categories of habitat suitability: high (>80% occupancy probability), medium-high (60% - 80%), medium (40% - 60%), and medium-low (20% - 40%), and low suitability (< 20%).

2.4 Cost analysis

To assess the operational cost required for snow track surveys and the feasibility of monitoring protocols, we estimated the cost of surveying a single township and compared costs among sampling scenarios. The three main areas of cost expenditure were equipment, personnel, and travel (Table A1). Because the equipment was a fixed cost and not associated with variability among in-situ operations per se (e.g. acquisition and maintenance of snowmobiles) we did not include this category in the final calculations (Gálvez et al., 2016).

Personnel costs were based on the US average field technician hourly wage of $20 per hour (including 33% overhead cost). We considered an average of 10 hours of work per day for a field crew of two people which is sufficient to survey one township. We also included lodging and food for the crew based on the US standard per diem rates. Travel costs considered field vehicle and snowmobile travel distance. We assumed a constant travel distance to all townships because the Maine Department of Inland and Fisheries Wildlife has many field stations throughout the state. We fixed the travel distance to a survey township to 180 km, and the snowmobile travel distance within townships to 80 km.

For any sampling scenario, the total project cost was given as the mean per-township cost multiplied by the total number of townships surveyed. For example, we multiplied the cost to survey one township by the average number of townships needed to detect a 30% decline in Canada lynx occupancy. We made this calculation for all monitoring protocols.

We performed power and cost analyses for the two survey periods separately and also for the average between them (i.e. averaging detection and occupancy probabilities between surveys), obtaining qualitatively similar results. Therefore, we only show the results for the most recent survey, and the other results are included in the Supplementary material Appendix A (Figs. A4-A8).

3 Results

We detected 949 Canada lynx tracks among 262 grid cells (311 tracks in the first period [14% of the cells] and 638 in the second period [39% of the cells]). Thirty-five townships (44%) had a lynx track in the first period (2003 - 2008), while in the second period (2015 - 2019) we recorded lynx tracks in 51 townships (87%).

3.1 Occupancy models

The detectability of the Canada lynx increased with travel distance ($\beta = 0.77$; SE = 0.14) and decreased with time since last snowfall ($\beta = -0.45$; SE = 0.25) in the first period. For the second period, we found that detection increased with time since last snowfall ($\beta = 0.24$; SE = 0.11) and also increased with travel distance ($\beta = 1.18$; SE = 0.14) (Fig. 2; Table 1).

We found that the probability of Canada lynx occupancy in the first period was greater in areas at higher latitude ($\beta = 0.76$; SE = 0.29) and with a larger proportion of conifer forest ($\beta = 0.54$; SE = 0.28). This pattern remained the same for the second period but with a stronger effect of latitude (β = 1.87; SE = 1.23) and conifer forest (β = 1.36; SE = 0.61) on the occupancy probability (Fig. 2; Table 1).

For both surveys, the model's estimated occupancy (i.e. average probability of occupancy across townships), after implementing the correction method with the camera trapping data, was very close to the naïve occupancy, with the average temporal increase in Canada lynx occupancy in Maine of 34% between the first and second survey periods (Fig. A9).

3.2 Sampling effort and cost-effective monitoring

The sampling effort required to detect different decline rates in occupancy varied considerably among protocols but were similar between periods (Fig. A4). For example, to detect a 10% decline in highly suitable habitats the sample size required was between 78 - 233 townships, whereas to detect a 50% decline in the same areas the sampling effort required was only between 7 - 12 townships (Fig. 3).

The estimated cost to survey one township was $627.54 (Table A1). Protocols able to detect < 20% declines were 5-fold more expensive than protocols focused on detecting larger changes (> 30%) in some instances. For example, the average project cost to detect a 10% change in high suitability habitats was $97 582 whereas to detect a 30% change in the same areas the cost was $15 374; a nearly 6-fold decrease (Fig. 4). However, the average cost differences for detecting declines between 30 and 50% in high suitability habitats were less drastic – a 2.5-fold increase in the budget would allow detection of a 30% decline ($15 374) in occupancy instead of 50% ($5 961).

4 Discussion

Understanding how to optimally allocate sampling effort is essential to developing cost-effective monitoring protocols, especially given limited conservation resources (McDonald-Madden et al., 2008; Wintle et al., 2010). Using Canada lynx detection data collected through snow track surveys, we found that detection probability was affected by travel distance and time since snowfall. The probability of occupancy increased with both the proportion of conifer forest and latitude (Fig. 2). Besides the spatial patterns in occupancy, we also found a temporal variation – the proportional occupancy probability of Canada lynx increased 34% on average between the two survey periods. Further, monitoring protocols with sufficient power to detect a small change in occupancy (<10%) were very expensive even for high suitability habitats. However, protocols focused on medium (30%) and large (50%) changes required relatively lower and similar budgets (a 2.5-fold difference in costs) and were consistent with the observed shifts in occupancy (34%) suggesting big gains in the minimal detectable change with a relatively small increase in the budget. Altogether, our results provide important guidelines to agencies on how to efficiently use conservation funds to properly implement targeted monitoring programs.

For high-suitability areas, detecting a 50% decline in occupancy required surveys of 7 - 12 townships, in comparison to 78 - 233 townships to detect a 10% decline (Fig. 3). The lower sampling effort for detecting a 50% decline in occupancy is an indication that practitioners should target their monitoring programs for smaller detectable changes (e.g. 30%) while ensuring a reasonable sampling scheme compatible with the size of the area monitored (Mortelliti et al., 2022). Importantly, before implementing these protocols, a careful design should de be planned following the basic sampling rules – surveying in a representative way throughout the environmental gradient that is biologically relevant for the species (Elzinga and Salzer, 2007). Other snow tracking studies have examined optimal sampling design to minimize errors in occupancy estimates (Aing et al., 2011) or the trade-off between spatial and temporal replicates to detect temporal declines in occupancy (Whittington et al., 2014). However, few have assessed the optimal sampling design required to detect a given change in occupancy and translated it into formal monitoring protocols (but see Hayward et al., 2002). Therefore, our study fills an important knowledge gap in developing effective and feasible snow track survey protocols that accounts for sample effort and fieldwork costs.

While the cost-effectiveness of a monitoring protocol will inevitably be species-specific and context-dependent, our study provides useful guidelines to conservation agencies on the monetary costs of comparing population estimates between any two periods. We show that it is practically unfeasible to monitor for small changes in occupancy (<10%) outside the high suitability habitats as the initial occupancy is lower in those areas requiring more effort to detect the species (Mackenzie and Royle, 2005). Nevertheless, monitoring outside the high suitability areas is also important because this allows tracking of changing conditions in the state variable (i.e. occupancy) throughout the population range (Aronsson and Persson, 2016). This is particularly relevant for monitoring different subpopulations of threatened species in which a subpopulation could go extinct if the monitoring program is only targeting a specific area (McDonald-Madden et al., 2008). Given limited conservation funding, it might be appropriate to implement a hybrid approach designed to detect a modest change (e.g. 30% decline) in high suitability areas while also monitoring for large changes in less suitable areas (e.g. 50% decline). Therefore, the impractically high costs of monitoring in low suitability habitats can be remedied by targeting large changes in occupancy in these areas. By monitoring areas that cover a wide range of habitat suitability, practitioners can have a better picture of the overall population status (Yoccoz et al., 2001; Lindenmayer et al., 2013).

Detection probability is crucial for designing the optimal effort allocation because as detection increases the sampling effort required to detect a trend tends to decrease (Hines et al., 2010; Steenweg et al., 2016; Lima et al., 2020). Similar to with previously established patterns of snow track surveys, we found that travel distance and time since snow influenced the detection probability of Canada lynx. The inconsistent relationship between detection probability and time since snowfall (compare Fig. 2A and 2E) suggests that snow quality (e.g. powder vs crust) (Hostetter et al., 2020), rather than time facilitates track detection. As our analysis is based on mean detection rates during each phase of the study, our conclusions related to survey efficiency reflect the snow conditions experienced during each survey period. We also found that the first survey period required a higher survey effort (130 km) to have a 98% chance of detecting at least one track than the second period (70 km; Fig. A3). The temporal change in detectability is an empirical example of the importance of adaptive monitoring: changing the monitoring regime to more rigorously quantify the changes in the population estimates (McDonald-Madden et al., 2010; Lindenmayer et al., 2013), and also calculating the cumulative detection probability (p^*) in occupancy models (Steenweg et al., 2016; Lima et al., 2020). Altogether, this suggests that both survey site and intensity affect the cost and feasibility of monitoring protocols and thus managers should seek to maximize detection to achieve greater confidence in the animal's presence or absence.

Our occupancy results are consistent with the known biology of the Canada lynx (Vashon et al., 2008; Hostetter et al., 2020), which are usually associated with young conifer forests due to the high density of snowshoe hares in these areas (Vashon et al., 2008). Because Maine is at the southern limit of the species range (King et al., 2020), the increase in the occupancy probability with latitude was also expected. We found that the occupancy increased by 34% between surveys demonstrating that our protocols are feasible and able to detect real changes in the species occupancy. Studies have documented that the Canada lynx is suffering range contractions and a decline in occupancy due to habitat loss and climate change in many parts of North America (Hostetter et al., 2020; King et al., 2020). However, the increase in occupancy in Maine is not surprising as this pattern has been reported repeatedly since the 1990s (Simons-Legaard et al., 2013). This may be related to disturbances regimes created by intense and partial timber harvest that generate habitats for snowshoe hare, and thus increase lynx density in such environments (Vashon et al., 2008). Despite the positive temporal change and its causes, we opted to develop protocols focusing on detecting declines and not increases in the occupancy estimates. Although the algorithm is sensitive to the direction of the change to be detected (Guillera-Arroita and Lahoz-Monfort, 2012), monitoring decline is always likely to be a higher priority for threatened species.

5 Conclusions

We developed optimal monitoring protocols to detect changes in Canada lynx occupancy between two time periods. Our analyses suggest that the high cost of implementing monitoring protocols able to detect small changes in occupancy (< 20% decline) might make snow track surveys unfeasible. However, a 2.5-fold increase can allow monitoring for intermediate changes in occupancy rather than large changes, which in our case were consistent with the observed shifts in occupancy (34%). Therefore, a modest increase in the survey investment may generate an excellent return in understanding a population's status. We also found that time since snowfall affected detection in a relatively complex way suggesting that snow quality (e.g.

powder vs crust) is more important than time. We suggest that careful consideration of snow quality is given to maximize detection rates. Surveying when snow conditions are poor could risk under-sampling relative to the mean detection rate, and thus data would not be consistent with sufficient power to detect desired trends. These results can be used as general rules that could guide conservation agencies worldwide as such patterns are likely to be relevant to other systems. Further, because we only accounted for the costs of in-situ operations our results are likely to hold for other survey techniques such as camera trapping (Mortelliti et al., 2022). Due to limited resources available for conservation, practitioners and researchers must work together to maximize monitoring efficiency while minimizing monetary costs.

7 Acknowledgments

We are grateful to numerous field technicians and staff who have helped collect lynx track data since 2003. This is Maine Agricultural and Forest Experiment Station Publication no. XXXX. Lynx silhouette is in the public domain, courtesy of Gabby Palamo-Munoz.

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Tables and Figures

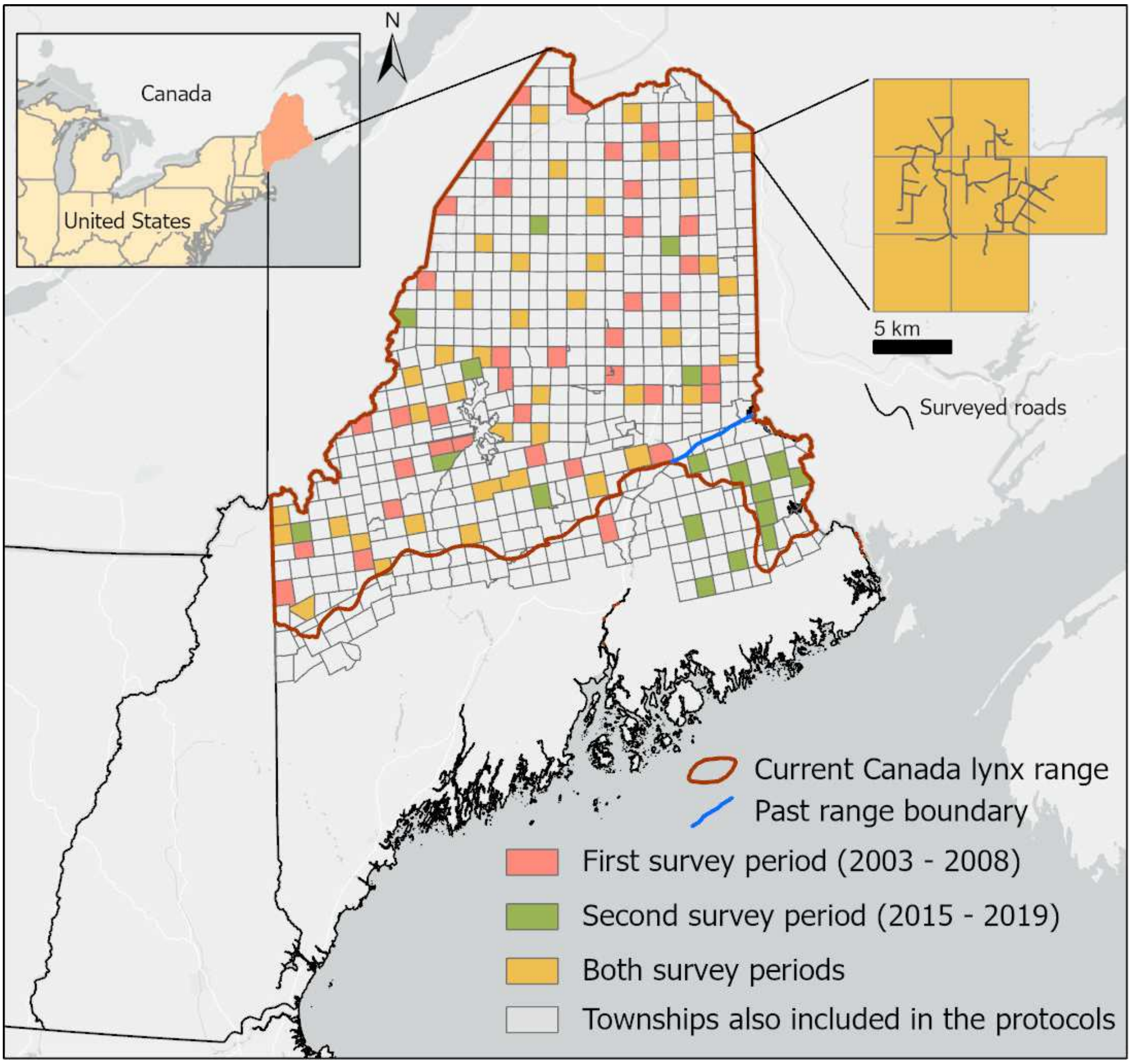

Fig. 1: *Map of the study area in Maine, northeastern Unites States. Townships (different colors in the map represent the survey period) were surveyed within current and past Canada lynx distribution range (red and blue lines respectively) in Maine. Townships outlined in gray are the townships that we did not survey but were considered when conducting optimal monitoring protocols assessments. The upper right panel shows an example of a 5 km x 5 km grid cell within a township with georeferenced survey routes.*

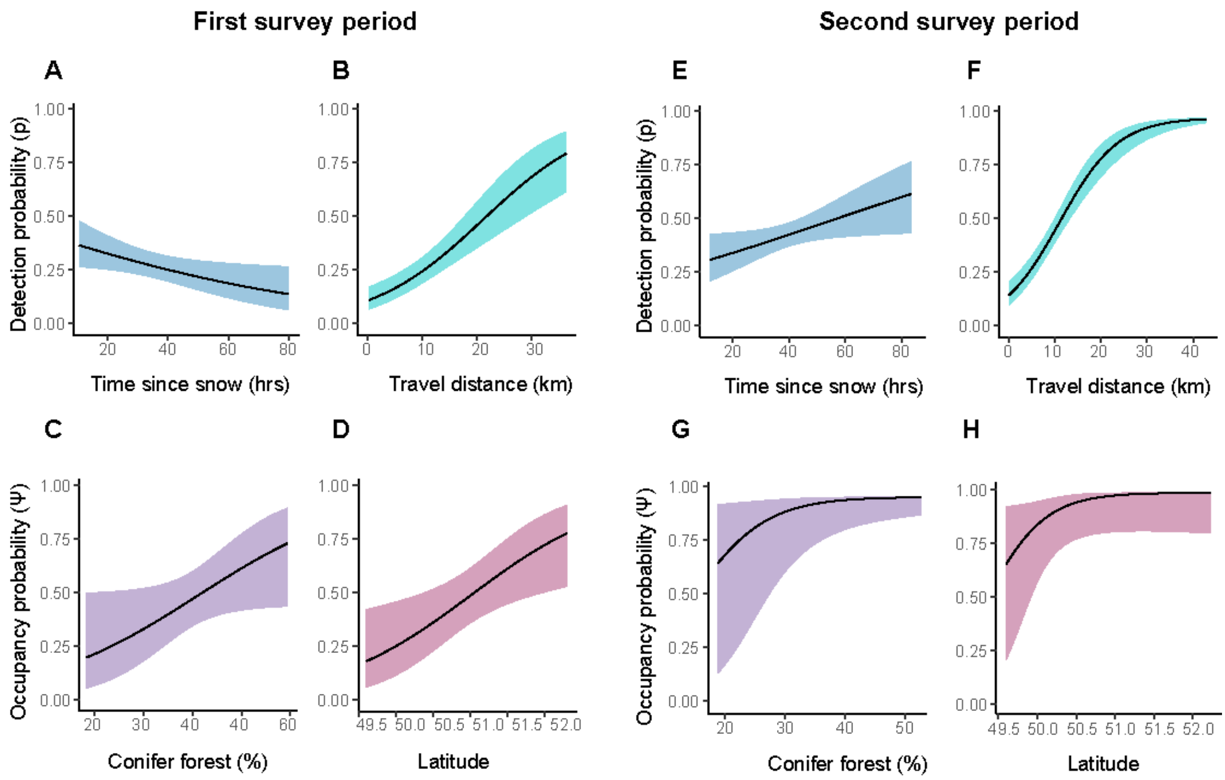

Fig. 2: *Predictions from the top-ranked single-season occupancy models. Surveys during the first period (2003-2008; panels A-D) were conducted in 78 townships while those of the second period (2015-2019; panels E-H) were conducted in 58 townships throughout Maine, USA. Canada lynx detection probability (p) increased with travel distance in both surveys and declined with time since snow in the first period while increased in the second period. Occupancy probability (Ψ) for both surveys increased with the proportion of conifer forest and latitude. Color ribbons indicate the 95% CI.*

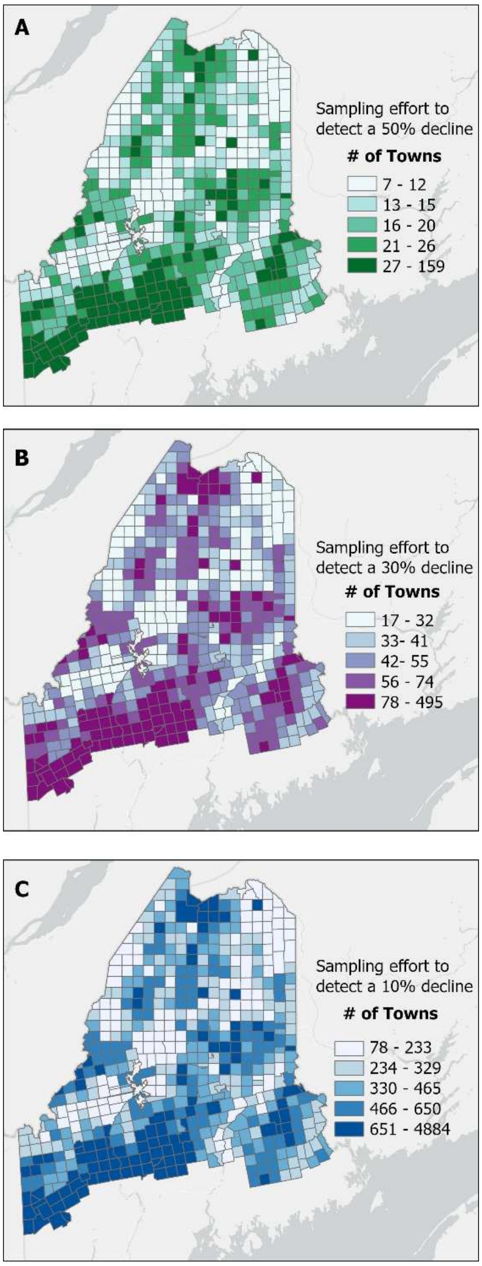

Fig. 3: *Optimal monitoring protocol for Canada lynx in Maine based on the survey conducted between the years 2015 – 2019. Each panel represents the sampling effort required to detect (a) 50%; (b) 30%; and (c) 10% decline in occupancy. Sampling effort refers to the total number of townships to be surveyed across the same category of habitat suitability. For example, to detect a 30% decline in Canada lynx occupancy across all areas colored in the lightest color (high suitable habitats), 17 to 32 townships are required.*

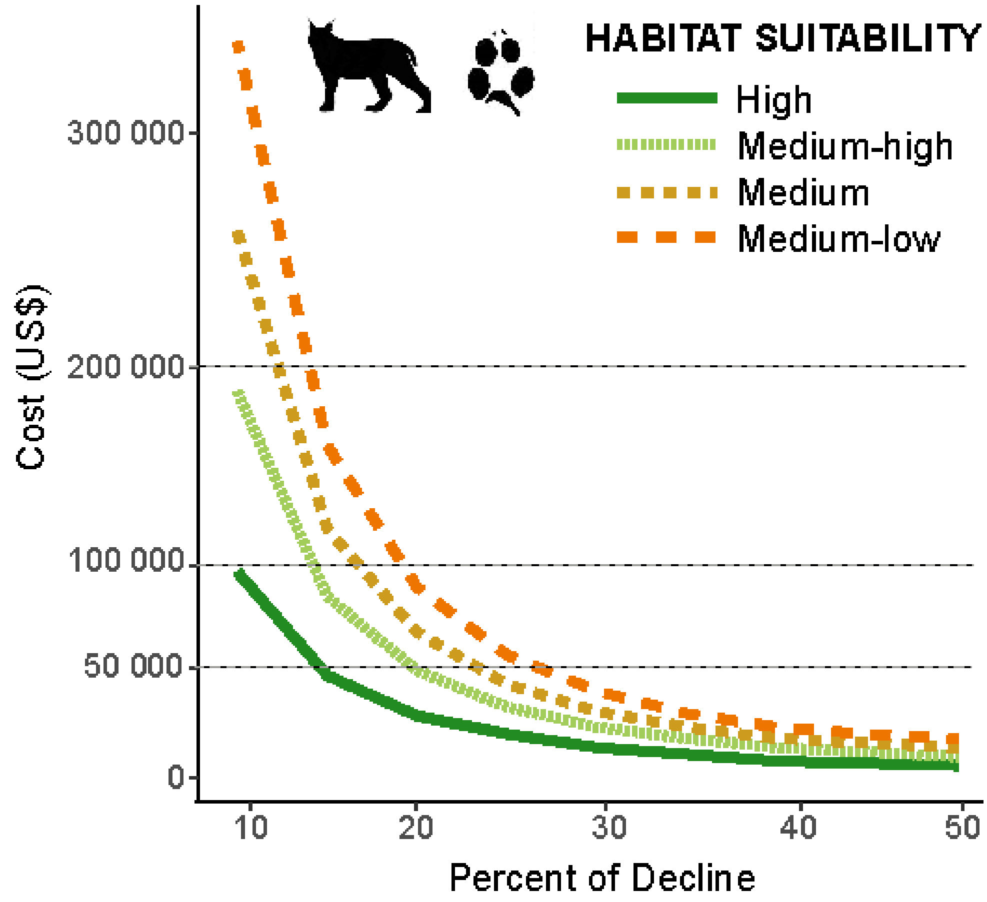

Fig. 4: *Cost-effectiveness of different monitoring protocols. This figure shows the average budget necessary to detect a range of 10 to 50% decline in Canada lynx occupancy in four levels of habitat suitability using data collected through snow track surveys between the years 2015 - 2019. To facilitate visualization we removed the low habitat suitability curve but the full figure with all categories is provided in Supplementary Material Appendix A (Fig. A6).*

Table 1: *Top ranking single-season occupancy models for the two Canada lynx survey periods (only models within 5 ΔAIC from the top model are shown). Models within 2 ΔAIC are in bold. Detection history data were collected between the years 2003 – 2008 in 78 townships and between the years 2015 – 2019 in 58 townships. Conifer = proportion of conifer; latitude = township centroid; disturbance = forest disturbance index; distance = travel distance in km; snow = time since the last snowfall; K = number or parameters; ΔAIC = Delta Akaike Information Criterion; AIC Weight = Akaike weight;* R^2 *= Nagelkerke's R squared.*

Survey period	Model	K	AIC	ΔAIC	AIC Weight	R^2
2003 - 2008	**Ψ(latitude + conifer town) p(distance + snow)**	**6**	**420.89**	**0.00**	**0.54**	**0.46**
	Ψ(latitude) p(distance + snow)	5	422.94	2.03	0.20	0.43
	Ψ(latitude + conifer 8k buffer) p(distance + snow)	6	424.89	4.00	0.07	0.43
	Ψ(latitude*disturbance town) p(distance + snow)	7	425.68	4.79	0.05	0.43
2015 - 2019	**Ψ(latitude + conifer 8k buffer) p(distance + snow)**	**6**	**490.17**	**0.00**	**0.65**	**0.84**
	Ψ(latitude + conifer town) p(distance + snow)	6	492.41	2.23	0.21	0.83
	Ψ(conifer 8k buffer) p(distance + snow)	5	494.71	4.54	0.06	0.82