Canadian Rockies Remote Camera Multi-Species Occupancy Project:

Examining trends in carnivore populations and their prey using remote cameras in Banff, Jasper, Kootenay, Yoho and Waterton Lakes National Parks

FINAL REPORT

Prepared for:
        Parks Canada

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DISCLAIMER

This report contains preliminary data from ongoing academic research directed by the University of Montana and Parks Canada that will form portions of graduate student theses and scientific publications. Results and opinions presented herein are therefore considered preliminary, are to be interpreted with caution, and are subject to revision.

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Table of Contents

EXECUTIVE SUMMARY

Remote cameras are a new technology that has the twin benefit of being a powerful tool for research and for producing photographs of wildlife that enhance the public's appreciation for nature. Remote cameras are a non-invasive research and monitoring tool that offer a unique opportunity to collect data on multiple species simultaneously and over large spatial scales. As a result, major biodiversity monitoring programs around the globe are quickly adopting this technology. In the Canadian Mountain National Parks, cameras provide essential information for the monitoring of Ecological Integrity. The goal of this report is to evaluate data-collection methods and test the ability of remote cameras to provide information to Parks Canada about the Canadian Rockies National Parks to help inform management of many large mammals, including grizzly bears, wolverines, and lynx. This report presents final results from contract #5P421 – 13 – 0001 between Parks Canada and University of Montana to evaluate the effectiveness of the large-scale remote camera monitoring network among Banff, Jasper, Yoho, Kootenay and Waterton Lakes National Parks. Within these five parks, 270 cameras are deployed year round, and thus far, these efforts have collected ~10,000,000 pictures that have been classified into ~190,000 observation events. A collaboration of this scale requires hours of dedicated effort from many resource conservation personnel.

   This report demonstrates the ability of remote cameras to provide robust trend-monitoring data for large-mammal species. For many species, monitoring trends in abundance may be prohibitively expensive. For other species, for example, common ones, monitoring abundance may be unnecessary. Remote camera trapping provides a means to monitor trends in the distribution, *i.e.*, occupancy, of multiple species simultaneously. By keeping track of sampled areas that are occupied by a species one year, and not the next, trends in the spatial distribution of species can be monitored very effectively. While ultimately, trends in population abundance may be the most important, monitoring population trend may not be possible for many species. Moreover, there is a theoretical basis for a positive relationship between abundance and occupancy, so if a population's occupancy declines by 50%, it might warrant additional monitoring to estimate the magnitude of decline in abundance. Despite the differences between occupancy and abundance, increasingly more monitoring programs are using trends in occupancy instead of abundance.

   The capacity of the National Parks remote cameras to track trends in occupancy differed across species and sampling designs. One key species we focused on was grizzly bears, a key-monitoring target for Parks Canada management. Our results show that the ability to track trends in grizzly bears distribution was very high. Using the established camera trapping design, Parks Canada has adequate ability (80% statistical power) to detect a 4% decline in grizzly bear occupancy over any 2 sampling periods. Our ability to track trends in grizzly bear occupancy improved with a higher numbers of cameras, longer duration of deployment, and when expanding our scale of analysis to the regional scale. When possible, parks should try to maintain at least 60 cameras, keep cameras deployed year round and continue collaborative and coordinated analyses among National Park units. These three parameters – number of cameras, sampling duration, and large scales – are key to maximizing the utility of these cameras to monitor all species' population trends. We also show that the ability to detect population changes is not affected by the spatial pattern of occupancy decline or the estimation method, but is affected by the species of interest. Remote cameras provide a powerful method to monitor rare species, such as lynx and commonly detected species, such as grizzly bears. Some species, like wolverines, have a very low detection probability, especially in summer. As a result, cameras need to be deployed during winter to improve out ability to track changes in their population and camera data should be combined with other data (*e.g.,* snow-tracking data) where possible, to maximize detection probabilities. Other *very* rare species, such as caribou, are restricted in their distribution and thus, require additional monitoring efforts to effectively monitoring their population.

   The potential value of remote cameras expands beyond providing valuable public relations media and tracking changes in population status of multiple species. For example, following initial reintroduction and monitoring of bison to Banff National Park, cameras will offer a robust additional method to document both bison expansion, and the responses of other wildlife species to bison restoration. Remote cameras are also useful for estimating wolf density, which is an important metric for understanding predator-prey relationships and caribou predation risk, and reproduction rates of grizzly bears and potentially other species. Remote cameras can also be used to capture the emergence of grizzly bears from their dens across entire parks and across many degrees of latitude to help understand precise timing of den emergence. Over time, this information may help understand how climate change affects grizzly bear emergence. Finally, remote cameras also offer a way to succinctly document changes in the distribution and occupancy of multiple species. We end this report with an outline of the theoretical foundation of how to development a camera-based metric of a multi-species occupancy.

1.0 INTRODUCTION

1.1 Goals and motivations

1.1.1 Scope of report

In this report, we summarize the main findings of the Canadian Rockies Multi-Species Occupancy Monitoring Project, a collaboration between Parks Canada and the University of Montana. The focus of our research is 270 remote cameras currently placed throughout 5 Canadian national parks: Banff, Jasper, Kootenay, Yoho, and Waterton Lakes National Parks, but we also use data from camera trapping efforts in Kananaskis country courtesy of Alberta Parks, and the Ya Ha Tinda Ranch area collected by the University of Montana. These data are used to help Parks Canada inform its remote camera monitoring efforts to track trends in large mammal populations. We investigate many of the key design and analytical considerations when using remote cameras for large-scale monitoring, drawing on the scientific literature, and on 4 years of camera data collection across the 5 parks.

The specific objectives of the contract were to:

1. Develop an optimal sampling design to monitor carnivore trends.

    a. Develop analytical methods for determining species occupancy and trends using remote cameras.

    b. Determine power to detect changes in species occupancy or density from a common sampling design.

    c. Determine the effects of trails, bear rub trees, animal communication trees, and lures on species-specific probabilities of detection (completed 2012).

    d. Recommend a common sampling design for implementation and testing across all Mountain National Parks (competed 2012).

2. Identify factors affecting fine and large scale distributions of grizzly bears, lynx, wolverine, and emerging species (e.g. white-tailed deer). Determine how changes in occupancy of one species will affect ecological processes and community composition.

3. Implement a study to examine the effects of sampling resolution, scale, home range size, and density on occupancy estimates and trends (completed 2012).

We have met all objectives of Parks Canada contract #5P421-13-0001, dated July 18, 2012, and thus, this is the final report under research and collection permit number BAN-2012-11113.

1.1.2 Motivations for remote camera trapping in the Canadian Rockies Mountain Parks

In the face of continued human development and climate change, wide-ranging species require large tracks of suitable habitat to allow for change in species distributions (Parmesan and Yohe 2003, Thomas et al. 2004). Large protected areas serve a key role, but are not immune to anthropogenic disturbances such as climate change (Brashares 2010, Carroll 2010) or habitat alteration and direct mortality in transport corridors (Benn and Herrero 2002, Chruszcz et al. 2003). Understanding the response of wide-ranging species to human disturbance requires an understanding of abiotic interactions (Peterson et al. 2002) and multi-species interactions at large spatial scales (Post et al. 2009). A significant challenge in understanding these relationships is the development of multi-species monitoring capabilities across broad spatial scales. National Parks across the Canadian Rockies have coordinated remote cameras efforts to standardize sampling strategies

and analytical techniques to address these large-scale conservation issues using remote cameras.

Parks Canada is mandated to manage protected areas to allow visitation while maintaining Ecological Integrity. Section 2 of the Canada National Parks Act defines Ecological Integrity as: "a condition that is determined to be characteristic of its natural region and likely to persist, including abiotic components and the composition and abundance of native species and biological communities, rates of change and supporting processes" (Canada National Parks Act. S.C. 2000). The Parks Canada website continues with this definition to explain in plain language that: "ecosystems have integrity when they have their native components (plants, animals and other organisms) and processes (such as growth and reproduction) intact". Remote cameras offer a new method for monitoring at large-scales for both these aspects of Ecological integrity: components and processes. For this reason, many Parks have adopted this technology for monitoring in both backcountry and front country areas.

As an emerging technology, however, the effectiveness of remote cameras for monitoring mammals at large spatial scales has been little tested. Many questions remain around the use of remote cameras for monitoring. For instance, how large a population decline can cameras adequately measure? How do measures of population status change with the number of cameras on the landscape or length of time that cameras are deployed in the field? When moving to multiple species monitoring, how are these considerations change across species? How do we combine population status across species to develop a succinct multi-species metric? Such field, theoretical, and ecological questions motivate this inclusive collaboration and the research in this report.

Remote cameras collect spatio-temporal data on the presence of multiple species. For species that are individually recognizeable because of unique pelage or fur colors or patterns, such as Bengal tigers, remote cameras can track individuals in space and time and estimate individual demographic rates, abundance, and population trends through mark-recapture modeling. Most species in the Canadian Rockies are not individually recognizable, however, and therefore camera data can only be

designated to the species-level and not the individual required for abundance estimation. Instead, we next explore the use of occupancy models for analyzing camera data and present alternative analytical frameworks for the analysis of remote camera trapping data.

1.2 Occupancy models

Occupancy is defined as the "proportion of area occupied by a species or the fraction of landscape units where the species is present" (MacKenzie et al. 2006, p.2). Occupancy, therefore, is a measure of a species' distribution. Occupancy models, as currently formulated, are hierarchical models that explicitly model and correct for observer error (Mackenzie et al. 20020). In fact, without other known-fate kinds of data such as from radio-telemetry, occupancy modeling allows for the only true measure of distribution because it accounts for imperfect detection (Kéry et al. 2010). Just as any estimate of abundance requires an adjustment for imperfect detection (Williams et al. 2002), so does any estimate of distribution.

1.2.1 As metric for trend monitoring

Occupancy models provide a robust method for estimating species' distributions and are likely the best method for analyzing data collected under the remote camera sampling methods employed by Parks Canada. Ecology is defined "the scientific study of the interactions that determine the distribution and abundance of organisms"(Krebs 1994). Ecologists, by extension, are concerned with what, how and why distributions and abundances change. Most management actions focus, however, on abundance and less attention is given to distribution. The move to focusing more on distribution has gained a lot of traction in the past decade for three main reasons. First, monitoring trends in abundance for many species is prohibitively expensive. Second, many common species do not really require abundance to be monitored, but managers would be alarmed in the event of a sudden decline in distribution or abundance. Finally, in addition to these perennial challenges in monitoring, the recent development of

occupancy models provides a rigorous statistical framework for monitoring changes in distribution or occupancy (MacKenzie et al. 2002).

The use of occupancy as a state variable to monitor trends in populations has numerous advocates (e.g.,MacKenzie and Nichols 2004, Noon et al. 2012). Some argue that using occupancy as a metric for population status relies on an underlying assumption of a ~1:1 relationship between occupancy and abundance (Stanley and Royle 2005). Although abundance-occupancy relationships are always positive, abundance-occupancy relationships can take different non-linear forms (Gaston et al. 2000), making inferences to abundance less straight forward. Rather than a proxy for abundance, however, occupancy itself can be used as a viable measure of population trend. In fact, COSEWIC uses occupancy metrics, such as "area of occupancy" and "extent of occurrence" in 2 of the 5 criteria for assessing the status of each species (COSEWIC 2011). These guidelines are adapted from the international standard set by the International Union for Conservation of Nature (IUCN 2014). Therefore, occupancy may provide a sufficient analytical end point for remote-camera data.

1.2.2 Status of occupancy analysis

Occupancy modeling has been championed for monitoring species that are rare or elusive, or when estimating abundance is prohibitively expensive due to low recapture rates or low density of target species (MacKenzie and Nichols 2004). Like all trend monitoring, large-scale population monitoring should account for imperfect detection through repeated sampling (Pollock et al. 2002). Occupancy modeling explicitly incorporates the detection process, correcting for this potential bias (MacKenzie et al. 2006). Although promising, using occupancy modeling to detect trends in population status over time has been rarely tested at large spatial scales in large mammal populations.

An assumption of occupancy models is that occupancy remains constant at each site during the entire survey; this is referred to as the closure assumption. During amphibian surveys, for example, where the occupancy of ponds is unlikely to change during a summer, this assumption is likely met. For

camera data, however, it is rare for animals to remain in cells containing the camera for the entire duration of camera data used in the analysis. A means to deal with this is violation of this closure assumption is to refine the definition of the estimated parameter of occupancy as 'use' (MacKenzie 2005). Rather than considering some discrete habitat as occupied by at least one individual during the survey, use is the probability that any individual uses a portion of the continuous landscape at one point during the survey. Adhering to this closure assumption when cameras are placed at a spatial scale that is smaller than an animal's annual home range, would restrict the entire survey period for analysis to the time it takes an animal to move from one cell to another (a matter of hours or days). Thus, the above refinement of the occupancy definition allows for more data to be included in analysis to improving estimate precision and still produces a metric that can be useful to managers (MacKenzie 2005).
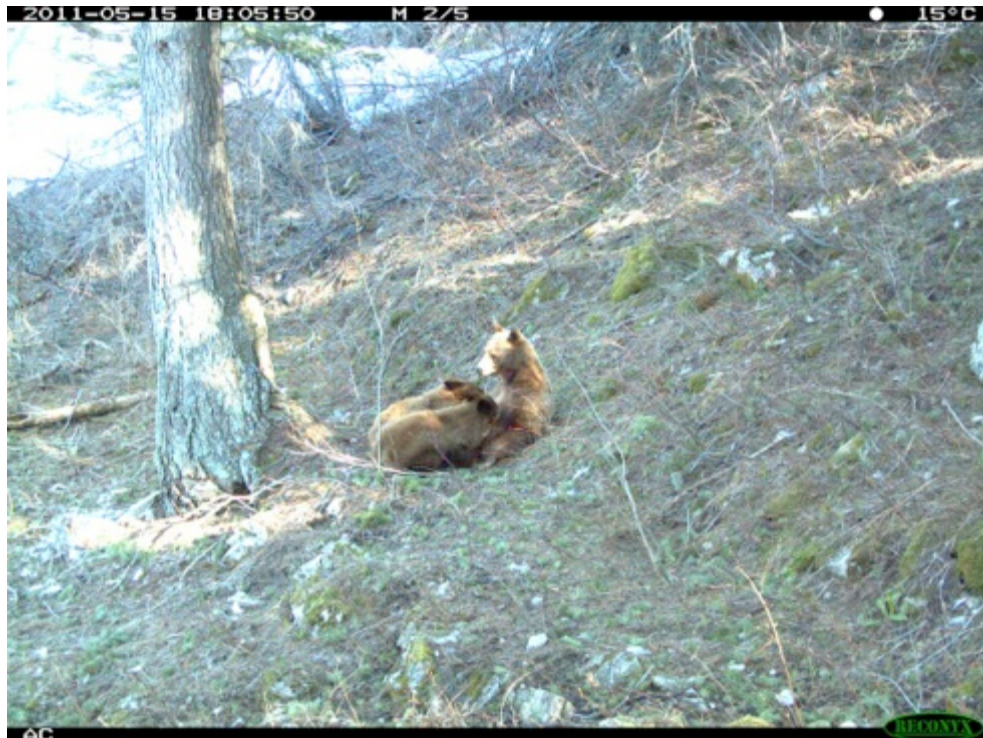
1.3 Remote cameras

1.3.1 As a tool for multi-species monitoring

The need for conservation is increasing around the globe, but budgets for conservation and monitoring remain tight, therefore, efficiency is needed to adequately monitor multiple species simultaneously (Simberloff 1998). The use of occupancy modeling is one of the fastest growing areas of ecological monitoring and has been proposed as a main conservation tool for many of the world's endangered species. To date, most camera-based occupancy studies have targeted one specific species, often a charismatic carnivore, umbrella, or indicator species (Kucera and Barrett 2011) . Even when targeting a specific species, remote cameras often collect far more pictures of non-target species, especially when using a general attractant to increase detection probability, like placing cameras on trails. Due to the indiscriminate way cameras collect data, they have a demonstrated capability to provide trend monitoring for multiple species simultaneously. For example, Ahumada *et al.* (2013) used cameras to monitor the population status of 13 mammal species in Costa Rica, ranging from jaguar (*Panthera onca*) and cougar (*Puma concolor*) to Baird's tapir (*Tapirus bardii*) and agouti (*Dasyprocta puctata*). A collaboration called the Tropical Ecology Assessment and Monitoring Network (TEAM; www.teamnetwork.org/) as been using these methods to monitor multiple species and biodiversity across the tropics. This is the world's largest camera trapping effort with 17 large camera arrays in 13 countries, all following identical standardized methods. Furthermore, data collected by TEAM is incorporated into a camera-specific metric to monitoring biodiversity called the wildlife picture index (O'Brien 2010, Ahumada et al. 2013). This index has great potential to provide Parks Canada with a multi-species occupancy metric as well (Whittington et al. 2015).

1.3.2 Status of remote camera science

With recent advances in camera technology and statistical methods, reduction in cost, and increased interest in remote camera photos as an outreach and education tool, the use of remote cameras has

grown exponentially for the past 10-15 years, doubling every 2.9 years (O'Brien and Kinnaird 2008, Rowcliffe and Carbone 2008, McCallum 2013, Burton et al. 2015). Remote cameras allow researchers to overcome difficulties of studying rare and elusive animals over large spatial extents (O'Connell et al. 2011). The application of remote cameras in wildlife science are diverse. If studies are designed correctly they can give information on diversity, reproduction, abundance, occupancy, community structure, and information on animal behavioural, such as nest predation, co-occurrence, daily activity patterns, timing of migration, etc. They are used, for example, to estimate carnivore abundance when species are individually recognizable in a mark-recapture framework (Karanth and Nichols 1998), to inventory total diversity (Tobler et al. 2008), and to study the level of sympatry between carnivores (Sollmann et al. 2012). The first evidence of wolverine expansion in California was documented by remote cameras set for completely different purposes (Moriarty et al. 2009), demonstrating their utility to monitor species range shifts as well.

Studies also now extend beyond the nuts and bolts mensuration of biodiversity components (abundance, distribution, species richness) to applications that address underlying causes of biodiversity change. For example, habitat loss and fragmentation are important drivers of biodiversity loss (Fahrig 2003). Remote cameras are an ideal tool to measure the effectiveness of highways overpasses to improve multi-species landscape connectivity (Barrueto et al. 2014) and to evaluate the effects of forest fragmentation on tropical species diversity and dominance (Ahumada et al. 2011). Different life stages respond differently to disturbances; cameras have identified key areas where landscape structure leads to higher reproductive success of grizzly bears (Fisher et al. 2014). Recently, remote camera researchers are tackling more complex ecological interactions through the simultaneous measuring of important drivers of animal behavior. For example, cameras were used to assess the impacts of both snow-pack and wolf presence on elk occurrence (Brodie et al. 2014) and to measure plant phenology and climate (Morisette et al. 2008). Cameras have even been used to determine how large-mammal food webs

respond to logging in the forests of Borneo (Brodie and Giordano 2013). The potential of remote camera data is vast; here we focus on the ability for cameras to track trends in population status.

1.3.3 Using occupancy for remote camera data

To monitor population status, remote camera data is often analyzed and presented in the literature in 4 main fashions: abundance, relative abundance, presence only and occupancy. Occupancy is defined as the "proportion of area occupied by a species or the fraction of landscape units where the species is present" (MacKenzie et al. 2006, p.2). Occupancy, therefore, is a measure of a species' distribution, where the measurement error due to a species' elusiveness, their ecology, or observer error can be explicitly accounted for to remove this negative bias. For this reason and other shortcomings of other methods below, occupancy models are the most appropriate analytical framework for camera data. Below, we briefly describe the feasibility of the 3 other groups of metrics and present some of the advantages and limitations for each one.

1.3.4 Other analytical options

Absolute abundance

Monitoring organizations are often interested in metrics of abundance, which form the backbone of endangered species legislation and the reporting requirements for many management agencies. Cameras have been used for abundance estimation in a mark-resight (*i.e.* mark recapture) framework (Karanth et al. 2006). These methods allow for the estimation of a total population based on the number of animals seen (marked) and using information from these marked animals (detection histories) to estimate the number of animals that were likely present but not observed (Williams et al. 2002). The "marking", however, requires individuals of the species to be uniquely identifiable. In classic mark-recapture studies, individuals can be marked, for example, by using collars, tags or genetic markers. For camera trap data, however, this is only possible for species with unique markings such as spots or strips.

It is also possible to mark animals with radio collars and combine with remote cameras to estimate abundance (Sollmann et al. 2013a). The only species present in the Mountain National Parks for which an absolute abundance estimate have been performed without wide collaring, is wolverine; but this required a special camera set up that was wolverine-specific to capture pictures of their chest markings (Royle et al. 2011). Most species in the Canadian Rockies are not uniquely identifiable and therefore cannot be used in a mark recapture analysis. Another analysis that allows for the estimation of abundance from remote camera data is the Royle-Nichols model, which capitalizes on the increase in detection probability with increased abundance (Royle and Nichols 2003). To date, however, there have been few applications of this method to remote camera data because it is unclear how to scale up the local abundances at camera sites to a study area scale (Sollmann et al. 2013b). Absolute abundance metrics, therefore, seems unattainable with Canadian Rocky species and data-collection methods at this time.

Relative abundance

Relative abundance indexes (RAI) provide an index of abundance, where a change in the RAI may correlate with a change in absolute abundance. Using remote camera data for an RAI has had many early adopters (Carbone et al. 2001) and has been commonly used (*e.g.,* Tobler et al. 2008). The most common metric used is catch per unit effort (for example, pictures per 100 trap days). There are many criticisms for using indexes in general (Pollock et al. 2002) and criticisms expand to indexes of remote-camera data more specifically (Sollmann et al. 2013). The problem is that indexes are confounded with detection probability such that a change in an index may mean a change in abundance but could also indicate only a change in detection probability (due, for example, to a change in behavior). Because of this bias, indexes should only be used for remote camera data when there is no way to account for detection probability (O'Brien 2011). Occupancy modeling offers one way to deal with detection probability in an analytical framework.

Presence only

Another possible analysis of remote-camera data involves treating them as presence-only data. Camera locations with at least one photo of a particular species confirm that it occurs at that specific location. Many data sets, like museum records, do not contain any information about absences. MAXENT is popular software developed to deal with presence-only data (Phillips et al. 2006). The biological interpretation of its output has been alternatively viewed as occupancy, persistence, or an index of habitat suitability. A thorough investigation into how this model works, however, shows that this software relies on questionable assumptions, such as setting the occupancy probability of a species under average conditions to 0.5, and data used in this software seldom meets other required assumptions of the model, such as random or representative sampling, and constant detectability across sites (Yackulic et al. 2013). It has been argued that the output can rarely be considered a measure of occupancy and is rather a vaguely defined index of habitat suitability (Royle et al. 2012). This criticism comes from the fact that the output of these models is confounded with observation error and site-selection bias. The correct interpretation of their output, therefore, is the conditional probability of a site being selected for sampling, of an animal being present at a site, and it being detected. If assumptions of representative and random sampling, as well as equal detection probability are met, then other analysis methods are possible for dealing with presence-only data (Royle et al. 2012); however, with remote camera data equal detection probabilities across sites is very unlikely to occur. Camera data should not, therefore, be analyzed as presence-only data.

1.4 Power analysis and research questions

As with any new monitoring program, prospective power analysis is essential to ensure the new method can adequately detect meaningful changes in the population. Power analysis helps evaluate our ability to detect trends over time given sampling intensity and an estimate of the variability in the estimators of

interest (Steidl et al. 1997). Statistical power has been long recognized in ecology as equally important as statistical significance (Gerrodette 1987, Peterman 1990). For monitoring questions, the null hypothesis tested is that there is no trend or difference between parameter estimates obtained from two or more sampling periods. Type I error, α, is the probability of falsely detecting a change (increase of decline) in the population when no change has occurred (*i.e.* a false alarm; commission error). Type II error, β, is defined as the probability of falsely concluding a population is not changing, when in reality it is changing (*i.e.* failing to detect a change; omission error). Power, $1 – \beta$, represents the probability of correctly rejecting a false null hypothesis, thus supporting the alternative hypothesis that a change in the population has occurred (Sokal and Rohlf 1995). There is a trade off between these two errors, and in the context of conservation, failing to detect a real decline of a threatened species can have much graver consequences (increased extinction risk with long time lags for recovery) than a false alarm (short-term financial cost; Dayton 1998, Field et al. 2004).

Power analysis frequently addresses the question of sufficient sample size to adequately detect some difference. Occupancy analysis, however, requires repeat sampling, which creates a trade off between the number of samples (*i.e.* locations sampled) and the number of repeat visits (Field et al. 2005, MacKenzie and Royle 2005, Bailey et al. 2007, Guillera-Arroita and Lahoz-Monfort 2012). When using remote cameras, the number of samples is equal to the number of cameras sites collecting data, and because data is collected continuously, how long cameras are deployed is analogous to the number of repeat visits. Three applied questions pertaining to remote camera study design can be addressed using power analysis.

1) First, at what spatial scale can a trend in occupancy be detected, *i.e.* at a park scale, or regional scale?

2) Second, how many cameras are required to detect trends with sufficient power?

3) Third, how long do cameras need to be deployed?

With a high number of cameras deployed, we hypothesize that statistical power to detect trends will be high at the regional scale, but that smaller parks may not have adequate power. We hypothesize that when monitoring a species with low daily detection probabilities like grizzly bears, cameras may need to be deployed year-round.

Furthermore, using power analysis, we also address three other questions pertinent to camera-based occupancy modeling.

1) First, for occupancy, it is unknown how the distribution of a species like grizzly bears will change when the population is declining. Through simulation, we investigate 4 different ways that grizzly bear distribution could decline, each of which may affect our ability to detect trends.

2) Second, there is little published advice on how to discretize camera data to create capture histories suitable for occupancy analysis. Power to detect trends can be maximized through well-thought-out study designs to maximize detection probability (MacKenzie and Royle 2005) and to correctly balance the number of repeat visits to each site with the total number of sites, depending on available resources (Bailey et al. 2007, Guillera-Arroita and Lahoz-Monfort 2012). For remote camera data, the number of repeat visits is flexible, as the data from cameras is continuous and need to be discretized into equal-length sampling replicates (Hines et al. 2010). While a recent approach developed a continuous time approach to address sampling (Guillera-Arroita et al. 2011, Borchers et al. 2014), most researchers commonly discretize data into sampling replicate durations of one day or one week with little or no explanation for the chosen length (Burton et al. 2015). We address this by discretizing the data into multiple time windows and evaluate model performance.

3) Third, because of their crucial role in propagating populations forward, large carnivore monitoring often focuses on adult females. Our main goal was to evaluate occupancy trend monitoring using all photos of grizzly bears. We compare power to detect trends for members of a species, starting with all grizzly bears and compare to power to detect trends in grizzly bear family groups.

1.5 Scaling up to multi-species monitoring

1.5.1 Monitoring multiple species simultaneously

As mentioned above, cost-effective monitoring encourages monitoring multiple species simultaneously and cameras offer a means to effectively accomplish this. Although all the above sampling considerations may affect the power to detect trends in occupancy, power will also depend on which species we are interested it. This difference among species will be driven by differences in species-specific occupancy and detection probabilities and possibly by the home-range size of that species. Both occupancy and detection probabilities influence our confidence in occupancy estimates, and thus effect statistical power. Ideally, once understood, these sampling and species-specific considerations can be incorporated into a program that effectively monitors multiple species and can succinctly summarize their trends in a multiple-species metric.

1.5.2 Towards a multi-species occupancy metric

Ultimately, one of the goals of the camera trapping effort across the National Parks is to develop a metric to track camera-based multi-species occupancy at a park scale. Occupancy models are ideal for estimating species-richness indices because they account for imperfect detection. Species richness estimates that do not corrected for imperfect detection, implicitly assume that detection probability (p) is constant across species. They also assume that, for each species p is constant across space, regardless of habitat (Kéry and Schmid 2004). Improvements to species richness estimation includes accounting both for species-specific p that can vary across space, and for species never detected (Dorazio and Royle 2005). Furthermore, these models have been extended to include open community dynamics to allow for temporary migration to and from the local community of species present (Kéry et al. 2009). Species-richness methods that account for imperfect detection have been used, for example, to test the effects of habitat fragmentation (Zipkin et al. 2009) and white-tailed hunting regulation (Zipkin et al. 2010) on community composition.

Currently, international efforts to develop multi-species occupancy metrics include a second major endeavor, in addition to the general species-richness metric outlined above. For remote camera monitoring projects, a camera-specific metric called the Wildlife Picture Index (WPI) has been developed (O'Brien et al. 2010, O'Brien 2010). This WPI integrates the occupancies probabilities of each species at all sites (using a geometric mean), which is then compared to the baseline WPI from the first year of monitoring. WPI for year one is set to 1 and WPI in the following years represent deviations from this baseline. WPI has been used to measure the status of a large-mammal communities in Mongolia over 3 years (Townsend et al. 2014) and in Costa Rica over 5 years (Ahumada et al. 2013). The main disadvantage of using WPI compared to other metrics is that precision drops precipitously when including species present in the study area but never detected on any camera (Tobler et al. 2015). This problem, however, may be negligible in temperate areas that have lower diversity than the tropical areas where many more species are never detected. Following the results from our analyses in this report, we make recommendations on how to synthesis our recommendations to scale up occupancy monitoring from single species, to multiple species, and finally to multiple species simultaneously.

1.6 Specific objectives of this report

The objective laid out in Parks Canada contract #5P421-13-0001, dated July 18, 2012, were to develop an optimal sampling design to monitor carnivore trends and to identify factors affecting fine and large scale distributions of important species of concern (grizzly bears, wolverine and lynx) and of an emerging species (white-tailed deer). We previously made study design recommendations (Steenweg et al. 2012) that have been implemented by all 5 national parks to improve trend monitoring.

The specific objectives of the contract were to:

1. Develop an optimal sampling design to monitor carnivore trends.

    a. Develop analytical methods for determining species occupancy and trends using remote cameras.

    b. Determine power to detect changes in species occupancy or density from a common sampling design.

    c. Determine the effects of trails, bear rub trees, animal communication trees, and lures on species-specific probabilities of detection (completed 2012).

    d. Recommend a common sampling design for implementation and testing across all Mountain National Parks (competed 2012).

2. Identify factors affecting fine and large scale distributions of grizzly bears, lynx, wolverine, and emerging species (e.g. white-tailed deer). Determine how changes in occupancy of one species will affect ecological processes and community composition.

3. Implement a study to examine the effects of sampling resolution, scale, home range size, and density on occupancy estimates and trends (completed 2012).

All objectives of the contract under Parks Canada contract #5P421-13-0001 have been met. This is the final report for this contract and under research and collection permit number BAN-2012-11113.

2.0 METHODS

2.1 Study Area

Data collected for this project was collected by Parks Canada Resource Conservation personnel across the entire area spanning over 4 degrees of latitude from the northern extent of Jasper National Park to Waterton Lakes National Park in the south, encompassing 5 National parks, and adjacent provincial lands in Alberta's foothills, including a portion of Spray Lakes Provincial Park (Figure 1). Throughout the study area, topography is extreme (elevation: 1000 – 3800m) and the weather is temperate with short, dry summers and long, cold winters, including 360 cm of annual snowfall on average (Holland and Coen 1983). Park sizes vary from 481 km^2 (WLNP) to 10,878 km^2 (JNP), and also include Banff (BNP; 6,641 km^2) Yoho (YNP; 1,313 km^2) and Kootenay (KNP; 1,406 km^2) National Parks.
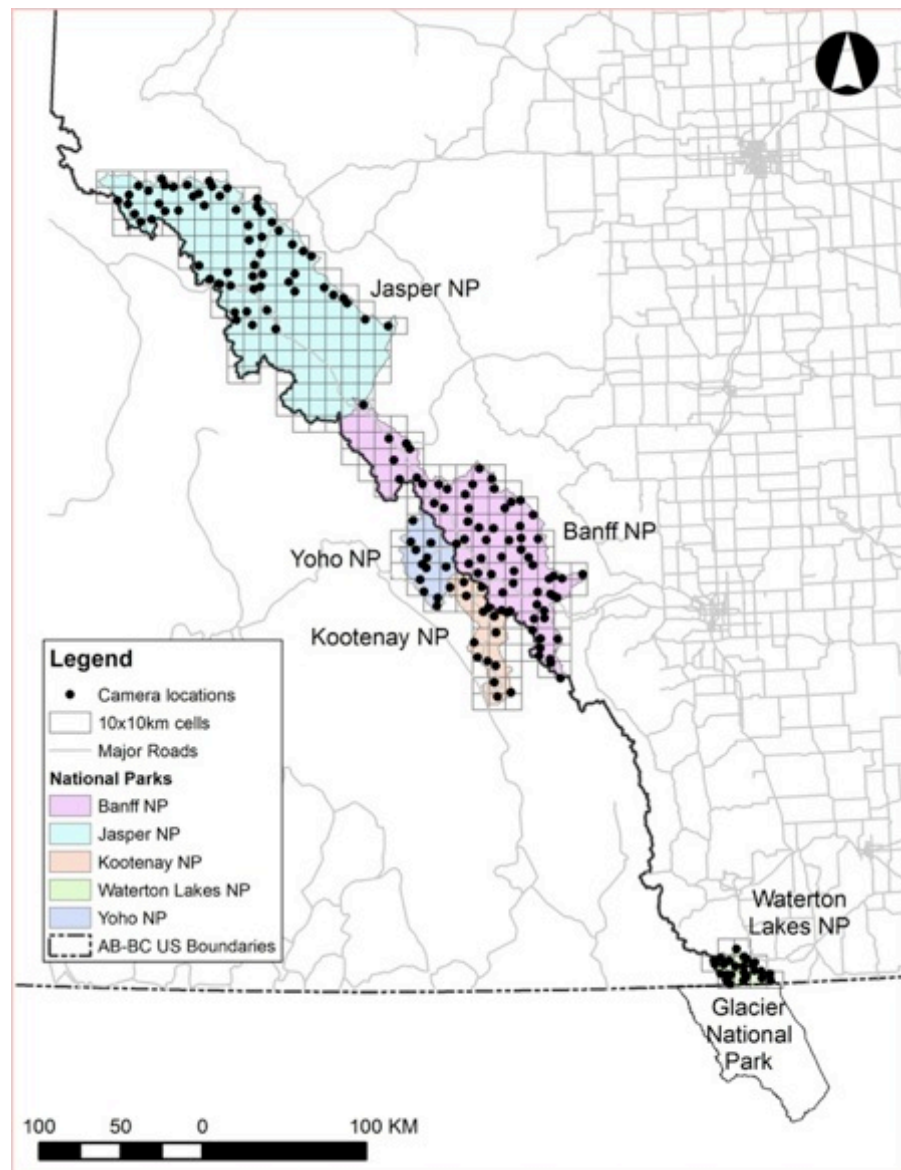
Figure 1: Study area of the Canadian Rockies remote camera multi-species occupancy project across 5 national parks. Grid in represents 10x10 km cells and cameras location represent *n* = 183 cameras set up systematically in 2012. Currently, sampling intensity has increased to *n* = 270 cameras.

2.2 Field methods

2.2.1 Camera deployment and sampling design

Deploying and servicing hundreds of remote cameras requires many long hours by resource

conservation personnel on the trail, moving by foot, ski, and horseback. Camera batteries last about 4 –

6 months, therefore, to keep camera operational year round, cameras are serviced approximately three

times per year. When changing batteries, data are downloaded, camera positioning is verified and

obstructing vegetation is removed as necessary. Excessive leaf motion in front of cameras can vastly

increase the number of pictures that need to be classified (up to 1000x more pictures). Most camera

work is performed in conjunction with other Ecological Integrity monitoring, research, or maintenance

work. Some parks also capitalize on the availability of volunteers to help service the cameras, promoting

increased citizen scientist involvement in the national parks.

Initial camera deployment involves finding a

suitable site on human-use or wildlife trails. Ideal sites

are in an area that naturally funnels animal

movement due to topography and at a junction of

human and/or wildlife trails. Cameras are attached to

trees at about waist height pointed slightly

downwards. Camera models used were

predominantly covert motion-trigger cameras

(Reconyx Hyperfire and Rapidfire) with few visible

glow Silent-image cameras (Reconyx , Holmen,

Wisconsin). Cameras are set to take 5 pictures per

movement trigger with no delay between triggers.

Following recommendations by Steenweg et

al. (2012; Objective 1d), resource conservation personnel have placed cameras at a density of one

camera per 10x10-km cell (1/100 km^2) in YNP, KNP, BNP and northern JNP. We chose to sample at a

scale of 10x10 km cells because it creates a density that is logistically feasible given the large area of

each park, it ensures near-complete sampling of each park, and it provides more than one camera per

average grizzly bear home range (~520 km^2, ~1405 km^2 for females and males respectively; Stevens and

Gibeau 2005). Because WLNP is a smaller park, however, it was feasible to intensify sampling to 1

camera per 5x5-km cell. We distributed cameras across elevations ranging from 1013m to 2521m

(mean: 1645m). Within sampling cells, we maximized detection probability by selecting sites where

animals were like to travel based on topography, the confluence of wildlife trails, and grizzly bear rub

(wildlife communication) trees (Clapham et al. 2014). Most cameras operated year round, but a few

cameras were inactive during the middle of winter when they were covered by deep snow. Camera data

images were classified into species, sex and age classes using program Timelapse (Greenberg and Godin

2012). We also classified the number of humans and horse riders at each camera site. Unlike photos

animals, photos of humans are deleted following classification.

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2.3 Occupancy model building

To address Objective 1a, we used occupancy models to estimate the relationship between landscape covariates and the probability of occupancy for multiple species in the study area (MacKenzie et al. 2002, MacKenzie et al. 2006). Occupancy is a site-level binary state (z) of whether or not a species is present or absence from a site. If a site, patch, or cell (*i)* is occupied, $z_i = 1$, and if it is unoccupied, $z_i = 0$. The probability of occupancy ψ (pronounced "psi") describes the probability that a site *i* is occupied, such that $\psi_i = Pr(z_i = 1)$. When this stochastic process is realized at the level of the study area for *n* spatially-indexed sites, the estimates of ψ can then be summarized to calculate the Proportion of Area Occupied (PAO = $\sum_{i=1}^{n} \psi i$) (Royle and Dorazio 2008). PAO can be used as an index of population trends and status. Detection probability (*p*) is used to estimate the proportion of sites where species were present but not detected. Detection probabilities can be added to occupancy models in a hierarchical fashion, whereby *p* is contingent upon whether or not an individual was present to be detected (*i.e*. ψ = 1). To estimate detection probabilities, we need multiple sampling (*e.g.* over time). For example, if a site were surveyed 4 times (or if camera data were split into 4 one-week intervals) then we can create detection histories with 0s and 1s for non-detections and detection, respectively. For example, if we detected a grizzly bear at a camera at site *I* the 1st and 3rd week but not the 2nd and 4th, the detection history would be '1010'. The likelihood at site *i* would then be: $\psi_i(p_i)(1–p_i)(p_i)(1–p_i)$ where 1-p is the probability of not detecting a grizzly bear. In words, this is the product of the probability the bear was present, times the probability it was detected, times the probability it was <u>not</u> detected, times the probability it was detected, times the probability it was <u>not</u> detected. This computation is straightforward for all possible detection histories except for '0000' that may indicate the bear was present but never detected or not present. Therefore the likelihood for this detection history at site *k* would be $\psi_k \prod_{t=1}^{4}(1 - p_k) + (1 - \psi_k)$. The product of all likelihoods calculated in this manner (one per site) gives a model likelihood that can be maximized given data, through changes in parameters *ψ* and *p*.

Note that in these examples, *p* remained constant across sampling sessions but occupancy was allowed to vary across sites; this methodology allows for different *p* across sessions and a constant *ψ* across sites. Covariates for both ψ and p can also be added to the equation, and missing data can also be accounted for easily (MacKenzie et al. 2002). For this report, we used the `unmarked` package in R to model occupancy using this maximum likelihood approach (Fiske and Chandler 2015).

To build the best occupancy models for power analysis (Objectives 1b and 2), we focused on grizzly bears and grizzly bear family groups. We restricted the data used to one camera per 10x10-km cell: 183 cameras during summer 2012, (May 1 – Oct 15). For grizzly bears, this time period captures 1007 picture events, defined as separate photos of grizzly bears that were at least 5 minutes apart, and which represents 96% of all grizzly bear photos for 2012. Data was first discretized into 1-week sampling sessions, but various sampling-session replicate lengths were investigated (see next section). Landscape covariates for occupancy models were then included for both detection and occupancy probabilities for various ecological and design-based reasons.

Grizzly bear resource selection function (RSF) models in the Canadian Rockies have revealed that bears select for areas of increased vegetation quality (NDVI), south-west facing aspects, closed forests near streams, open herbaceous and open-forest areas including burns (Ciarniello et al. 2007, Nielsen et al. 2009). At large spatial scales, regional-level occupancy in Alberta is driven by the avoidance of agriculture. At a finer scale, Apps et al. (2004) found that grizzly occurrence was associated with rugged terrain containing higher elevations, steeper slopes and landscape types of avalanche chutes, alpine tundra, and burned forests. Bears were negatively associated with human access (*i.e.*, increased road distance from towns). Burned areas are important for bear foods (McLellan and Hovey 2001), especially for promoting the growth of berries in BNP (Hamer and Herrero 1987). Grizzly bears show positive selection for burned areas, both young and old (Apps et al. 2004, Milakovic et al. 2012).

To represent these relationships, we included site and GIS-based landscape covariates as

predictors of detection and occupancy probabilities (see Appendix A for full description of landscape covariates used). Animals respond to different landscape cues at different scales (Johnson 1980, DeCesare et al. 2012). It was unknown at what scale the occurrence of bears will respond to landscape features such as topography, vegetation, distance to human disturbance, etc. To examine the scale-dependent effect of landscape covariates on grizzly occupancy, we used a moving-window algorithm to aggregate GIS-based landscape features around each camera location at 4 scales. For the largest scale, we used a radius of 12.6 km around the camera location, creating an area of 500 km^2, corresponding to the size of average female grizzly bear home ranges in BNP (~520 km2; Stevens and Gibeau 2005). The middle scale was a radius of 5.6 km, creating an area of 100 km^2 approximating the sampling scale of 10x10-km cells. The second-smallest scale approximated a grizzly bear's average daily movement in the Rocky Mountains, using a 2.5-km radius (Apps et al. 2004). Finally, the smallest scale was the point location of the camera site. Landscape covariates can also affect detection probability; for example, the type of vegetation surrounding a camera site may affect how much food is available to bears or may affect bear mobility. For details of all GIS variables we included in our analysis, please see Appendix A. Cameras also capture human activity on these trails that may affect grizzly bear use of trails (Rogala et al. 2011). We included the log-transformed total number of people and log-transformed total number of horses captured at each camera site. We also included some site-specific features of camera sites as covariates for detection probability: trail type, camera type, the presence of rub trees, and the presence of a natural mineral lick (see Appendix A). All continuous covariates were scaled to their mean and 1 standard deviation to improve numerical optimization in `unmarked`.

Using a multi-step approach to model selection (Harrell et al. 1996), we first estimated univariate effects of each covariate on detection probabilities (Kéry et al. 2010), assessing their model fit using AICc (Burnham and Anderson 2002). To avoid collinearity, we plotted significant covariates using paired plots, contingency tables and boxplots to compare two continuous, two categorical, or one of each covariate

type, respectively (Zuur et al. 2007). For continuous covariates, we used a Pearson correlation

coefficient cut off of 0.6 to remove collinear covariates. We then nested significant, non-collinear

covariates to develop our final model, examining changes to beta coefficients while nesting multiple

covariates on *p* and removing non-informative covariates in the final model (Arnold 2010). After refining

the detection portion of the model, we followed the same procedure for occupancy probability. To

check model fit, we used 1000 parametric bootstrap replicates on a Chi-squared statistic that is

appropriate for binary data (Fiske and Chandler 2015).

2.3.1 Discretizing continuous data

Occupancy models require repeated sampling to estimate and account for imperfect detection. Because

camera data is collected continuously, it must be discretized to fit the data requirements of occupancy

models. A method has been developed to avoid this step and use continuous time to estimate detection

probability (Guillera-Arroita et al. 2011). Although it has also been developed for occupancy data from

transects, it could be extended to camera trap data but has not been implemented in occupancy

analysis software (e.g. PRESENCE, `unmarked`, MARK), thus continuing to necessitate a manual

discretizing of camera data for many projects. When discretizing continuous data for occupancy models,

it has been recommended to use the smallest sampling window possible while considering the ecology

of the species; this retains as much information in the data as possible (J. Andrew Royle, personal communication). To investigate how best to discretize remote camera data w e used a 60-day subset of the data (Jun 15 – Aug 13) because 60 days can easily be discretized into many different sampling-replicate lengths (1–6, 10, 12, 15, 20 and 30 days). For each discretization of the same data set, we estimated occupancy models with no covariates on occupancy or detection probabilities and compared model performance and precision of parameter estimates. For each sampling replicate length, we also calculated cumulative probability of detecting bears at least once during the survey ($p*$) where $p* = 1 - (1-p)^k,$ and k is the number of sampling replicates and p is the sampling-replicate-specific detection probability.

2.3.2 Effects of trail and camera type on detection probability

Site-specific camera placement may affect detection probabilities for multiple species. Detection probabilities for 11 species were analyzed across different camera model types and different trail types. Three Reconyx camera models were used: Hyperfire, Rapidfire and Silent Image, in increasing order of model age. The most important advancement between model types is the inclusion of a covert Infrared flash in the Hyperfire and Rapidfire models which have been hypothesized to cause fewer animals to be startled when photos are taken, when compared to the regular white LED flash of the Silent Image model (Gibeau and McTavish 2009). A startled response may cause some species to avoid known camera locations in the future, creating a trap-shy bias (Wegge et al. 2004). Cameras were deployed on 3 different trail types as well: wildlife trails, human-use trails and road beds.

2.3.3 Effect of lure on detection probability

To address objective 3 in our contract, we deployed 12 cameras to sites on wildlife trails (i.e. off of human-use trails). In Banff National Park and Spray Lakes Provincial Park. Half of these cameras received lure upon deployment in early July and the other half received lure 6 weeks following deployment. All cameras were revisited approximately 6 weeks after setup to remove lure from those

with lure, and add lure to those sites that did not have lure initially in a crossover experimental design.

Wooden shelters were created for the lure, to allow removal of lure from the site. Each off human-use

trail camera was paired with a previously deployed camera on a human-use trail for a total of n=24

cameras. To minimize the differences between cameras on and off trails, similar

elevation/aspect/habitat type for were used for off-trail cameras and the on-trail camera counterpart

and the same camera type. Each off-trail camera location was >2km from its on-trail camera partner to

avoid any spill-over effect of the lure. Each lured camera location was also >300m away from any

human-use trails for public safety reasons.

Using the null occupancy model, *i.e.*, no

covariates for detection probability (*p*) or for

occupancy probability (psi), and using a sampling

session length of 1 week, we modeled *p* for 11

species: grizzly bear, wolf, lynx, cougar, black bear,

coyote, elk, moose, mule deer, white-tailed deer and

red fox. Results are presented for when cameras were

on human-use trails, off human use trails with lure,

and off human use trails without lure.

2.4 Power analysis

We used simulations to assess the effects of key aspects of study design on the power to detect trends

in occupancy to address objectives 1b and 2. We used our top occupancy model above to identify sites

occupied by grizzly bears. To estimate the total number of sites occupied we used 1000 parametric

bootstrap replications of the empirical Bayes method available in the function, `ranef`, in the

`unmarked` extension package. Essentially, this function estimates the posterior distributions of the

latent variable (occupancy) at each site, which can be summed to estimate the total number of sites

occupied. We calculated both the mode and mean of this posterior distribution to obtain the empirical

best-unbiased predictors using the `bup` function in `unmarked`. The mode of the posterior distribution

is equivalent to using a 50% threshold to classify sites as likely occupied or not, and leads to slightly

lower estimate than the mean (Fiske and Chandler 2015). We used the more conservative output of this

top model, the mode, to simulate in a paired design, the power to detect a decline between two

sampling years: between 2012 and a subsequent, simulated year. The paired design is most appropriate

because camera locations do not move between years and thus, our two samples are not independent.

Power to detect trends was determined using a paired t-test design where the resulting

estimated site-specific occupancy probabilities from a simulated decline was compared to the site-

specific probabilities in 2012, with an α level of 0.05 (Thomas and Juanes 1996). The paired t-test is

appropriate because in our design, camera sites did not change between sampling years but animals

move sufficiently between years for the samples to be independent from one another. We consider

only 2 sampling years, rather than >2 years because the power to detect a trend between the first and

last years does not differ significantly from detecting a trend across all years (see Table 1 in Guillera-

Arroita and Lahoz-Monfort 2012). We ran 1000 simulations for each decline scenario. We calculated

power as the percentage of simulations where a significant difference was detected (Thomas and Juanes

1996). We used 80% power as our target threshold for study designs having adequate power (Gelman

and Hill 2006).

2.4.1 Effect of spatial extent, number of cameras and duration of camera deployment

To examine at what spatial extent a change in grizzly bear occupancy could be detected, we performed

these power analysis simulations across each park and for all parks combined. To answer the questions

pertaining to sample size required (Objective 1c), we also randomly varied the number of camera sites

from 20 – 120. To understand how long cameras needed to be deployed, we varied amount of data used

for the simulations from 40 – 160 days, effectively simulating shorter lengths of time that cameras were deployed in the field.

2.4.2 Effect of sampling design and estimation method

When cameras sites are chosen randomly across the landscape, the resulting occupancy estimate is naturally representative of the population. For the current sampling design however, cameras were spread out using a grid and locations within a grid cell depend on the best location on trails to maximize detection probability. The full sampling of the parks (one camera in each cell) allows inference to be made to the entire park. The locations of sites within cells, however, does not provide a random sample of camera locations, but camera sites are kept in the same location each there, therefore providing information on the changes in cell occupancy across years. With random location, we could use a Wald test to document changes in occupancy among years ((Guillera-Arroita et al. 2011), but with cameras located in the same locations year to year, we can use the more powerful paired t-test. Next, we investigated the affect of using random versus fixed locations on power to detect trends by calculating and comparing statistical power when using both a Wald's test and a paired t-test to address objective

1b Furthermore, many occupancy analyses are being performed using a Bayesian estimation method, rather than the Maximum likelihood method we are using. We use both estimation frameworks to calculate power using both the Wald's t-test and paired t-test to evaluate any possibly differences when choosing different estimation methods.

2.4.3 Effect of spatial pattern of decline

It is difficult to know what decline would cause a species to become extirpated (Reed and Blaustein 1997), therefore, we simulated a range of biologically significant declines in absolute occupancy ranging from 0.05 to 0.40. Starting with baseline occupancy of 2012, we simulated the decline in four different spatial patterns (*i.e.* different ecological mechanisms). Firstly, we sampled a loss of occupied sites randomly, whereby occupied sites were randomly chosen to be unoccupied during the simulated year of sampling. Secondly, assuming ideal free distribution of bear occupancy (Beckmann and Berger 2003), lower quality habitat cells were lost first (i.e. random cells with the lowest occupancy probabilities were lost first). Third, because some of the best grizzly bear habitat is located in valley bottoms, close to roads (Nielsen et al. 2006), it is possible that occupancy decline may be associated with an ecological trap instead, thus cells at the higher end of occupancy probability were lost first. Lastly, global ranges tend to decline from their periphery (Laliberte and Ripple 2004) which for our study area is the east side of the parks (Festa-Bianchet and Kansas 2010). In this scenario, we simulated more eastern sites were more likely to become unoccupied using the geographic coordinates of each camera site.

2.4.4 Effect of sampling scale

Most occupancy studies target one specific species, often a charismatic carnivore, umbrella, or indicator species (Kucera and Barrett 2011). Sampling is tailored to maximize probability of detection and match the scale of sampling to the within home-range scale of movements of the focal species. There have been many advances in our understanding of species occurrence and density from such species-specific studies (MacKenzie 2006) that maximize the power to detect trends in the focal species. However,

remote cameras inadvertently collect much more data on non-target species than target species. This "superfluous" data span the spectrum of species abundance and trophic levels. To understand one of the complications of analyzing multispecies data (Objective 3), we using three nested sampling scales of remote camera trapping at 5, 10 and 20km grid cells to investigate the effects of sampling scale on multi-species occupancy. The three cell sizes correspond to home-range sizes for 3 focal carnivores in the Canadian Rockies: grizzly bear, cougar and fox. The 5x5-km cells represent a more intensive sampling than the 10x10 cells described above and approximates the home range scale of red fox, ~25 km^2, (Knick 1990). By randomly sub sampling these 5x5-km cells, we reduce this data to 1 per 10x10-km cell, approximating the home ranges of cougars (87-97 km^2 and 140-334 km^2 for females and males respectively, depending on the season (Ross and Jalkotzy 1992). Further sub- sampling to 1 camera per 20x20-km cell roughly corresponds to the smallest home range size of female grizzly bears in this area (~520 km^2, (Stevens and Gibeau 2005). We repeated this intensive sampling in 3 study areas (Figure 2). Here we present preliminary results from only the Ya Ha Tinda area.
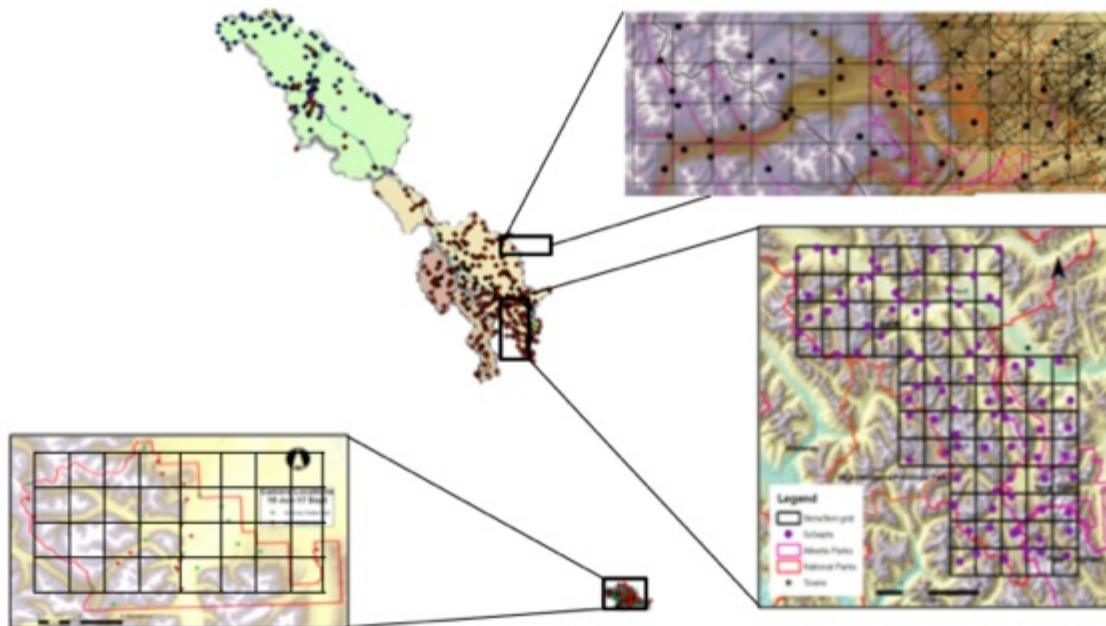
Figure 2: Increased sampling intensity in 3 areas of the Canadian Rockies to investigate the effects of sampling scale on occupancy estimation across different species. Three areas are Ya Ha Tinda

area, Banff NP – Kananaskis Country, and Waterton Lakes NP (from top to bottom). Each has cameras deployed at a scale of 1 per 5x5 km cell during 2013-2014, 2012 and 2012-2014 respectively.

2.4.5 Effects of species-specific occupancy (Ψ) and detection (*p*) probabilities

Each species has its own detection probability and prevalence on the landscape (i.e. occupancy

probability). To investigate how differences in species-specific occupancy and detection probabilities will

affect power to detect trends in their occupancy, we calculated the ability of the current sampling

design to detect a decline with 80% power. Using a published closed-form formula for calculating power

to detect a decline between two sampling years (Guillera-Arroita and Lahoz-Monfort 2012), we

calculated power across all combinations of occupancy probability (0.1 – 0.9) and detection probability

(0.1 – 0.9). Keeping the number of sites constant at n = 183 and the number of sessions constant at 26

weeks (*i.e.* half a year), we explore the relationship between power and both Ψ and p. Using an alpha

level of 0.05, we document the minimum decline that can be detected with 80% power. Using data from

2012, we estimated Ψ and p for 13 large mammal species. Using null models with no covariates, we

then plotted these species-specific parameters relative to one-another and relative to the simulated

power across all Ψ and p.

3.0 RESULTS AND DISCUSSION

3.1 Field consideration

Each year, resource conservation personnel have serviced 100s of cameras (Table 1), often while conducting other fieldwork. This effort included the deployment of upward of 150 *new* camera locations each year, as old camera locations are retired due to poor location or because the temporary research project had finished. **Together, the 5 national parks have classified over 180,000 events** (Table 2). An event is defined as a picture of a single or group of animals (or humans) that is at least 5min from a previous picture of the same species, unless it is clear that they are different individuals due to coloration, size, or other discernable features (e.g. antlers). Each event comprises of ~5 pictures because cameras are set to take 5 pictures in rapid succession. For every picture of an animal, ~50 pictures of no animal are taken due to vegetation triggering the motion sensor. This leads to the rough estimate that resource conservation personnel have, thus far, gone through ~10 million pictures, about 2 million per year on average.

Table 1: Total *new* camera sites deployed each by resource conservation personnel across 5 National Parks. Note, in some years, the same cameras were set up at multiple locations.

	New cameras deployed each year					Total cameras currently deployed
	<2011	2011	2012	2013	2014	
Jasper NP	31	44	74	29	1	**89**
Banff NP	35	31	99	72	21	**76**
Lake Louise (BNP)	11	8	23	2	5	**37**
Kootenay NP	12	6	14	0	0	**17**
Yoho NP	7	9	6	7	1	**20**
Waterton Lakes NP	68	7	13	0	0	**31**
TOTAL	164	105	229	110	28	**270**

Table 2. Total events classified by resource conservation personnel each year for each park. Events are pictures of animals (or groups of animals) at least 5 min apart.

	<2010	2010	2011	2012	2013	Total
Jasper NP	13,909	3,922	5,771	11,267	8,723	**43,592**
Banff NP	8,286	12,633	10,145	32,207	15,719	**78,990**
Lake Louise (BNP)	590	528	890	2,214	2,736	**6,958**
Kootenay NP	1,793	396	1,931	2,645	621	**7,386**
Yoho NP	-	4,025	1,515	1,696	2,466	**9,702**
Waterton Lakes NP	2,405	665	10,488	15,841	9,019	**38,418**
TOTAL	26,983	22,169	30,740	65,870	39,284	**185,046**

3.1.1 Using lure

Grizzly bears had significantly higher detection probabilities with cameras set on human-use trails than off human-use trails when no lure was used (Figure 3). The use of lure off trails, however, seems to counteract this difference, possibly pulling grizzlies off of human-use trail to lesser-used wildlife trails to investigate the lure scent. No other species showed significant differences among treatments, however, off human-use trail cameras tended to show lower detection probabilities when no lure was used, as would be expected. For 9 of the 11 species, human-use trail cameras tended to have higher detection probabilities than off-trail lured cameras (although differences are non-significant). These results suggest that **the use of lure would not improve detection probabilities in the National Parks because of the safety requirement for lured cameras to be set off of human-use trails.**
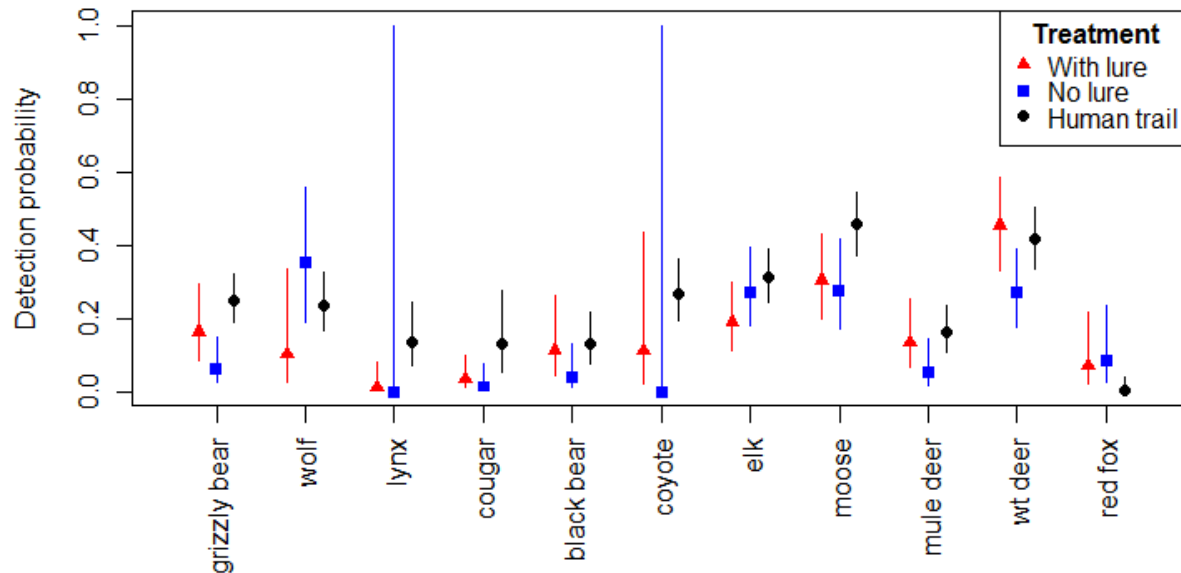
Figure 3. Effect of using lure on detection probability for 11 large mammal species in the Canadian Rockies (mean and 95% confidence intervals). Results are shown for 3 treatments: cameras set off human-use trails with and without lure and cameras on human-use trails without lure (n=24).

3.1.2 Trail type

Trail type did not significantly affect detection probabilities across most species. The only significant difference to note is that black bears were more likely to be detected on wildlife trails than on human-use trails (Figure 4). Besides black bears and mule deer, it was interesting to note, however, that **there was a tendency for detection probabilities to be higher on human-use trails than on wildlife trails**, or for detection probabilities to be similar. Large confidence intervals for road bed camera sites were likley due to small sample size (*n* = 6). Human-use trails, therefore, seem to have higher detection probabilities for multiple species, with the exception of black bear and possibly mule deer. Note that only sites where trailtype was known and was easily categorized as on a human-use trail (*n* = 43), on a wildlife trail (*n* = 17) or on a road bed (*n* = 6) were used. No sites that used lure were included in this analysis.
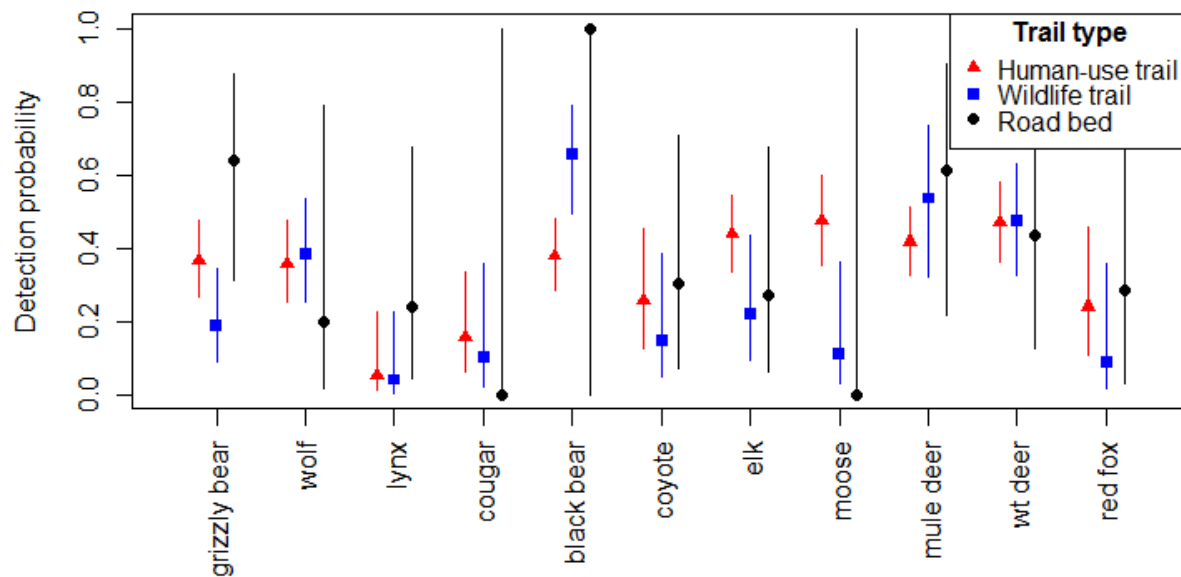
Figure 4. Effect of trail type on detection probability (mean and 95% confidence intervals) for 11 large mammal species in the Canadian Rockies (n=66).

3.1.3 Camera type

Different camera models affected the detection probabilities for black bear and white-tailed deer, but

not for any other of the 9 species investigated (Figure 5). This suggests that older models such as Silent

Image cameras do provide reliable data despite features

such as a visible LED flash. Using only a short window of

data, this analysis did not account for how long cameras can

remain running in the field. **Ultimately, battery life and**

other field logistics concerns may still warrant prioritizing

using newer models, even if ecologically, the data

collected are of similar quality.
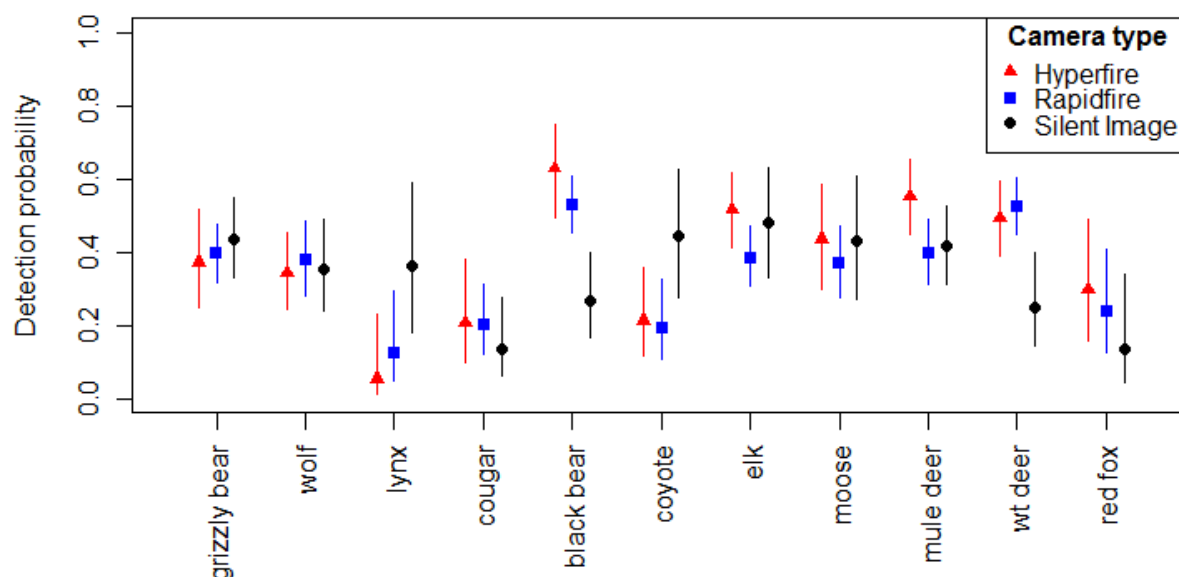
Figure 5. Effect of camera type on detection probability (mean and 95% confidence intervals) for 11 large mammal species in the Canadian Rockies (n=106).

3.2 Occupancy models by species

We focused species-specific occupancy model development on grizzly bears, lynx, wolverine and white-tailed deer. Grizzly bears are a species of specific management concern through the national parks. Wolverine and lynx are rare species of interest for which little is know about their distributions and whose population statuses are difficult to monitor (Whittington et al. 2014). White-tailed deer are an expanding species that may have food-web-wide effects.

3.2.1 Grizzly bears

Grizzly bears were detected at least once at 129 of 183 camera sites, resulting in a naïve occupancy estimate of 0.70. Four landscape covariates helped explain grizzly bear occupancy and detection probabilities in the top grizzly bear occupancy model (Table 3): the presence of rubtrees, distance from roads, topographic position index and human activity levels on trails. Detection probability increased when cameras were placed facing trees used by grizzly bears as rub trees. Detection probability was higher on trails with low human activity levels (<1,000 people per summer) when compared to both

trails with no human activity and high human activity, indicating that grizzly bears used trails with lower human activity more frequently. Essentially, trials with high human activity had similar detection probabilities that are not used by humans and are likely lower quality trails for movement, such as wildlife trails.

Detection probability also increased as camera sites were placed further from roads. Similarly, occupancy probability also increased as distance from road increased. Furthermore, occupancy decreased as cameras were placed in areas away from valleys bottoms and more towards mid-slopes and ridges.

The best estimates of the number of occupied sites in the study area were 145 and 137 (mean, mode respectively; C.I. of mean: 133 – 158) out of 183 sites. This is equivalent to **a mean estimated occupancy probability of 0.79 (0.73 – 0.86), and is a substantial increase from the naïve occupancy of 0.70, corroborating the usefulness of occupancy models to account for imperfect detection**. There was no evidence for lack of model fit (p = 0.087).

Table 3: Top occupancy models for grizzly bears (*Ursus arctos*) and grizzly bear family groups in the Canadian Rockies using remote-camera-based-occupancy modeling with data from *n* = 183 cameras deployed May 1 – Oct 15, 2012. Estimates of beta coefficients are reported for standardized covariates, scaled to mean and standard deviation. Human activity level coefficients are relative to a level of no human activity on trails.

All Grizzly bears	Covariate	Estimate	SE	z	Pr(>|z|)
Occupancy	(Intercept)	1.536	0.264	5.81	< 0.001
	Distance to road	0.624	0.232	2.69	0.007
	TPI_{100km}	-0.693	0.230	-3.01	0.003
Detection	(Intercept)	-3.352	0.487	-6.88	< 0.001
	Distance to road	0.260	0.090	2.90	0.004
	Rub tree	0.318	0.100	3.18	0.001
	Human activity level				
	1–1000 people	1.339	0.486	2.76	0.006
	>1000 people	0.316	0.570	0.56	0.579
Family groups only					
Occupancy	(Intercept)	-0.309	0.379	-0.82	0.414
	$Percent\ burned_{500m}$	0.696	0.325	2.15	0.032
Detection	(Intercept)	-3.905	0.252	-15.47	< 0.001
	Distance to road	0.655	0.322	2.03	0.042

The top occupancy model for grizzly bear family groups also had good model fit (*p* = 0.099), but contained fewer covariates than the top model for all grizzly bears (Table AB). Similar to all grizzly bears, female detection probability increased with increasing distance to secondary road but was not significantly affected by the presence of rub trees or high human traffic. Furthermore, variation in occupancy of grizzly bear family groups was only explained by percent of area burned within 500km^2 of the camera site.

Using the top model for grizzly bear occupancy, we analyzed the most current data classified for all 5 parks, 2013 where *n* = 315 cameras were operational. The resulting occupancy map (Figure 6) shows considerable increase in camera coverage compared to 2012. Grizzly bear occupancy remains high for all 5 parks with lowest occupancy probabilities among cameras in large main valleys.
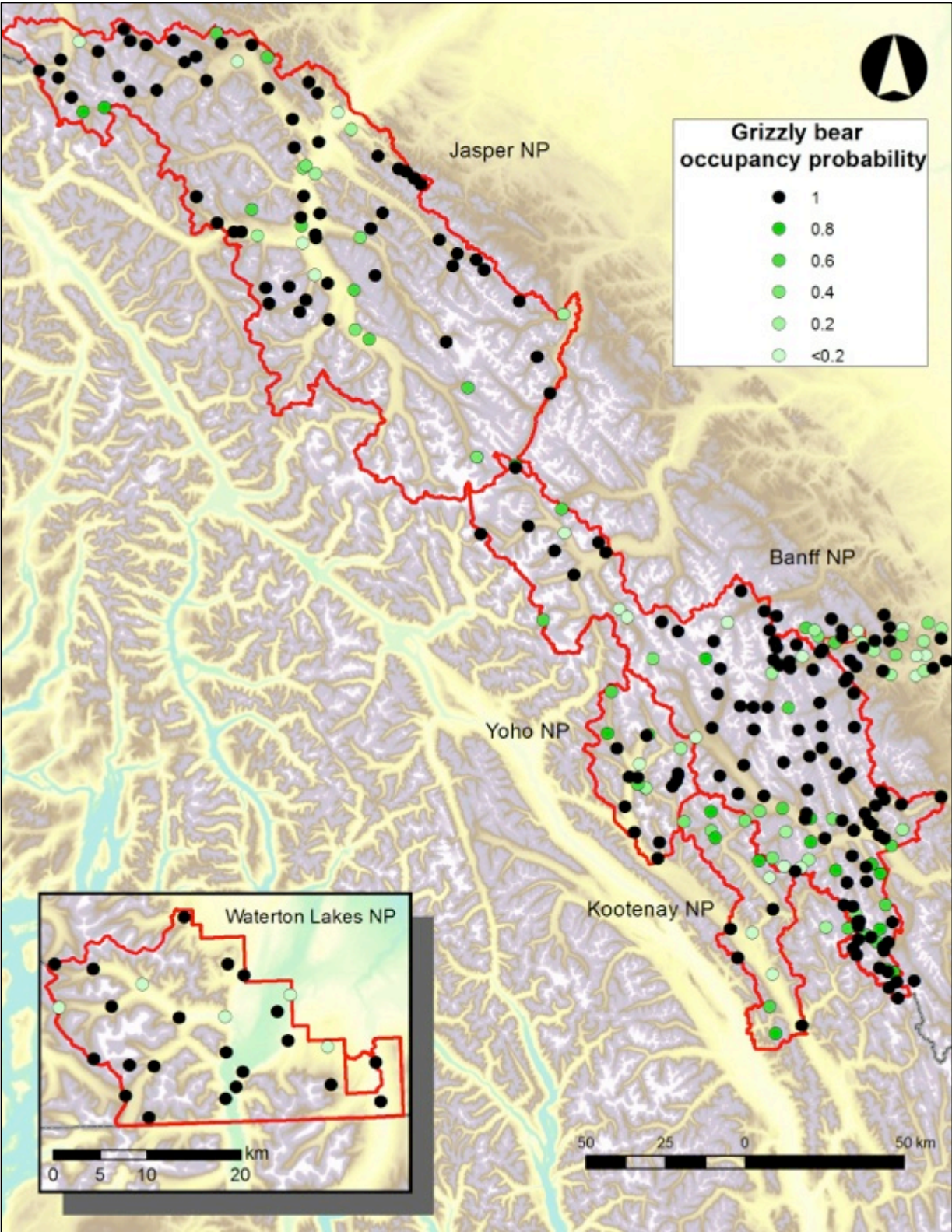
Figure 6: Probability of grizzly bear occupancy across 5 National Parks. Camera data from 2013 was analyzed using the top model occupancy model. When occupancy probability = 1 (black circles), grizzly bears were detected at least once at that site. Green circles depict probability of occupancy despite grizzly bears never having been detected.

3.2.2 Wolverine

Wolverines were detected at least once at 32/356 sites in summer 2012 and at least once at 46/231 sites during winter 2012-2013 (Table 4). The difference in naïve occupancy rate was double, from 0.09 to 0.20. Variables explaining detection and occupancy probabilities in the top occupancy models by season were similar, with the covariates in the summer model reflecting a subset of the covariates in the winter model (Table 5). In both seasons, wolverine detection probability was higher when cameras were placed in front of bear rub trees. In winter, detection was also higher further from roads, on human trails when compared to wildlife trails, and at lower annual human traffic levels. Occupancy rate depended in both seasons on elevations. In summer, wolverine occupancy was higher at higher elevation. In winter, wolverine occupancy was also higher at higher elevation, but they showed selection for mid elevations. The distribution of wolverine occupancy does not seem to differ much between seasons (Figures 7 and 8). Despite similar top models and distribution, **it is clear that cameras are better able to detect wolverines during winter.** The summer estimated occupancy rate of 0.26 (0.15 – 0.35) is much lower than the winter rate 0.34 (0.26 – 0.43). For some species, like wolverine, developing occupancy models for multiple seasons may highlight important ecological or sampling efficacy differences between seasons.

Table 4. Differences in data availability and in estimates from top occupancy models for wolverine in summer and winter. Naive occupancy is equivalent to total sites with at least one detection.

	Summer	Winter
Dates	May - Oct 2012	Nov 2012 - Apr 2013
Total cameras running	356	231
Naïve occupancy (rate)	32 (0.09)	46 (0.20)
Mean estimated occupancy (CI)	0.26 (0.15 – 0.35)	0.34 (0.26 – 0.43)

Table 5. Top occupancy models for wolverine (*Gulo gulo*) using data from cameras deployed summer (May – Oct, 2012; *n* =356) and winter (Nov 2012 – Apr 2013; *n* = 231). Estimates of beta coefficients are reported for standardized covariates, scaled to mean and standard deviation. Effect of wildlife trail is relative to human-use trails and annual human traffic is total number of people using the trail throughout the year.

Summer (*n* = 356)	Covariate	Estimate	SE	z	Pr(>|z|)
Occupancy	(Intercept)	-1.363	0.303	-4.500	< 0.001
	Elevation	0.911	0.290	3.140	0.002
Detection	(Intercept)	-3.840	0.325	-11.820	< 0.001
	Rub tree	1.440	0.354	4.070	< 0.001
Winter (*n* = 231)					
Occupancy	(Intercept)	-0.749	0.219	-3.420	0.001
	Elevation	4.658	2.336	1.990	0.046
	Elevation2	-4.556	2.314	-1.970	0.049
Detection	(Intercept)	-2.908	0.318	-9.150	< 0.001
	Distance to road	1.150	0.449	2.560	0.010
	Rub tree	0.524	0.246	2.130	0.033
	Wildlife trail	-2.928	1.064	-2.750	0.006
	Annual human traffic	< 0.001	< 0.001	-2.100	0.035
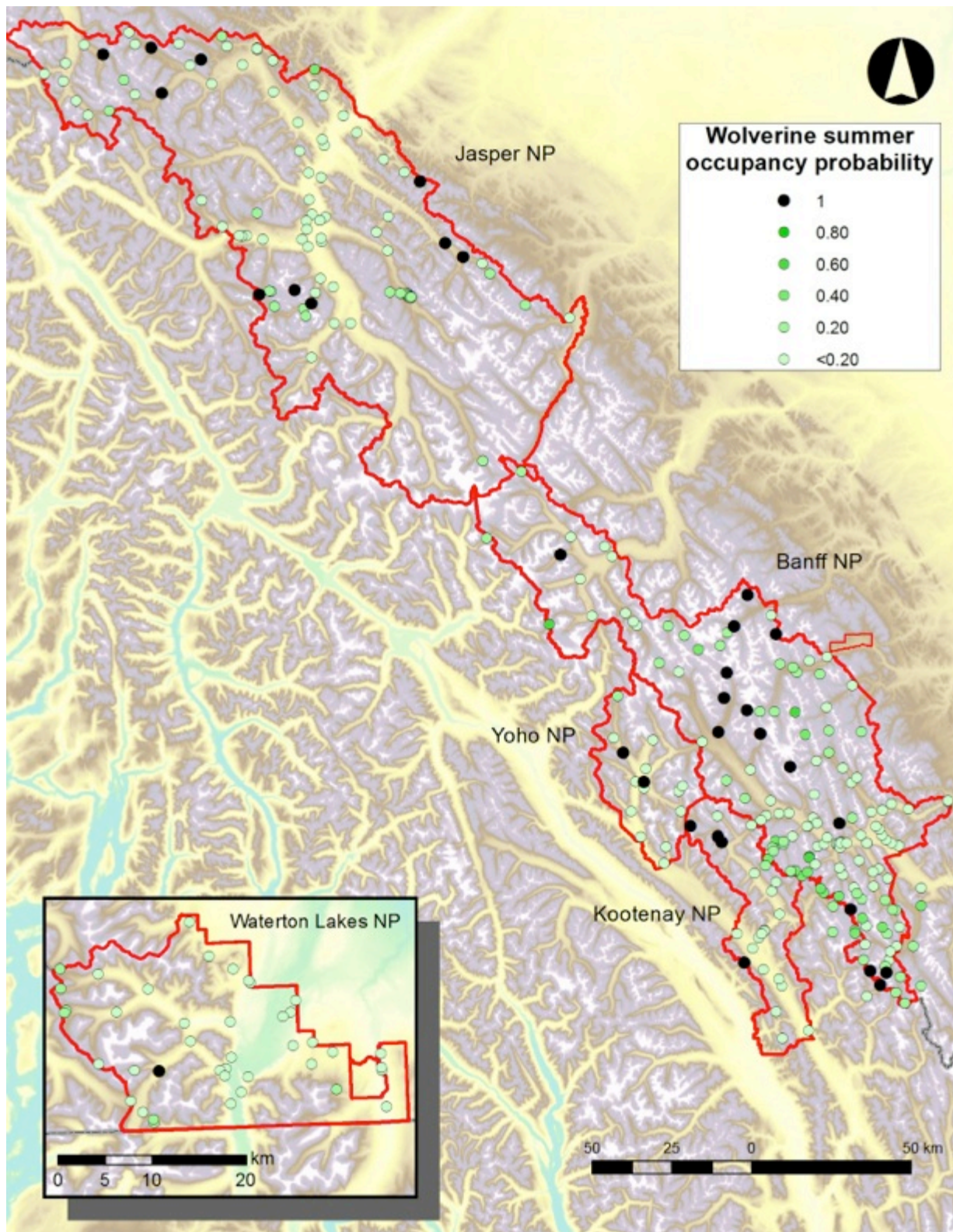
Figure 7. Probability of summer wolverine occupancy across 5 National Parks. Camera data from May – Oct 2012 was analyzed to develop a top summer occupancy model. When occupancy probability = 1 (black circles), wolverines were detected at least once at that site. Green circles depict probability of occupancy despite wolverines never having been detected.
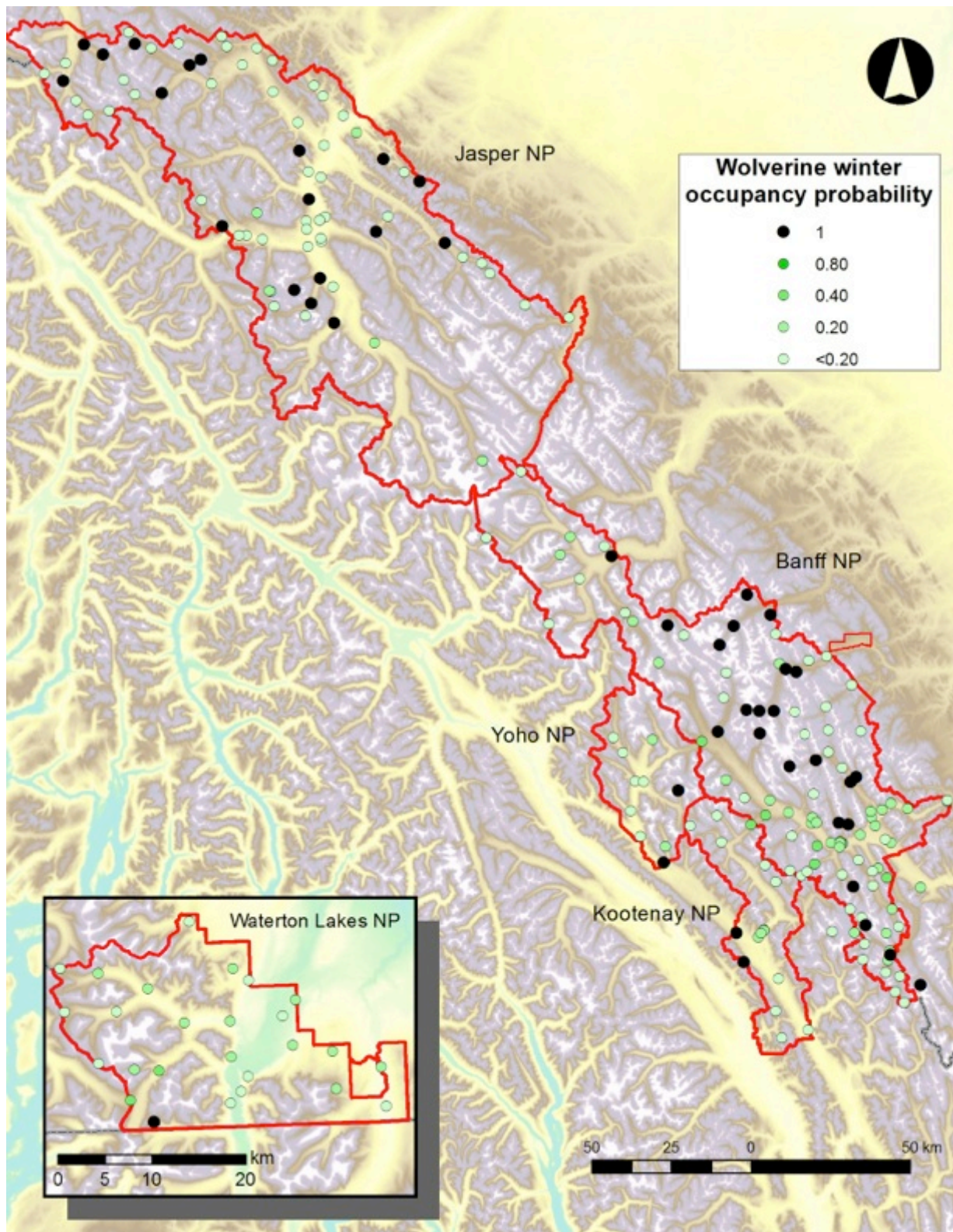
Figure 8. Probability of winter wolverine occupancy across 5 National Parks. Camera data from Nov 2012 – Apr 2013 was analyzed to develop a top winter occupancy model. When occupancy probability = 1 (black circles), wolverines were detected at least once at that site. Green circles depict probability of occupancy despite wolverines never having been detected.

3.2.3 Lynx

Lynx were detected at least once at 62/356 sites in summer 2012 and at least once at 24/231 sites during winter 2012-2013 (Table 6). The difference in naïve occupancy rate between summer and winter is nearly half: from 0.17 in summer to 0.10 in winter. Variables explaining detection and occupancy probabilities in the top occupancy models by season were similar, but there were much fewer covariates on the winter model due to dew detections and low rate of occupancy (Table 7). In both seasons, lynx detection probability was higher when cameras were placed in front of bear rub trees. In summer, detection was also higher when sites were placed further from railroads but in valley bottoms compared to ridges (as measured by TPI at the 500km^2 scale). In winter, occupancy rate depended only on increased crown closure in the area with in 20km^2 of the camera site. In contrast, during summer lynx occupancy was higher at higher elevation. In winter, lynx occupancy was higher at cameras on ridges than in valley bottoms (Table 7). Compared to summer (Figure 9) the low number of detections in winter, is readily apparent when plotted across the study area (Figure 10) and **emphasizes the need to combine data from remote cameras with snow tracking to improve estimates of lynx occupancy and provide the best means to monitor their population trend (Whittington et al. 2014)**. Similar to wolverine, the difference in apparent lynx distribution in summer and winter also highlights the importance of developing occupancy models for multiple seasons for some species.

Table 6. Differences in data availability and in estimates from top occupancy models for lynx in summer and winter. Naive occupancy is equivalent to total number of sites with at least one detection.

	Summer	Winter
Dates	May - Oct 2012	Nov 2012 - Apr 2013
Total cameras running	356	231
Naïve occupancy (rate)	62 (0.17)	24 (0.10)
Mean estimated occupancy (CI)	0.31 (0.24 – 0.38)	0.14 (0.08 – 0.18)

Table 7. Top occupancy models for lynx (*Lynx canadensis*) using data from cameras deployed summer (May – Oct, 2012; *n* = 356) and winter (Nov 2012 – Apr 2013; *n* = 231). Estimates of beta coefficients are reported for standardized covariates, scaled to mean and standard deviation. Subscripts are scale of covariate (*e.g.*, 500-km scale).

Summer (*n* = 356)	Covariate	Estimate	SE	z	Pr(>|z|)
Occupancy	(Intercept)	-0.905	0.183	-4.950	< 0.001
	TPI_{500}	0.686	0.231	2.970	0.003
Detection	(Intercept)	-2.851	0.204	-13.95	< 0.001
	Rub tree	0.740	0.201	3.68	< 0.001
	TPI_{500}	-0.629	0.123	-5.12	< 0.001
	Distance to rail	1.160	0.426	2.72	0.006
Winter (*n* = 231)					
Occupancy	(Intercept)	-1.986	0.255	-7.80	< 0.001
	$Crown Closure_{20}$	0.664	0.248	2.68	0.007
Detection	(Intercept)	-2.580	0.264	-9.78	< 0.001
	Rub tree	0.695	0.312	2.23	0.026
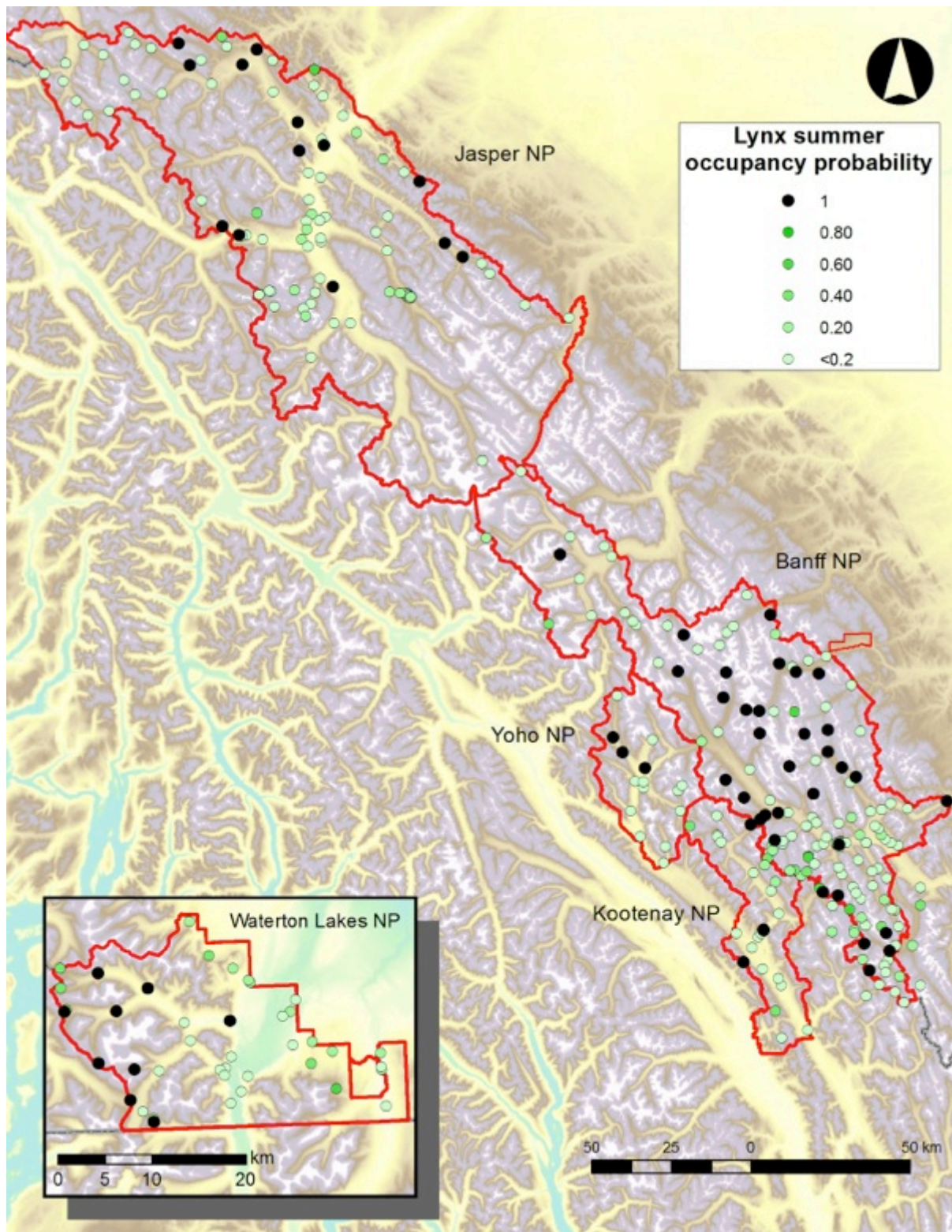
Figure 9. Probability of summer lynx occupancy across 5 National Parks. Camera data from May – Oct 2012 was analyzed to develop a top summer occupancy model. When occupancy probability = 1 (black circles), lynx were detected at least once at that site. Green circles depict probability of occupancy despite lynx never having been detected.
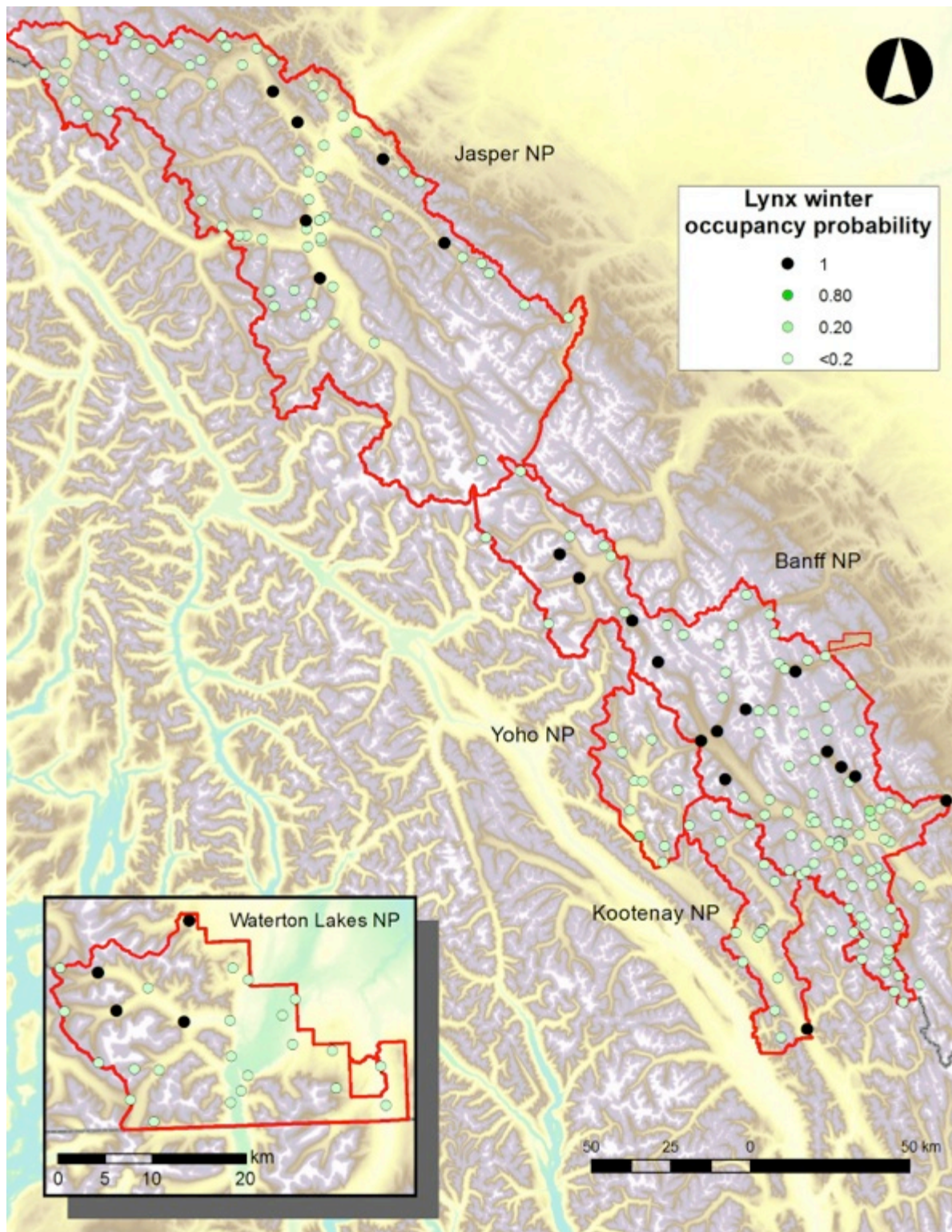
Figure 10. Probability of winter lynx occupancy across 5 National Parks. Camera data from Nov 2012 – Apr 2013 was analyzed to develop a top winter occupancy model. When occupancy probability = 1 (black circles), lynx were detected at least once at that site. Green circles depict probability of occupancy despite lynx never having been detected.

3.2.4 White-tailed deer

White-tailed deer were detected at least once in summer 2012 at 104/183 sites, resulting in a naïve occupancy rate of 0.57. For the occupancy model analysis, one site was dropped to meet assumptions of categorical data and ensure all group-expected frequencies did not equal zero. White-tailed deer occupancy depended on two variables (Table 8). Occupancy decreases with increasing elevation and was higher in the south-most park (Waterton Lakes NP) relative to the 4 northern parks. In fact, **all but one camera in Waterton Lakes used in this analysis captured at least one picture of white-tailed deer**. Variability in detection probability was described by 4 covariates. Cameras that were placed closer to roads had higher detection probability, as did cameras placed in valley bottom when compared to ridges or mid slope at special scales of 20 km^2. Trails with low human activity (1-1000 people in the summer) had similar detection probabilities to trials with no human activity, but **when activity was >1000 people, detection probability decreased significantly**. Interestingly, this is response is slightly different for white-tailed deer than grizzly bears. Grizzly bears had lower detection probability on *both* trails with high human activity and no human activity. Deer may use these latter trails, which are often wildlife trails, as a means to avoid predators like grizzly bears that spend more time on main trails. Finally, detection probability was higher in herbaceous areas when compared to closed-conifer forests, but lower in open-confider, mixed-deciduous or shrub-dominated areas. Model fit was good (*p* = 0.287). When accounting for imperfect detection, the top occupancy model estimated the total number of sites occupied to be a mean of 115 (CI: 103 – 129), which is equivalent to an occupancy rate of 0.63 (0.57 – 0.71).

Table 8. Top occupancy models for white-tailed deer (*Odocoileus virginianus*) in the Canadian Rockies using remote-camera-based-occupancy modeling with data from *n* = 183 cameras deployed May 1 – Oct 31, 2012. Estimates of beta coefficients are reported for standardized covariates, scaled to mean and standard deviation. Human activity level coefficients are relative to a level of no human activity on trails. Coefficients for landcover classes are relative to conifer-closed.

	Covariate	Estimate	SE	z	Pr(>|z|)
Occupancy	(Intercept)	0.507	0.218	2.330	0.020
	Elevation	-1.188	0.233	-5.100	< 0.001
	Park location (WLNP)	2.166	0.880	2.460	0.014
Detection	(Intercept)	-1.111	0.376	-2.952	0.003
	Distance to road	-0.383	0.051	-7.442	< 0.001
	TPI$_{20km}$	0.503	0.064	7.870	< 0.001
	Human activity level				
	1–1000 people	-0.238	0.379	-0.627	0.531
	>1000 people	-1.652	0.566	-2.918	0.004
	Landcover				
	Conifer-open	-1.111	0.376	-2.952	0.003
	Deciduous-mixed	-0.287	0.139	-2.061	0.039
	Herbaceous	1.580	0.210	7.526	< 0.001
	Shrub	-0.917	0.308	-2.977	0.003
	Rock-barren	0.229	0.457	0.501	0.617
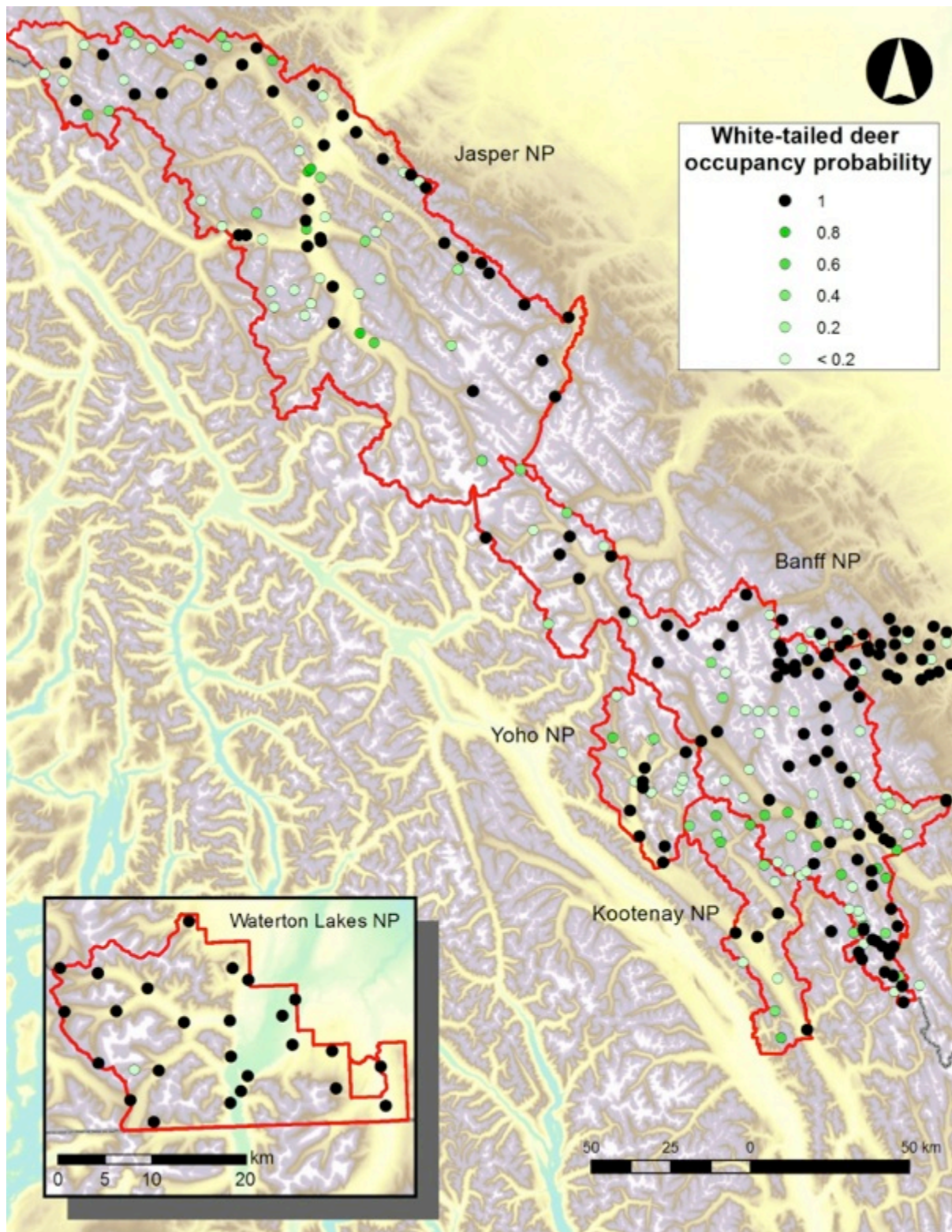
Figure 11. Probability of white-tailed deer occupancy across 5 National Parks. Camera data from 2013 was analyzed using the top model occupancy model. When occupancy probability = 1 (black circles), deer were detected at least once at that site. Green circles depict probability of occupancy despite deer never having been detected.

3.3 Power to detect declines

Remote-camera-based occupancy models have the potential to provide a robust method to meet goals of large-scale monitoring for difficult-to-monitor populations of low density, wide-ranging carnivores such as grizzly bears. This power depends on the spatial extent of interest, the number of cameras deployed, how long cameras are deployed, species-specific occupancy and detection probabilities, and some analytical considerations such as how data is discretized and choice of statistical test. We address each of these effects in turn.

3.3.1 Effect of spatial extent of interest

At the regional spatial scale, power to detect trends in grizzly bear occupancy was high (Figure 12A). Using the conventional 80% power as our target threshold for study designs having adequate power (Gelman and Hill 2006), **we have adequate power with 183 cameras to detect a ~4% decline in grizzly bear occupancy between two sampling years**. At the park scale, statistical power is lower and variable among parks. In Banff, Yoho and Kootenay National Parks (BYK), we can detect an ~7% decline (Figure 12B; n = 94); in JNP, we can detect an ~10% decline (Figure 12C; n = 64); and in WLNP we can detect an ~24% decline (Figure 12D; n = 25). These declines in power when considering the park scale, rather than the regional scale, is due mostly to sample size, *i.e.*, the number of cameras deployed in each park. Occupancy is a spatial attribute; the more samples of space we have, the higher our power. Therefore, with more cameras at the regional scale, we have higher power to detect trends in occupancy.
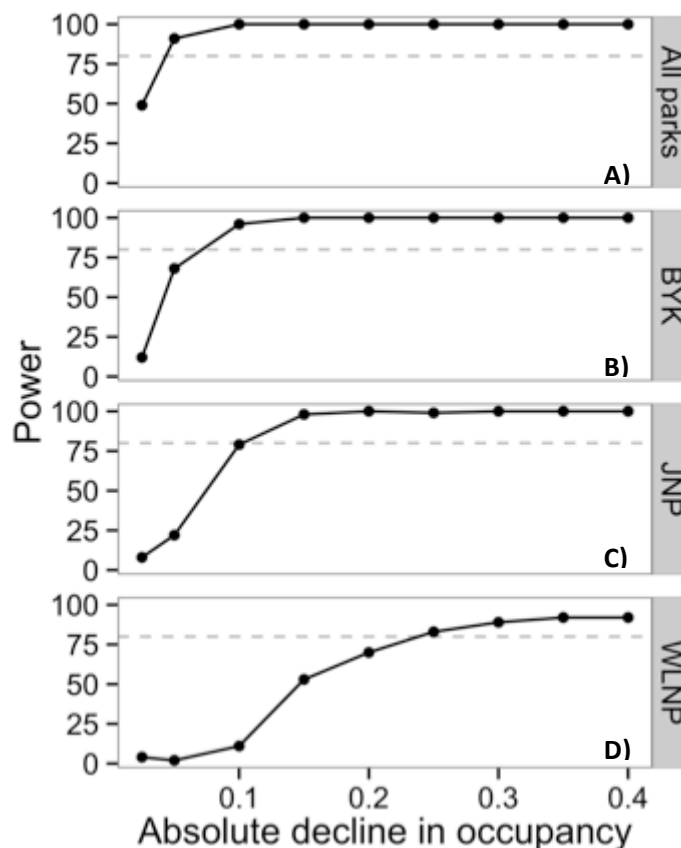
Figure 12. Power to detect trends in remote-camera-based occupancy of grizzly bears (*Ursus arctos*) across 5 National Parks; across the 3 reporting units of varying sizes: Banff Kootenay and Yoho National Parks together (BYK; *n* = 94); Jasper National park (JNP; *n* = 64); Waterton Lakes National Park (WLNP; *n* = 25). Dashed lines are at conventional cut off of 80% statistical power.

3.3.2 Effects of number of cameras and duration of deployment

Power to detect trends in grizzly bear population occupancy decreases when cameras are deployed for

fewer days and when fewer cameras are deployed (Figure 13). Many cameras studies only deploy

cameras for 1 or 2 months (Burton et al. 2015). We can see in Figure 13A, however, that with low daily

detection probabilities for grizzly bears, having camera deployed for a shorter than the entire 6-month

period of Mar – Oct, causes our power to detect declines to drop precipitously. Therefore, **we**

recommend continuing to deploy cameras year-round. When we rarefied the data and fewer cameras

were used in analysis, it is clear that power to detect declines decreases with fewer cameras. The

different in statistical power among parks when discussing the scale of interest above, is a direct result

of the number of cameras in each park (*i.e.*, of sample size). From Figure 13B, it appears that the gain in statistical power is substantial when increasing the number of cameras, up until about 60 camera are established. Above *n* = 60 cameras, the return of increased power for each camera invested declines. **We recommend that a sample size of 60 cameras would be ideal to maximize power to detect trends using camera-based occupancy models.** When helping design the global camera Tropical Ecology and Assessment Monitoring network, Obrien (2010) came to this same conclusion, that 60 cameras provided an ideal sample size for monitoring wide-range elusive species.
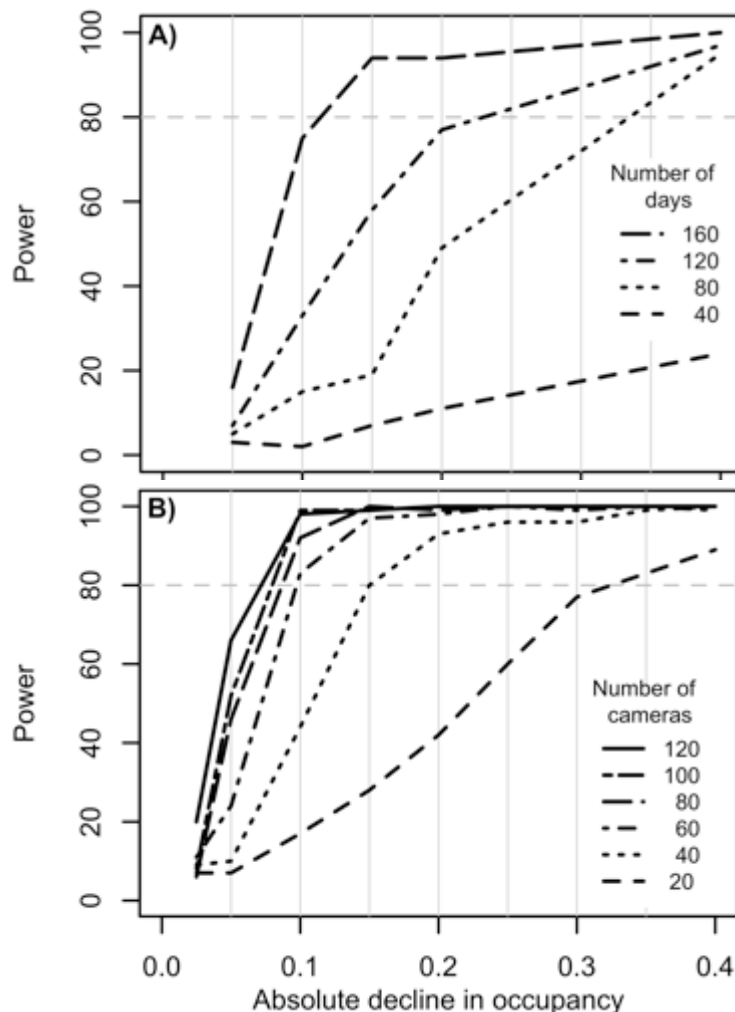
Figure 13. Effects of the number of cameras (A) and the number of days that cameras are deployed in the field (B), on power to detect trends in grizzly bear (*Ursus arctos*) occupancy in the Canadian Rockies. Note that for subfigure B, *n* = 60 cameras.

The relationship between power and the length of camera deployment can be understood when the cumulative detection probability (p^*) is considered. Cumulative detection probability is the probability of detecting the species *at least once* during the entire sampling period. It is calculated as 1 – the probability of missing the species during each of the individual sampling sessions (k) so that $p^* = 1 - (1 - p)^k$. In Figure 14 we show the relationship of p* with number of days cameras are deployed when daily detection probability is 0.04. Even with a very low detection probability, once the camera has been deployed for 80-100 days, p^* approaches 1, almost assuring the camera will capture at least one picture of the species, if it is present. **When designing non-invasive monitoring projects, it has recommended elsewhere to extend survey duration until $p^* > 0.8$ (Long and Zielinski 2008); keeping cameras out for the entire time grizzly bears are active meets this recommendation.**

$$p_{daily} = 0.04$$
$$p^* = 1 - (1 - p)^{days}$$
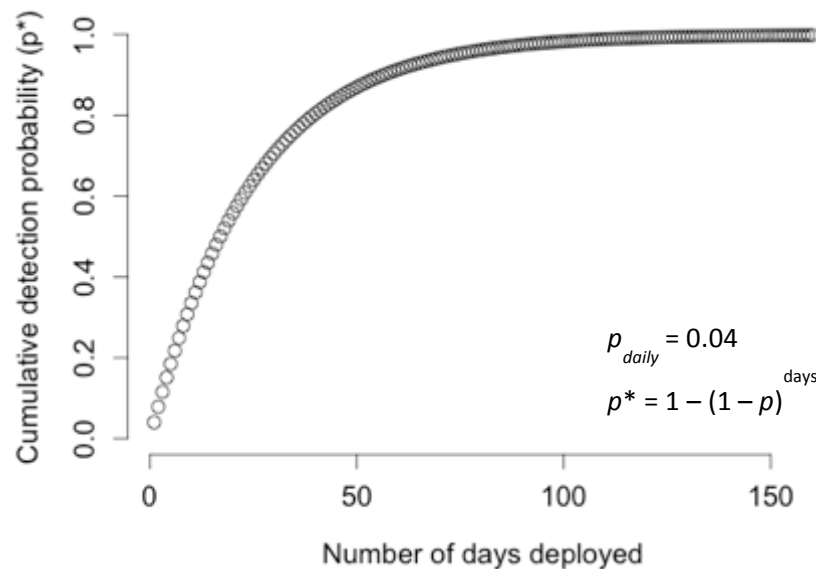
Figure 14. The relationship between cumulative detection probability (the probability of detecting a species at least once) and the length of the survey. The longer the survey period, the closer p* comes to 1, even for low detection probabilities. The parameters for this graph are daily detection rate of 0.04; *p** is calculated using the equation represented.

3.3.3 Effects of sampling design and analytical framework

Using a paired t-test, we had much higher power to detect declines in occupancy than when using a Wald's test (Figure 15). Determining which test of significant difference to use depends on the sampling design. The Wald's test is calculated using the population-level occupancy (summed occupancy averaged across all sites) and is only appropriate when the two samples are independent, for example, if we were comparing occupancy estimates from two years of camera data that were collected from sites that were randomly selected each year (e.g. Guillera-Arroita et al. 2011). The paired t-test is only appropriate when sites do not change from year to year and occupancy can be attributed to specific sites to be compared across two years. **Not moving cameras, therefore, has a great advantage for detecting declines because of the ability to use a paired t-test rather than a Wald's test.** Using this test is akin to using a finite sample occupancy estimate, which reduces uncertainty in our parameter estimates because at many of the sites we observed grizzly bears with no uncertainty (when pictures of grizzly bears were taken). This distinction between population- and sample-level occupancy parameters is seldom recognized, but has important implications for many occupancy studies (Royle and Dorazio 2008). On the other hand, there are minimal effects of using either maximum likelihood (Max Lik) or Bayesian (MCMC) estimation methods on estimated power (Figure 15). Both methods provide similar

power graphs for grizzly bear occupancy, but MCMC estimation takes orders of magnitude more time. When model structure is simple (i.e. when looking at single species occupancy) Maximum Likelihood methods should suffice.
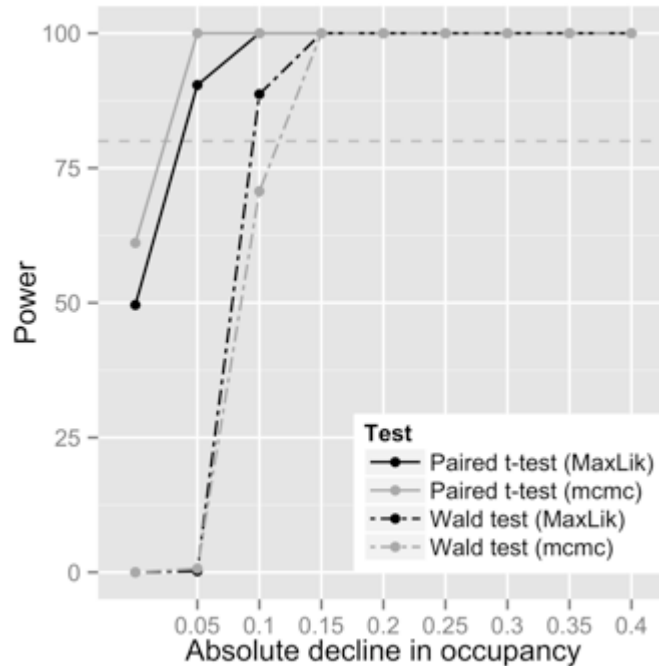
Figure 15. Effect of using a different test of significant difference (Paired t-test vs Wald test) and the effect of using different estimation frameworks (Maximum Likelihood, MaxLik vs Bayesian, mcmc) on power to detect trends in grizzly bear populations across 5 national parks.

Using an occupancy model with no covariates to estimate occupancy and detection parameters, *i.e.*, the p(.)psi(.) model, provides similar estimates for occupancy than the top covariate model. With no covariates the mean estimate for the number of the 183 sites occupied is 140 (CI: 127 – 152), which is equivalent to an occupancy rate of 0.77 (CI: 0.69 – 0.83). These estimates are slightly lower and slightly less precise when compared to results presented above using the top occupancy model with 4 covariates (Table AB) where the number of sites occupied was this 145 (CI: 133 – 157) resulting in an occupancy rate of 0.79 (CI: 0.73 – 0.86). Despite the similarity in results, and the model with no covariates no longer passes the basic Chi-squared test (p = 0.001), indicating evidence for lack of fit. The use of covariates in occupancy models, therefore, improves precision and goodness of fit.

3.3.4 Effect of considering grizzly family groups only

Grizzly bear family groups had lower occupancy (mean: 0.44, C.I. 0.29 – 0.66; mode: 0.28) when

compared to all grizzly bears, but interestingly, **we generally had higher statistical power to detect**

declines in grizzly bear family groups (Figure 16). For example, when using cameras from 3 national

parks (BYKNPs), we have adequate power to detect a 4% decline in the occupancy compared to 7%

when considering all grizzly bears (Figure 16).
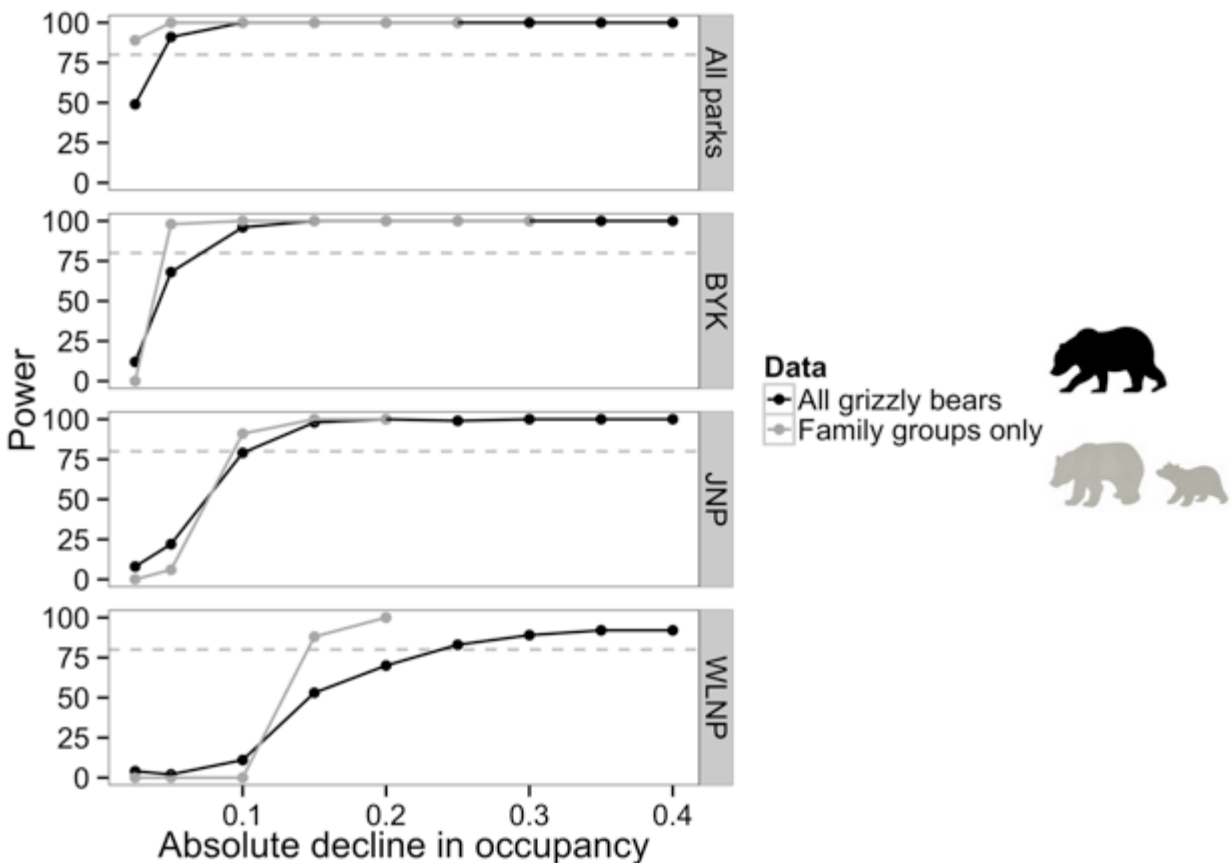
Figure 16. Power to detect trends in remote-camera-based occupancy grizzlybear family groups, across the 3 reporting units of varying sizes: Banff, Kootenay and Yoho National Parks together (BYK; *n* = 94); Jasper National park (JNP; *n* = 64); Waterton Lakes National Park (WLNP; *n* = 25). Dashed lines are at conventional cut off of 80% statistical power. Note that it was not possible to simulate an absolute occupancy decline below the baseline occupancy rate of grizzly bear family groups (ψ = 0.24 – 0.3, depending on the park). Data for all grizzly bears is the same as presented in figure 3a.

Despite fewer detections of grizzly bear family groups (50 observation-level detections

compared to 528 for all grizzly bears), we had higher or similar statistical power to detect trends in their

population. This may be related the nature of the binomial distribution of occupancy probability. The variance of a binomial distribution is proportional to $p(1 - p)$ and therefore largest at $p = 0.5$ and lowest at both extremities, 0 and 1. The high power to detect trends in all grizzly bears and in grizzly bear family groups, may be similar because their baseline occupancy rates used to model occupancy declines were similar distances from 0.5; $\Psi = 0.28$ for grizzly bear family groups compared to 0.75 for grizzly bears. Further discussion of this topic is presented in the section below on the effects of species-specific detection and occupancy probabilities on power to detect trends.

3.3.5 Effect of spatial decline of pattern of decline

The spatial pattern with which occupied sites became unoccupied had no effect on power to detect trends (Figure 17). Power to detect trends in grizzly bear occupancy remained constant across all simulated mechanisms of how occupancy could decline. Therefore, regardless of the simulated spatial pattern of occupancy decline, statistical power is constant. Although intuitively a non-interesting result, this lack of effect indicates, however, that there is no evidence for covariance between our sampling design and any particular mechanism of decline. In other words, this result speaks to the ability of the

current sampling protocol to capture a decline in occupancy regardless of the spatial mechanism of

occupancy decline.
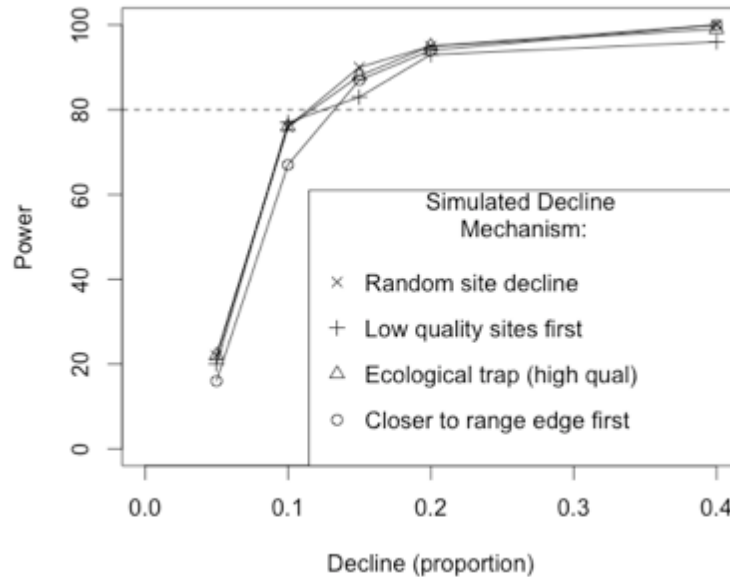
Figure 17. Effect of four different simulated mechanisms of occupancy decline on the power to detect trends in grizzly bear occupancy in the Canadian Rockies (*n* = 60 cameras).

3.3.6 Effect of sampling scale

Both the estimates of occupancy and their precision are affected by sampling scales (Figure 18 and Table

9). For grizzly bears, estimated occupancy at the smallest scale, the fox home range (HR) size, is slightly

higher in the Ya Ha Tinda region 0.86 (0.60 - 0.96) when compared to the 5 national parks of 0.79 (0.73 –

0.86), and precision is lower. As sampling scale increases to the cougar HR scale, occupancy appears to

increase and precision to improve, but rather, the estimation algorithm is no longer producing valid

estimates because of boundary issues; confidence intervals for binomial data cannot be confidently

estimated. This result continues when subsampled to the grizzly HR scale (where only 3 cameras are

running). Cougar estimates are very imprecise, even at the fox HR scale. The wide confidence intervals

are a direct result of low detection probability of 0.10 (0.03 - 0.31). At cougar and grizzly HR scales,

boundary issues become a problem once again. Fox, on the other had, retains reasonable estimates at

both fox and cougar HR scales. This is likely because with an initial occupancy rate of 0.41 (0.26 - 0.59), sub-sampling the data maintains occupancy at a rate far from boundary. In general, the loss of precision as scale of sampling increased for all 3 species is a direct results of the decreasing sample size (n = 48 cameras at fox HR scale, n = 12 at cougar HR , n = 3 at grizzly HR scale). Therefore **this preliminary analysis highlights 3 important considerations when matching the scale of sampling to the HR scale**. First, just as our analysis above showed, precision in occupancy estimates, and therefore power to detect trends, is largely affected by sample size (Figure 13). Future analyses will include n = 78 cameras from Banff National Park and Kananaskis country as well as n = 26 cameras from Waterton Lakes NP. Second, cougar occupancy shows the effect that low detection probability can have on occupancy estimates. Third, fox occupancy shows the effect that different occupancy rates can have on occupancy estimation. The next section explores the relationship between power/precision and species-specific occupancy and detection rates.
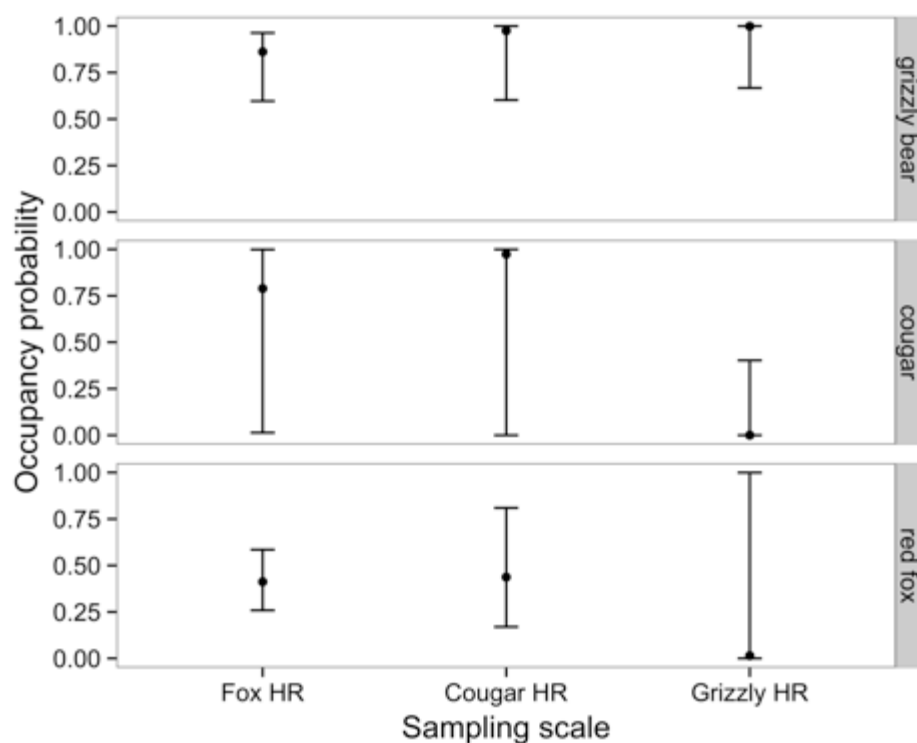
Figure 18. Effect of sampling scale on occupancy estimates across 3 species. Summer 2014 data from 48 cameras in the Ya Ha Tinda area were analyzed at 3 different home-range (HR) scales (x-axis) for 3 species (facets). Home ranges are approximated to be: fox HR = $25km^2$, cougar HR = $100 km^2$, and grizzly bear HR = $400km^2$.

Table 9. Effect of sampling scale on occupancy estimates across 3 species. Summer 2014 data from 48 cameras in the Ya Ha Tinda area were analyzed at 3 different home-range (HR) scales (x-axis) for 3 species (facets). Home ranges are approximated to be: fox HR = $25km^2$, cougar HR = $100 km^2$, and grizzly bear HR = $400km^2$.

Species	Occupancy Estimate	Detection probability	Scale of Analysis
Grizzly bear	0.86 (0.60 - 0.96)	0.43 (0.33 - 0.54)	Fox HR
	0.98 (0.60 - 1.00)	0.44 (0.24 - 0.69)	Cougar HR
	1.00 (0.67 - 1.00)	0.61 (0.13 - 1.00)	Grizzly HR
Cougar	0.79 (0.01 - 1.00)	0.10 (0.03 - 0.31)	Fox HR
	0.98 (0.00 - 1.00)	0.08 (0.00 - 0.38)	Cougar HR
	0.00 (0.00 - 0.40)	0.00 (0.00 - 0.66)	Grizzly HR
Red fox	0.41 (0.26 - 0.59)	0.47 (0.34 - 0.61)	Fox HR
	0.43 (0.17 - 0.79)	0.48 (0.20 - 0.81)	Cougar HR
	0.02 (0.00 - 1.00)	0.06 (0.00 - 1.00)	Grizzly HR

3.3.7 Effects of species-specific occupancy (Ψ) and detection (p) probabilities

As was evident in the multi-scale analysis above, species-specific occupancy and detection probabilities can affect precision of occupancy estimates. Statistical power was largely driven by the precision of the parameter of interest (here, Ψ). Detection probability (p) also affects the precision of Ψ. Therefore, **both Ψ and p affect our ability to detect trends in occupancy, and this effect changes across species.** First we investigated the differences in Ψ and p across species. Using summer 2012 data and a null model with no covariates, *i.e.* the p(.)psi). model, both Ψ and p differed substantially by species. Occupancy estimates ranged from 0.79 for grizzly bears to 0.04 for caribou (Figure 19 and Table 10). With the given sampling design, therefore, grizzly bears are more widely distributed than other species captured on camera. Common species, such as mule and white-tailed deer, elk and moose, were also widely distributed with occupancy rates between 0.55 – 0.65 (Figure 19, Table 10). Wolf and black bears were also widely distributed with occupacy rates of 0.68 and 0.58, respectively. Species that are generally less common and less commonly seen had much lower occupancy rates, e.g. cougar, wolverine, lynx, re fox and coyote. As expected, detection probabilities also varied across species in a relatively similar fashion as occupancy probabilities with more common species having higher detection rates. As noted in the above section on discretizing camera data, detection probability increases when sampling session replication length is widened (compare Figures 19 and 20; and see Table 10). This increase in detection probability does not, however, have much effect on occupancy estimates, but does decrease precision in occupancy estimates consistently across species. This lack of change is due to cumulative detection (p*) remaining relatively constant (Table 10). This consistency in cumulative detection probability is true for all species, except wolverine, which is the only species to have p* < 0.8 (Table 10).
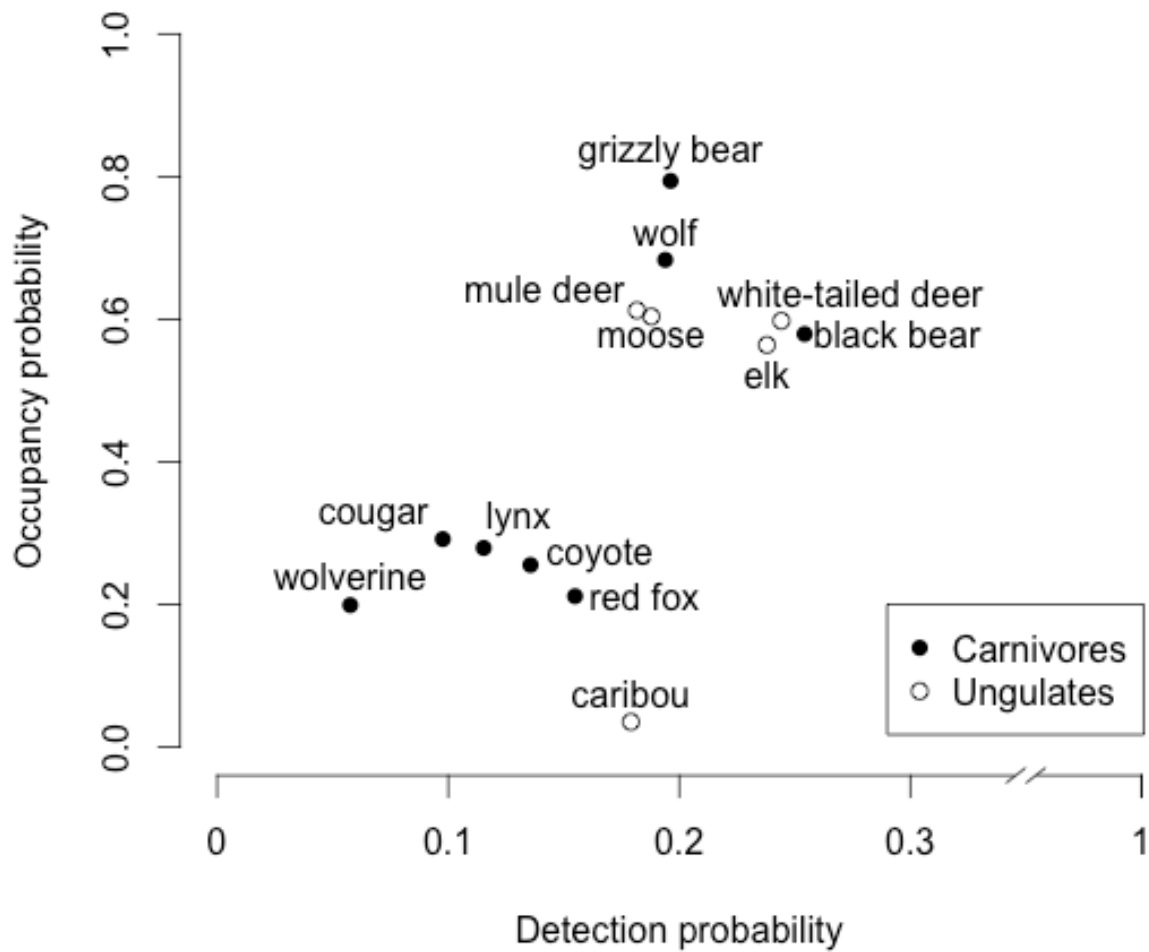
Figure 19. Summer occupancy and detection probabilities as a function of species across 5 Canadian National Parks. Analysis based on data from $n = 183$ cameras from May 1 – Oct 31, 2012 and with no covariates, *i.e.* p(.)psi(.) models. Note that detection probabilities depend on chosen replicate interval length, here: 7-day intervals. Also note the break in the x-axis.
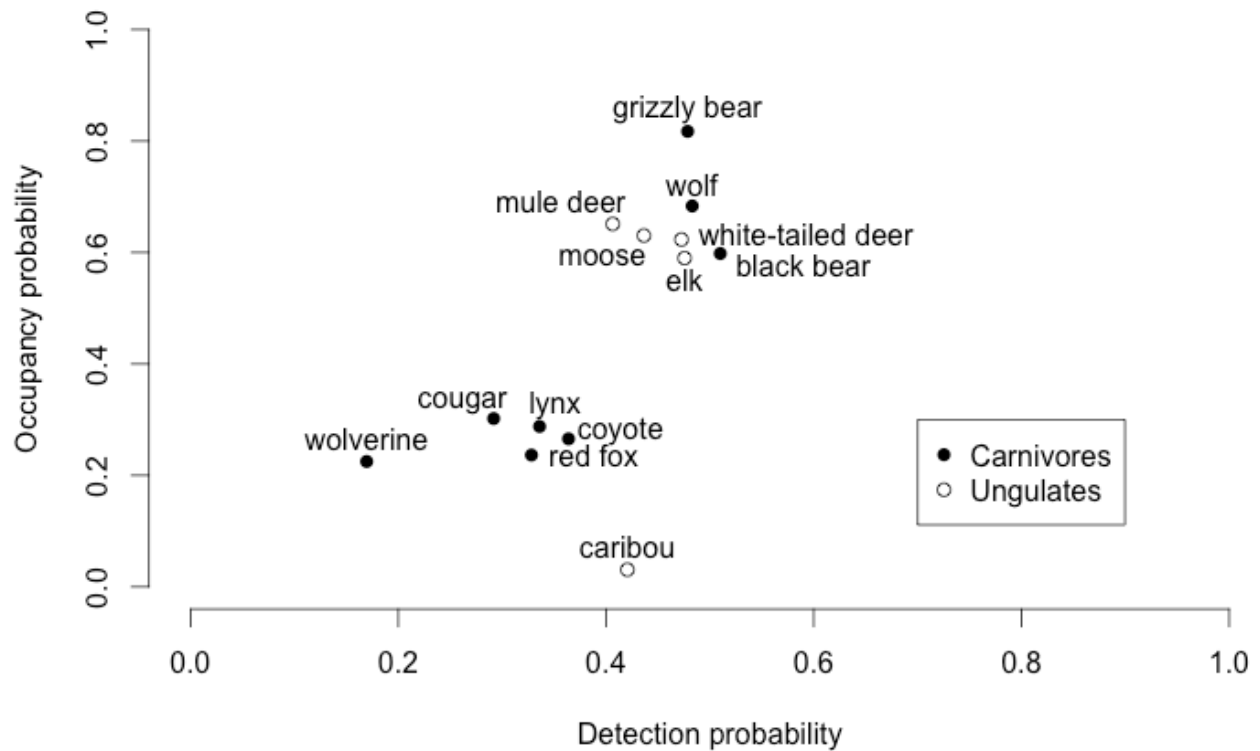
Figure 20. The effect of increasing sampling session length from 1 week (see Figure 19 above) to 1 month (this Figure) on occupancy and detection probabilities for 13 large mammal species across 5 national parks in the Canadian Rockies. Analysis based on data from *n* = 183 cameras from May 1 – Oct 31, 2012 and with no covariates, *i.e.* p(.)psi(.) models.

Table 10. Effects of species-specific occupancy and detection probabilities on the minimum decline in occupancy the current sampling design is able to detect with 80% power and *n* = 183 cameras. Estimates are based on null, psi(.)p(.), models. Summer 2012 Camera data was discretized into 26, 1-week sessions and 6, 1-month sessions. Data from this table used to create Figures 19 and 20.

Data:	Min. decline detected		Occupancy probability (psi)		Detection probability (p)		Cumulative p (p*)	
	26 weeks	6 months	26 weeks	6 months	26 weeks	6 months	26 wk	6 mo
Grizzly bear	0.065	0.066	0.79 (0.72 - 0.85)	0.82 (0.74 - 0.88)	0.20 (0.18 - 0.21)	0.48 (0.44 - 0.52)	0.997	0.980
Wolf	0.073	0.075	0.68 (0.61 - 0.75)	0.68 (0.60 - 0.75)	0.19 (0.18 - 0.21)	0.48 (0.44 - 0.53)	0.996	0.981
Mule deer	0.076	0.079	0.61 (0.53 - 0.69)	0.65 (0.56 - 0.73)	0.18 (0.17 - 0.20)	0.41 (0.36 - 0.46)	0.995	0.956
Moose	0.076	0.078	0.60 (0.53 - 0.68)	0.63 (0.55 - 0.71)	0.19 (0.17 - 0.21)	0.44 (0.39 - 0.49)	0.996	0.968
WT deer	0.076	0.077	0.60 (0.52 - 0.67)	0.62 (0.54 - 0.70)	0.24 (0.23 - 0.26)	0.47 (0.43 - 0.52)	0.999	0.978
Black bear	0.076	0.077	0.58 (0.50 - 0.65)	0.60 (0.52 - 0.67)	0.25 (0.23 - 0.27)	0.51 (0.46 - 0.56)	1.000	0.986
Elk	0.076	0.078	0.56 (0.49 - 0.64)	0.59 (0.51 - 0.67)	0.24 (0.22 - 0.26)	0.48 (0.43 - 0.52)	0.999	0.979
Cougar	0.070	0.077	0.29 (0.22 - 0.38)	0.30 (0.22 - 0.40)	0.10 (0.08 - 0.12)	0.29 (0.23 - 0.37)	0.931	0.874
Lynx	0.068	0.072	0.28 (0.21 - 0.36)	0.29 (0.22 - 0.37)	0.12 (0.09 - 0.14)	0.34 (0.27 - 0.41)	0.959	0.914
Coyote	0.064	0.068	0.26 (0.19 - 0.33)	0.27 (0.20 - 0.35)	0.14 (0.11 - 0.16)	0.36 (0.29 - 0.44)	0.977	0.934
Red fox	0.059	0.066	0.21 (0.15 - 0.28)	0.24 (0.17 - 0.32)	0.15 (0.13 - 0.18)	0.33 (0.25 - 0.41)	0.987	0.908
Wolverine	0.071	0.092	0.20 (0.12 - 0.31)	0.22 (0.13 - 0.37)	0.06 (0.04 - 0.09)	0.17 (0.10 - 0.28)	0.786	0.672
Caribou	0.023	0.022	0.04 (0.02 - 0.08)	0.03 (0.01 - 0.07)	0.18 (0.12 - 0.26)	0.42 (0.23 - 0.64)	0.994	0.962
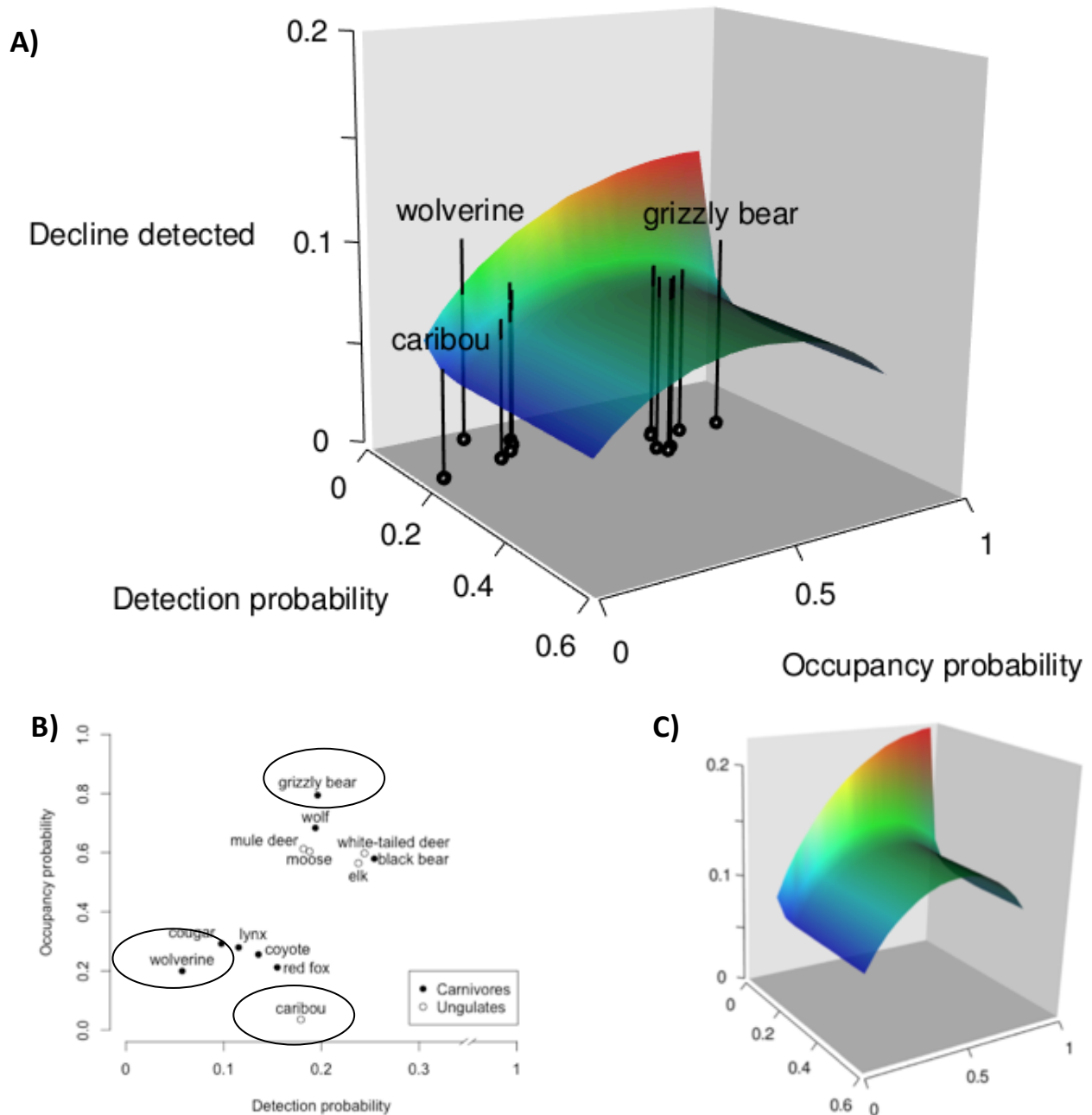
Figure 21: A) Minimum decline in occupancy between two years that can be detected with 80% power (z axis), as a function of detection (0.1 – 0.9) and occupancy probabilities (0.1 – 0.9). *n* = 183 cameras are simulated with 26 weeks of deployment. Included on the bottom plane are analysis results from May – Oct, 2012 camera data for 13 species. Subfigure B) is a reproduction of figure 19 with 3 species highlighted to help orient the bottom plane of subfigure A. Each species intersects the plane at the minimum decline that is possible to detect, given the species' occupancy and detection probabilities. The higher the intersection point on the plane, the lower the statistical power. Subfigure C) shows the effect of reducing the number of cameras to *n* = 60; the plane of minimum declined detected, rises across all values of *Ψ* and *p*, reiterating the reduced power with fewer cameras.

The minimum decline we can detect is a function of both species-specific occupancy and detection probabilities (Figure 21). This relationship is driven largely by the variance in occupancy estimates. Under imperfect detection, the variance of occupancy probability has two parts: the variance of a binomial distribution and a correction for imperfect detection (MacKenzie and Royle 2005). When p* approaches 1, the latter portion goes to 0. The half-cylindrical shape of the Figure 21, therefore, results from the variance of binomial distribution because p* approaches 1 for all p > 0.2. Given n = 183 cameras and 26 1-week sampling replicates, power to detect trends depends solely on psi and does not change with p. The increased 'lip' of the half cylinder when detection probability is low, in contrast, indicates a decrease in power when p* is <u>not</u> close to 1. Most species detection probabilities are low, thus power depends on both psi and p. Just as the grizzly bear analysis showed (Figure 13), decreasing the number of cameras decreases the power to detect trends (Figure 21C). Note that despite the increased minimum decline detected with 80% power, the shape remains the same (Figure 21C).

There is little consensus in the statistical literature about how to estimate precision of binomial proportions near boundaries (*e.g.* ψ near 0 or 1). A general statistical rule of thumb states that for binomial data, the number of successes and the number of failures must each be at least 5 (Brown et al. 2001), others recommend at least 10 (Steve Kanters, Pers. Comm.). Note that caribou does not intersect the power surface in figure 21. Across the 5 national parks, caribou have very low occupancy (Ψ = 0.035), which is < 0.1 and may be an unreliable estimate. It is interesting that if the analysis were restricted to cameras in Jasper, the only park where caribou are present, this would increase total occupancy rate, but the number of cameras with caribou detections remains below 5. In a park with 60 cameras, species with occupancy rates of <5/60 or >55/60 (corresponding to ψ < 0.083 and > 0.917, respectively) will have erratic confidence integral estimations. Note that more cameras have been added since 2012, increasing the likelihood that the assumptions of binomial analyses are met. These

assumptions are important at both ends of the occupancy spectrum (0,1). **Species that are too common or too rare will have lower power because of the low confidence in these occupancy estimates.**

Wolverines demonstrate the issues of low detection probability rather than low occupancy probability. Wolverines intersect the surface at a much higher point that other species, indicating we have lower power to detect changes in their occupancy. This lower power is due to a low detection probability (0.06), which is < 0.1 and, therefore can cause estimate problems (as mentioned above). Detecting trends in occupancy is still possible, but with lower power. Increasing the sample session length to artificially increase detection probability to 0.17 does not improve power to detect trends (compare Figures 22A and B), because cumulative detection probability does not increase (Table 10).

A) 1-week data   **B) 1-month data**
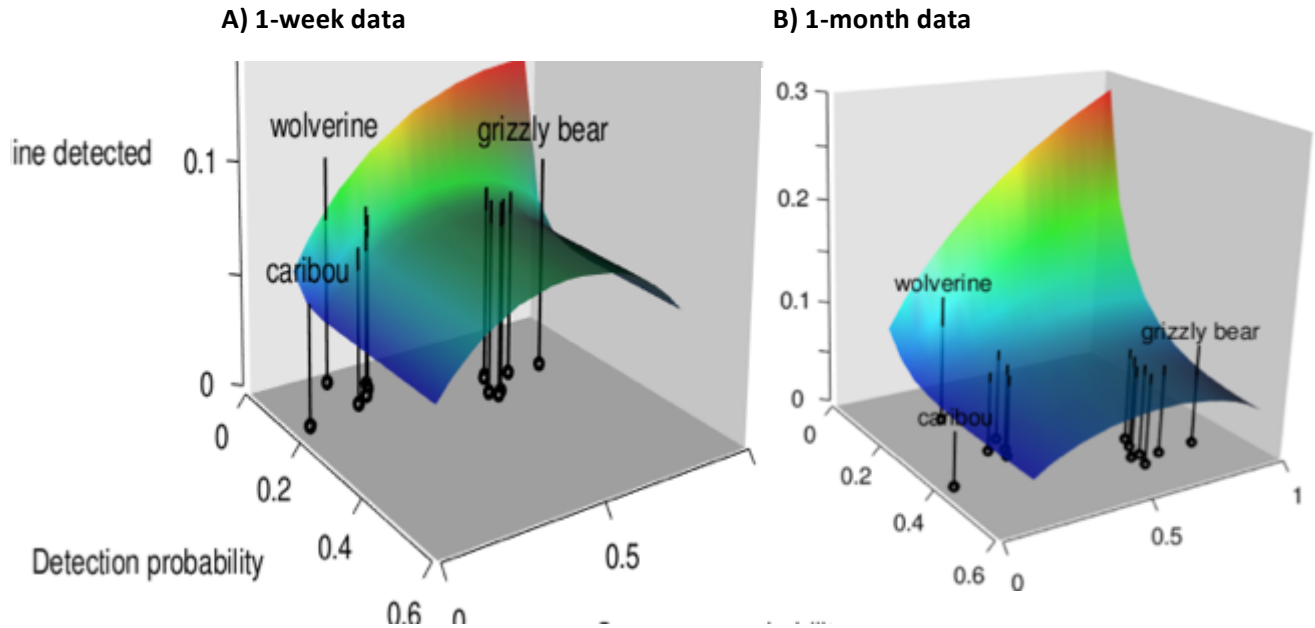
Figure 22. The effect of using 1-month data rather than 1-week data on the power to detect trends in occupancy of 13 large mammal species. Essentially, discretizing data into 1-month session replicate lengths does not improve power, not even for species with low detection probabilities like wolverine.

3.4 Notes on the scope of inference for current camera design

Occupancy modeling moves interest from the number of individuals present to the number of sampling units that are occupied (Royle and Nichols 2003). Sampling design considerations are important to ensure sampled units are representative of the population of interest (Cochran 1977, Thompson 2012). When using occupancy models, sampling design dictates the definition of occupancy being estimated. When cameras are deployed for only one month, for example, the occupancy definition is defined for that one month, which may be representative of the whole year, or may be a key month of interest (e.g. during breeding or when an animal is easy to capture). Using the current sampling design, however, the parameter we estimated (i.e. grizzly bear use at anytime during the year) clarifies the scope of inference when compared to shorter camera-trapping projects. Given that cameras are located on trails, estimates of occupancy are most relevant for species that use trails. The occupancy of smaller mammals that are indifferent to trails, for example, may not well captured with remote cameras placed on trails. Finally**,**

a systematic sampling design with one camera per cell provides a census of a study area and enables

inference to be made to the scale of the study area (*e.g.* an entire park). Most parks in this study were

able to place cameras in all cells that contained grizzly bear habitat (*i.e.* cells that are not mostly rock

and ice). For parks that cannot census their entire landscape, inferences are limited to the sampled

areas because of the non-random selection of cells. We recommend that for large study areas with

many more cells than cameras or logistical capacity, cells that receive cameras should be chosen

randomly to allow the area of inference to extend to the entire park.

3.5 Appropriate species for camera monitoring

We have shown that with the current remote-camera monitoring program, we have high statistical

power to detect declines in the distribution of sensitive species through using occupancy models. Power,

however, is dependent on the species-specific occupancy and detection probabilities and on other

design-based considerations such as the number of cameras, duration of camera deployment and scale

of interest. Given these considerations, we summarize the appropriateness of using camera-based

monitoring for 4 groups of species: commonly detected species, rare species, very rare species and

future expanding species.

3.5.1 Commonly detected species, e.g. grizzly bear

The current camera trapping monitoring has **high statistical power to detect trends in the population**

occupancy of commonly detected species, like grizzly bears, at both regional scales and park scales

where sufficient cameras are deployed (*i.e. n* > 60). The reasons for high power are 4 fold. Firstly, unlike

when using abundance as the state variable of interest for monitoring populations where the sample

size is equal to the number of animals, when using occupancy as the state variable of interest, the

number of cameras is equivalent to the sample size. With 270 cameras currently on the landscape, high

sample size contributes to the high power of this monitoring method. Secondly, the long deployment of

cameras (year-round) provides sufficient sampling to increase cumulative detection probability ($p*$)

close to 1 (see section above on effects of number of cameras and duration of deployment). Thirdly,

high power to detect trends is also attributable to our field protocol of using the same locations for both

sampling years, allowing us to capitalize on the additional power of a *paired* t-test, rather than

performing a t-test or Wald's test on population-level occupancy probabilities (e.g. Guillera-Arroita et al.

2011). Finally, the high power is also due to grizzly bear occupancy rate being far from 0.5, where power

is lowest (see Figures 21 and 22 above). Such high occupancy rates of 0.79 (0.73 – 0.86) allow the

current monitoring program to have higher power than for species with occupancy rates near 0.5.

Grizzly bears therefore appear well-suited for monitoring with remote cameras.

3.5.2 Difficult-to-detect species, e.g. wolverine

Wolverines are rare across Alberta, although little is known about their conservation status. This uncertainty is reflected in the designation of wolverines as "data deficient" by the province of Alberta (Alberta Fish and Wildlife Division 2008). Methods to monitor wolverines are emerging, include the use of baited sites to collect camera pictures and DNA (Fisher et al. 2013a) and snow tracking (Whittington et al. 2014). Their rarity is also well captured by non-baited remote cameras across the study area with low estimates of occupancy probability during both summer 0.26 (0.15 – 0.35) and winter 0.34 (0.26 – 0.43) (Table 4). However, lower occupancy rates can lead to higher power to detect changes in the population. Species with lower occupancy rates generally intercept the plane of minimum decline we are able to detect at low values, indicating high power (Figures 21 and 22). Wolverines are, unfortunately, also difficult to detect which hampers our ability to detect declines in their population. Whether looking at their weekly detection probability [0.06 (0.04 - 0.09); see Table 10] or monthly detection probability [0.17 (0.10 - 0.28)], their low detection rate can cause power to detect declines in the wolverine population to be lower than for many other species. There are three readily available ways to increase detection probability. The first, is the use of bait or lure (e.g. Fisher et al. 2013b). This method can also provide an estimate of abundance, but required continuous re-baiting and may not be logistically sustainable (see discussion above on the use of lure). The second method to increase detection probability, and thus power, is to increase the length of surveying, which increases cumulative detection probability ($p*$). The multi-species analyses in Figures 19-22 and Table 10, in fact, were performed only on *summer* 2012 data. Using data from the entire year should increase $p*$ adequately and emphasizes the importance of year-round monitoring for species that are difficult to detect. The third method to increase detection probability would be to combine camera data with snow tracking data as well (Whittington et al. 2014). **Once detection probability is increased sufficiently, camera-based occupancy monitoring will likely be a powerful means to track wolverine population status.**

3.5.3 Very rare species, e.g. caribou

Caribou are not widespread throughout the study area. Although present in Banff NP until 2009

(Hebblewhite et al. 2009), caribou are only extant in Jasper NP. As a result, their occupancy rate is very

low. When using summer 2012 data from the systematic grid design, caribou only have an occupancy

rate of 0.04 (CI: 0.02 - 0.08; see Table 10). As a result, their overall occupancy is insufficient to

confidently evaluate the power to detect trends (Figure 21). Furthermore, cameras are placed most

often on trials, while caribou often spend much of their time in alpine areas with few well-defined trails.

As a result, **additional monitoring methods may be needed to have sufficient power for trend**

monitoring. Cameras do, however, capture other important ecological information in relation to

caribou conservation such as the occupancy of other ungulate species, predators such as wolves, and

community responses to human disturbance and fire. Cameras are place on trails can capture

movements of wolves on linear features to gain access to caribou habitat (Whittington et al. 2005,

Whittington et al. 2011).

3.5.4 Future expanding species, e.g. bison

Occupancy models are ideally suited for monitoring species range changes (MacKenzie et al. 2006).

Bison will soon be reintroduced into the Panther region of Banff National Park. Initially, many bison will

be radio collared, but as the population grows, a smaller proportion of the population will be collared.

Remote cameras offer an excellent additional method to monitor bison expansion as their population

grows in the medium term. Camera-based occupancy models, therefore, may become the best way to

monitor the bison population in the future. Moreover, a key ecological question will be the effects of

bison restoration on other species; remote camera monitoring will allow evaluation of bison impacts on

the entire large mammal community over time.

4.0 FUTURE OPPORTUNITIES

4.1 Towards a multi-species occupancy metric

One of the ultimate outcomes of this research is to synthesize these findings and develop a

framework to monitoring multi-species occupancy across the national parks. Such metrics have been

developed for remote-camera and other multi-species data, but they remain in their infancy and future

research must evaluate them. Like any index, theoretical and applied research need to ensure indices

adequately track actual changes species diversity (Hayward et al. 2015). Based on the research

summarized in this report, we recommend the following approach to developing such a metric.

Given the broad similarities in methods among occupancy-based species richness indices, it is

appropriate to consider the index developed specifically for camera data, the Wildlife Picture Index

(O'Brien et al. 2010). The methods provided in Ahumada *et al.* (2013) appear to be well documented and

well suited for application to the data in the Parks Canada database. Rather than using an arbitrary

session length for discretizing camera data, however, our results show that the smallest sampling

replicate length window should be used to maximize precision of occupancy estimates for each species,
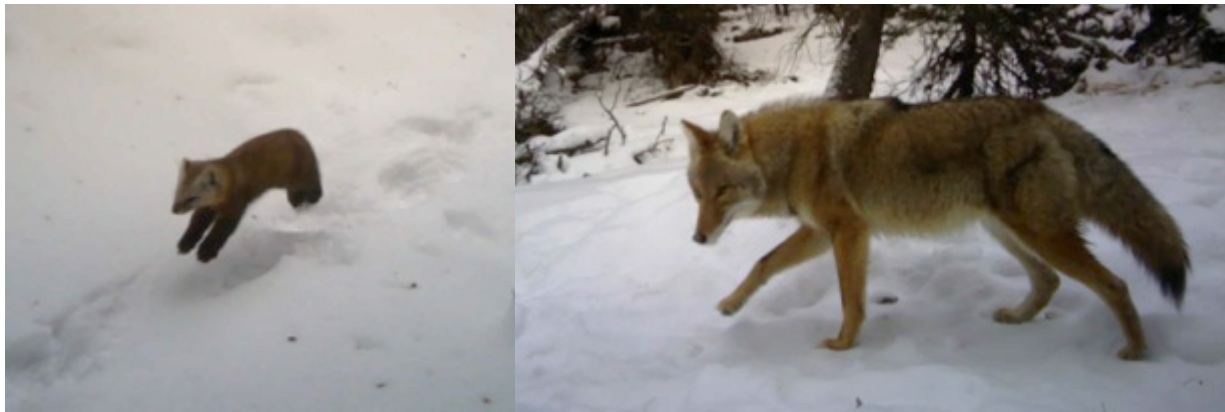
and therefore, maximize precision of WPI estimates. Furthermore, given the large sample size, the inclusion of landscape covariates or each species' occupancy model would also improve precision. Parks Canada camera data has been classified for all species, down to the size of many rodents (*e.g.,* pika, *Ochotona princeps*). When considering which species to include in a diversity index, species should be restricted to those that regularly use trails, rather than species that merely provide incidental data (e.g. mountain goats, *Oreamnos americanus*). Furthermore, there should be awareness that the inclusion of very rare species with very low occupancy rates (e.g. caribou), may strongly affect estimate precision, especially when interested at the park scale. As presented above, there is little consensus in the statistical literature about how to estimate precision of binomial proportions near boundaries (e.g. ψ near 0 or 1). The general rule of thumb states that the number of successes and the number of failures must be at least 5 (Brown et al. 2001). Therefore, in a park with 60 cameras, species with occupancy rates of <5/60 or >55/60 (corresponding to ψ < 0.083 and > 0.917,

respectively) will have erratic confidence interval estimation. Such very rare species may decrease precision in WPI measures unnecessarily when considering only the park scale.

Furthermore, methods should be explored to capitalize on additional cameras that are deployed temporarily throughout each park. In the systematic sampling design, a 10x10 km grid was placed over each park to spread out sampling and provide a more spatially balanced sampling design. In addition to the core camera sites that are monitored annually, one per 10x10 cell, additional cameras are often placed in each cell. These additional cameras are deployed for different monitoring objectives and often for shorter periods of time. These additional cameras per cell could be combined in an additional hierarchy to provide more information for occupancy estimation. When utilizing this data, however, the unit of sampling changes from the camera sites, to the cell that contains the camera sites. Therefore, tradeoffs need to be explored between the improvements in the precision of occupancy estimates and the effects of changing the sampling unit.

Occupancy is defined as the "proportion of area occupied by a species or the fraction of landscape units where the species is present" (MacKenzie et al. 2006, p.2). For discrete habitat, each patch of habitat is considered a landscape unit (e.g. ponds in amphibian studies; MacKenzie et al. 2002). If each landscape unit is sampled once, then each habitat patch can be considered a sampling unit. When discretizing continuous habitat, however, things become more complicated (Efford and Dawson 2012). When sampling design is restricted to one camera per 10x10 km cell, the grid spreads out cameras more effectively. The grid is removed from consideration, however, during trend analyses (as presented in this report). The camera sites themselves are the units of analysis and the proportion of sites occupied provides the index for the proportion of the park that is occupied by each species. When adding replicate sites per cell, the cell becomes the sampling unit, rather than the site. This model formulation should be explored to better utilize all data collected, both systematically and intermittently.

Lastly, preliminary results show that occupancy levels and the covariates affecting occupancy, varies across seasons. To use data collected during the entire year, we recommend splitting data into two ecologically-significant seasons, a common practice for temperate studies. Splitting the year into summer and winter, 6-months each, would allow the variation in occupancy and detection probability estimates caused by seasonal variation to be accounted for. Such multi-season multi-species occupancy methods have recently been developed (Tobler et al. 2015).

4.2 Occupancy-abundance relationships

Using occupancy rather than abundance as a state variable to monitor trends in populations has numerous advocates (e.g. MacKenzie and Nichols 2004, Noon et al. 2012). Some argue that using occupancy as a metric for population status relies on an underlying assumption of a ~1:1 relationship between occupancy and abundance (Stanley and Royle 2005). Although abundance-occupancy relationships are always positive, abundance-occupancy relationships can take different non-linear forms (Gaston et al. 2000), making inferences to abundance less straight forward. Rather than a proxy for abundance, however, occupancy itself can be used as a viable measure of population trend. Range-size, for example, can be the best predictor of extinction risk (Harris and Pimm 2008). COSEWIC and IUCN uses the occupancy metrics "area of occupancy" and "extent of occurrence" in 2 of the 5 criteria for assessing the threatened status of a species (Mace et al. 2008, COSEWIC 2012, IUCN 2012). Therefore, **occupancy may provide a sufficient analytical end point for remote-camera data**. Many properties of occupancy, however, remain relatively unexplored. The abundance-occupancy relationship, for example, has captured a lot of attention of researchers (Gaston et al. 2000, He and Gaston 2000). One example where the occupancy-abundance relationship has been well characterized is for bobcat (Clare et al. 2015), but more research is needed to compare this relationship across species, population trends, and different scientific methods.

Current monitoring and research objectives within Parks Canada have the opportunity to address this need. With bison reintroduction into Banff National Park imminent, high quality abundance and ocucpancy data will be collected in the initial year of the program. Camera trapping will also continue to occur in the region during this time. Both occupancy and abundance are expected to increase during the first years following bison reintroduction, therefore the combination of remote cameras, radio collars and close monitoring will provide the first golden opportunity to examine the occupancy-abundance relationship for a large herbivore.

Grizzly bear abundance estimates are also in progress around the mountain parks. In the Waterton Lakes NP and Southwestern Alberta, grizzly bear rub trees are currently being used to collect hair for DNA-based mark recapture estimates starting in 2012 (A. Morehouse, Pers. Comm.). Banff National Park is gearing up for a second round of DNA-based mark recapture (first round completed in 2008; Sawaya et al. 2012) for grizzly bears in the Bow Valley. Finally, sampling efforts will begin in Southern Jasper to estimate grizzly bear abundance there are well, using similar methods (G. Stenhouse, Pers. Comm.). These 3 projects will be completed in conjunction with ongoing camera trapping and will provide key information into the occupancy-abundance relationship to relate estimates from remote cameras to density.

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6.0 APPENDIX

Appendix A: Description of site and GIS-based landscape covariates used for grizzly bear occupancy models

To develop occupancy models for each species, we included a suite of site and GIS-based covariates as predictors for both occupancy and detection probabilities. They are loosely categorized into 3 categories: biotic, abiotic and anthropogenic covariates (Table A1.) For Normalized Difference Vegetation Index (NDVI), we used maximum annual NDVI from year 2006. For human disturbance, we included distance to nearest primary road (highways), distance to nearest secondary (or primary) road, and distance to railroad. To model terrain ruggedness, we created a topographical position index (TPI) using Land Facet Corridor Designer tools (Majka et al. 2007); this compares the terrain at a location to its surrounding area at a specific spatial scale (see Methods in main text for 3 scales we used). Elevation, slope and aspect were estimated from a 30m resolution Digital Elevation Model. We calculated slope using the Spatial Analyst extension for ArcGIS 9.3. For proportion of area burned, we calculated the proportion of the landscape that has burned in the last 115 years. We also included percent crown closure and created a distance to streams covariate from a stream layer downloaded from GeoBase.ca. To categorize vegetation across the study area, we modified the landcover classification created by McDermid (2006) which used Landsat 5 Thematic Mapper (TM) and Landsat 7 TM sensors. We updated and consolidate this classification into 7 categories: open-coniferous, closed-coniferous, mixed-deciduous, herbaceous, shrubs, water, rock-barren following the rules in Table A2. All other raster covariates were also at 30m resolution except NVDI (250m). Site-level covariates included the camera model type used, whether a rubtree was present or not (Green and Mattson 2003), whether a natural mineral lick was present or not.

The effects of human features on grizzly bear behavior is likely to dissipate with distance (Merrill et al. 1999). All distance covariates were transformed with an exponential decay of the form $1 - e^{-\alpha d}$

where d is the distance in kilometers and α is set to 2 (Apps et al. 2004, Whittington et al. 2011). As a result, at very small distances from the feature, the effect of the feature is strong and then decays to 0 at far distances, becoming essentially negligible beyond 2 km. To remain consistent with how beta coefficients for distance covariates are interpreted, we subtracted the transformed covariates from 1 to inverse the covariates such that lower values are associated with short distances (Nielsen et al. 2009).

Table A1. Site and GIS-based landscape covariates used for grizzly bear (*Ursus arctos*) remote-camera-based occupancy models in the Canadian Rockies.

Biotic covariates	Covariate on occupancy	Covariate on detection
Proportion of area burned (at 3 scales)	X	
NDVI (average at 3 scales and site location)	X	
Crown closure (at 3 scales)	X	
Distance to stream	X	X
Presece of bear rub trees (binary: yes, no)		X
Presence of a mineral lick (binary: yes, no)		X
Land-cover type, 7 levels: open-coniferous	X	
closed-coniferous	X	
mixed-deciduous	X	
herbaceous	X	
shrubs	X	
water	X	
rock-barren	X	
Abiotic covariates		
Elevation (and elevation2 for quadratic)	X	
Slope	X	
Aspect (eastness and northness)	X	
Topographic Position Index (TPI, at 3 scales)	X	X
Anthropogenic covariates		
Human activity on trails (from cameras)	X	X
Horse activity on trails (from cameras)	X	X
Distance to primary roads (major highways)	X	X
Distance to secondary roads	X	X
Distance to Rail	X	X
Trail type (binary: human-use, wildlife)		X
Camera model (3 different models)		X

Table A2. Method for updating and consolidating landscape covariate classifications

New classification	Formula using pre-existing layers
conifer-closed	(Previous landcovers "closed conifer" or "open conifer") & percent conifer > 60 & crown closure > 60 (i.e. based on Upland Trees, Wetland Trees)
conifer-open	(Previous landcovers "closed conifer" or "open conifer") & percent conifer > 60 & crown closure <= 60
deciduous-mixed	(Previous landcovers "closed conifer" or "open conifer") & percent conifer <= 60
herb	Previous landcovers "Upland Herbs" or "Wetland Herbs"
shrub	>5% shrub cover; any moisture regime. Landcover=5
water	Previous landcover "water", updated with water_polygons = 1 (for rivers Jasper and Banff)
rock-barren	Previous landcovers "barren", "snow-ice", "cloud", or "shadow"