

## Monitoring Mammals in Alberta: Recommendations for Remote Camera Trapping



Bighorn sheep, Willmore Wilderness, Reconyx camera-trap survey  
Credit: AITF and Alberta Parks

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Black bear, Willmore Wilderness, Reconyx camera-trap survey  
Credit: AITF and Alberta Parks

## 1. SUMMARY

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The Alberta Biodiversity Monitoring Institute (ABMI) is designed to monitor the status of diverse taxa across the province of Alberta, and currently monitors mid- and large-sized mammals using winter snow tracking surveys. These surveys have detected a broad range of mammal species but also have several limitations, including dependence on suitable snow conditions, exclusion of hibernating species, and difficulty in distinguishing among species with similar tracks. Camera trapping is increasingly being used as a method for monitoring mammal communities. We provide a review and recommendations for the use of camera trapping by ABMI to monitor mammals.

We recommend using occupancy as the target state variable for a camera trap monitoring program. Camera trap data are flexibly transformed from continuous datasets to discreet repeat surveys, facilitating their use within an occupancy modelling framework to generate robust estimates of occurrence probability accounting for imperfect detection. An occupancy framework can be used to assess community-level changes through integrated modeling of multiple species and robust estimation of species richness when some species may go undetected. Occupancy estimates are also suitable for use in other composite, multispecies monitoring indicators, such as ABMI's measure of biodiversity intactness.

Species from all 12 mammalian families occurring in Alberta can be targeted with a provincial-scale camera trapping program. However, it would be too costly to focus on the rarest species, and targeting small mammals (< 0.05 kg) would also require additional focused sampling. We recommend that the design aim to capture the maximum number of species at a level of effort sufficient to achieve statistically reliable sample sizes for the least detectable of the "common" species (*e.g.*, detection probability of ~ 0.10 per camera-week of sampling). Where possible, we recommend obtaining data on detection rates from other camera trap studies in Alberta to complement those reviewed here and further inform sampling design. We suggest that sampling during summer will provide the best opportunity for maximising the diversity

of surveyed mammals, including species of management interest like bears. However, we recommend specific calibration of camera trap data relative to those from winter snow tracking to ensure continuity of population time series within ABMI.

A camera trap sampling design for use in an occupancy modelling framework should seek to address the assumption of site closure and provide data to examine how estimates of detectability vary with survey duration, number of replicate sampling occasions, and spatial and temporal dispersion of sampling units. Given the wide variety of species targeted by the ABMI multi-mammal monitoring program, and the high variance in detectability for these species, finding an optimal design may prove difficult. We recommend a pilot sampling design focused on maximizing detection probability for target species by testing an attractant (*e.g.*, scent lure) and sampling for at least 18 weeks per site. Resulting data can be used to examine how probabilities of false absence decline over time, thereby helping identify a sampling duration that maximizes the reliability of inference across multiple species. We recommend a design that includes 2-4 cameras at each sampling unit to facilitate assessment of the closure assumption and improve inference *via* multi-scale occupancy analysis. The existing ABMI systematic sampling grid and within-site point count stations can be used as the basis for deploying camera traps. Analysis of pilot data will inform the trade-off between allocating multiple cameras at a site vs. spreading them out at additional sites.

We recommend that the camera trap monitoring protocol be standardized with respect to the type of camera unit and attractant used. Key considerations for cameras include trigger speed and sensitivity, image resolution and storage capacity, battery life, and flash type. Additional camera-related equipment must be factored in during budget preparation (*e.g.*, batteries, memory cards, locks, mounting equipment). Important factors regarding choice of attractant include availability in bulk, ease of storage and application, longevity, and documented performance in attracting focal species. More research into camera and attractant options is warranted, but Reconyx HyperFire camera units (~\$600-800 with accessories) and commercial scent lures (*e.g.* O’Gorman’s) may be suitable.

The logistics and costs of staffing, travel, site access, *etc.*, for camera trap monitoring should be similar to those for other ABMI summer terrestrial protocols, and we recommend that opportunities for coordination be sought to maximize efficiency, such as deploying camera traps during standard ABMI site preparation, and retrieving cameras during the summer protocol. A standardized protocol for labelling, storing and processing digital images is also an essential component of a camera trap monitoring program.

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### 3. INTRODUCTION

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Managing for biodiversity conservation requires information on species' current status, temporal trends, and responses to environmental change (Lindenmayer and Likens 2009). Large-scale, broad-spectrum multispecies monitoring is a cost-effective approach for obtaining information on biodiversity, and programs such as the Alberta Biodiversity Monitoring Institute (ABMI) have become pioneers in this field (Boutin *et al.* 2009; Haughland *et al.* 2010). Multispecies monitoring programs collect data on a broad array of species and ecological communities, allowing scientists to address questions about current and potential future effects of landscape change on biodiversity.

However, the effectiveness of a given monitoring approach is not uniform for all species, as detectability differs among species and decreases with decreasing abundance (Green and Young 1993; Mackenzie and Kendall 2002; Mackenzie *et al.* 2005, 2006). Rare or elusive species can go undetected in a systematic survey design not specifically targeted for them (McDonald 2004). Unfortunately, broadly applicable and effective methods for monitoring many rare and uncommon species are only now being developed and tested (Thompson 2004; Long *et al.* 2008). Infra-red remote cameras (IRCs) have become a popular technique increasingly used for sampling mammals, both elusive and common (Karanth 1995; Gompper *et al.* 2006; Balme *et al.* 2009; O'Connell *et al.* 2006, 2010). IRC data can be used to characterize the current status of species and communities in a landscape (*e.g.*, density, Trolle and Kéry 2003; diversity, Azlan *et al.* 2006, Tobler *et al.* 2008), as well as track changes in populations and community structure over time (Karanth *et al.* 2006; O'Brien *et al.* 2010). The same data can also be used for complementary research on, for example, behavioural activity patterns (Ridout and Linkie 2009; Bridges and Noss 2010) and morphological variation (Allen *et al.* 2011). Camera trap surveys provide additional benefits relative to other common mammal survey techniques; for instance, photographic evidence can be easily archived and reviewed by independent experts (thus meeting high evidentiary standards, cf. McKelvey *et al.* 2008), and images are useful in building awareness and support for

monitoring among policy makers and the general public. Several recently established, broad scale, multispecies mammal monitoring programs use camera trapping as the primary survey methodology (*e.g.*, TEAM, Ahumada *et al.* 2011; WPI, O'Brien *et al.* 2010; Tanzanian carnivores, Pettoirelli *et al.* 2010; BCI, Kays *et al.* 2011). As with these applications, the data garnered from camera traps could benefit a large-scale provincial monitoring program such as the ABMI.

The ABMI program currently collects data on about 2000 species across a systematic sampling grid covering the entire province of Alberta ([www.abmi.ca](http://www.abmi.ca)). A key objective underlying the program is to monitor the cumulative effects of landscape change on multiple taxa across broad spatial scales, thus requiring cost-effective methods capable of tracking multiple species simultaneously. Current ABMI mammal monitoring protocols use winter snow track surveys along 10-km transects to assess the occurrence and relative abundance of mid- to large sized mammals (ABMI 2010). From 2002-2010, ABMI winter surveys collected data on 26 species (or species groups) of wild mammals (in addition to some bird species and domestic animals; Table 1). Many of these species are rarely observed: 12 have been detected at less than 5% of transects sampled. The most commonly detected mammals include smaller species like snowshoe hares, red squirrels, and weasels, as well as larger species like moose, coyote and deer. Lynx and fisher—two species listed provincially as “Sensitive” (Alberta SRD 2010)—have been frequently detected, whereas other species at risk, like caribou and wolverine, are less well represented (Table 1).

Limitations associated with the snow tracking methodology include: the requirement for suitable snow conditions (*i.e.*, 3-6 days after a track-obliterating snowfall); the exclusion of hibernating species (*e.g.*, bears); and the difficulty in distinguishing among species with similar tracks (*e.g.*, marten, fisher, and weasels; white-tailed and mule deer). Furthermore, the accuracy of species identifications from snow tracks depends on the capabilities of individual trackers, as there is often no evidence collected to allow external review. This necessitates considerable training and likely introduces greater potential for observer error across the large spatial and

temporal scales over which ABMI monitoring is designed to operate. Analysis of tracking data can also be complicated by the need for an appropriate correction factor for track accumulation (and deterioration), and by the nature of the sampling units, given that the 10-km survey transects follow linear disturbances that may traverse a diversity of habitats and human footprints, and that the nested 250-m segments are not independent. The single-survey approach is also less suited to model-based estimation of detection probabilities (*sensu* MacKenzie *et al.* 2006, although see Hines *et al.* 2010, Solymos *et al.* 2012), and estimates of absolute abundance are not feasible from snow track data since individual animals are not identified.

Despite such challenges, the snow tracking method has been effective at detecting most of Alberta's mid- and large-sized mammals (Table 1), and previous assessments have noted advantages to this method such as high detection rates across multiple species, no interference with animal behaviour, and no need for specialized technical equipment (Bayne *et al.* 2005, Heinemeyer *et al.* 2008). Camera trapping may provide a means of addressing some of the limitations of snow tracking, however studies directly comparing snow tracking with other monitoring methods such as camera traps are rare. Camera traps have performed well in several published methodological comparisons (*e.g.* Silveira *et al.* 2003), although results often vary by species, and some authors have recommended a combination of approaches (Gompper *et al.* 2006, O'Connell *et al.* 2006). Unfortunately, the detection rates derived from ABMI snow tracking (Table 1) are not directly comparable to available occupancy estimates derived from camera-trapping (Table 2), as both the response metrics and survey effort differ markedly. A direct comparison of simultaneously-conducted snow tracking and camera trapping is required. To this end, we review the major conceptual and technical decisions to be made in designing a mammalian monitoring program using camera traps. Based on best evidence from previous camera trapping studies, we recommend protocols for a pilot study that seeks to monitor mammalian communities across large and diverse landscapes.

**Table 1. Summary of species detected and their relative abundances for 459 winter snow-track transect surveys conducted between 2002-2010 as part of the ABMI mammal monitoring program.** Two indices of relative abundance are given: the proportion of transects on which a species was detected, and the frequency of detections (*i.e.*, number of 1-km transect segments with detections) per 100 km-days of tracking effort.

Scientific name	Common name	Prop. transects with detection	Segment detections per 100 km-days
<i>Canis lupus</i>	Grey wolf	0.35	1.92
<i>Canis latrans</i>	Coyote	0.76	8.71
<i>Vulpes vulpes</i>	Red fox	0.17	0.70
<i>Lynx canadensis</i>	Lynx	0.56	4.63
<i>Puma concolor</i>	Cougar	0.02	0.05
<i>Gulo gulo</i>	Wolverine	0.02	0.11
<i>Martes pennanti</i>	Fisher	0.33	1.64
<i>Martes americana</i>	Marten	0.58	4.79
<i>Mustela vison</i>	Mink	0.11	0.40
<i>Mustela spp</i> <sup>a</sup>	Weasel <sup>a</sup>	0.88	9.02
<i>Alces alces</i>	Moose	0.77	7.38
<i>Odocoileus spp</i> <sup>b</sup>	Deer <sup>b</sup>	0.74	9.68
<i>Rangifer tarandus</i>	Caribou	0.05	0.27
<i>Cervus elaphus</i>	Elk	0.03	0.21
<i>Lepus americanus</i> <sup>c</sup>	Snowshoe hare <sup>c</sup>	0.92	13.6
<i>Tamiasciurus hudsonicus</i> <sup>d</sup>	Red squirrel <sup>d</sup>	0.86	11.6
(various species) <sup>e,f</sup>	Mouse/Vole <sup>e,f</sup>	0.90	8.88
<i>Castor canadensis</i> <sup>f</sup>	Beaver <sup>f</sup>	0.02	0.05
<i>Ondatra zibethicus</i> <sup>f</sup>	Muskrat <sup>f</sup>	0.01	0.03
<i>Lontra canadensis</i>	River otter	0.12	0.39
<i>Erethizon dorsatum</i>	Porcupine	0.04	0.12
<i>Antilocapra americana</i>	Pronghorn	<0.01	0.01
<i>Bison bison</i>	Bison	0.01	0.04
<i>Mephitis mephitis</i>	Striped skunk	<0.01	0.02
<i>Taxidea taxus</i>	Badger	<0.01	<0.01
<i>Sylvilagus nuttallii</i>	Mountain cottontail	<0.01	<0.01
(various species) <sup>g</sup>	Ground birds <sup>g</sup>	0.57	4.79

<sup>a</sup> Weasel could include short-tailed (*Mustela ermina*), long-tailed (*M. frenata*), or least (*M. nivalis*).

<sup>b</sup> Includes both mule deer (*Odocoileus hemionus*) and white-tailed deer (*O. virginianus*).

<sup>c</sup> In southern parts of province, hare data could include tracks of white-tailed jackrabbit (*Lepus townsendii*).

<sup>d</sup> Squirrel data could include some tracks of the northern flying squirrel (*Glaucomys sabrinus*).

<sup>e</sup> "Mouse/vole" includes various species such as *Peromyscus maniculatus*, *Microtus spp.*, etc.

<sup>f</sup> Note that winter behaviour of several species is not well-suited to the snow-tracking monitoring methodology (*e.g.* subnivean behaviour of many small mammals, muskrat and beaver below ice).

<sup>g</sup> Ground birds include grouse and ptarmigan (Family Phasianidae).

Note that some data are collected for other birds, including corvids and various "song birds", but these species are not reliably tracked by winter snow tracking. Similarly, some data are recorded for tracks of humans and domestic animals (*e.g.* dogs), but these may not be recorded in a consistent, standardized manner.

## 4. STATE VARIABLES

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A central component in the design of any monitoring program is the choice of state variable to monitor (Yoccoz *et al.* 2001, Nichols and Williams 2006). The current ABMI mammal protocol focuses on estimating the occurrence and relative abundance of mammal species based on detections of tracks along winter transects (ABMI 2010, 2011). Camera trap surveys generate data suitable to estimating these and other state variables, with different options offering different advantages to a multi-mammal monitoring program. A given camera-trap station yields a continuous sample of detections of individual animals that pass within its detection zone (and are digitally imaged) during the time period over which it is active (with date and time of each image). Image data can be summarized in different ways, from simple binary “presence-absence” for each species over the duration of camera deployment, to various indices of relative abundance (*e.g.* detections per camera-day; Kays and Slauson 2008). In a more complex treatment, the continuous sample can be broken down into a series of repeated temporal sampling units (*e.g.* daily or weekly periods), yielding a detection-non-detection history for each species (and individual, where these can be reliably distinguished). Detection histories can be modelled using analytical frameworks that explicitly model detection probability, thereby addressing the notable problem of false absence – failing to detect a sampled species or individual - and providing a more robust assessment of target populations (Pollock *et al.* 2002, Williams *et al.* 2002, MacKenzie *et al.* 2006).

### 4.1. Single species variables

#### 4.1.1. Occupancy

Where individual animals are not identifiable from photographs – which is the case for most mammal species in North America – remote cameras yield presence-absence (or more precisely, detection – non-detection) data. Presence-absence data are relatively easily obtained across large study areas, making them invaluable in large-scale research studies. However, presence-absence data can be problematic; when a species

is not detected at a site we cannot be sure whether it is (1) truly absent from the site, or (2) present but undetected (Mackenzie *et al.* 2002; Mackenzie 2005). Accurately sampling species' probability of occupying a site (occupancy,  $\psi$ ) depends on the species' presence at time of sampling, and the ability of the sampling method to detect that animal when present. Mackenzie *et al.* (2002) formulated this basic problem and provided a solution for estimating occupancy and detection. They illustrated that species occupancy at a site can be modelled in conjunction with its probability of detection: the probability of detecting that species when it is, in fact, present. This probability of detection ( $p$ ) is often less than one (Mackenzie *et al.* 2002), meaning that unadjusted, or naïve, counts of occurrence are negatively biased. Detection probabilities may also vary over space and time, introducing bias into naïve comparisons of occurrence or relative abundance between locations or sampling periods. (Mackenzie *et al.* 2006). Estimating  $p$  and how it varies with sampling- and site-level covariates provides key information to more accurately estimate species occupancy at sites across a study landscape.

Occupancy models are based on a number of requirements and assumptions: (1) site surveys are repeated within a season; (2) surveys are independent of one another; and (3) occupancy does not change among surveys within a season, that is, sites are closed to changes in occupancy by species (not by individuals) within seasons. IRC surveys provide a continuous dataset of repeated presences that can be divided into discreet surveys; if these are independent, the resulting detection histories can be modelled in an occupancy modelling framework (*e.g.* Burton *et al.* 2011; Fisher *et al.* 2011, Fisher *et al.* in review). The assumption of site closure is sometimes controversial, especially when occupancy models are applied to vagile species such as birds (Bayne *et al.* in review; Rota *et al.* 2009) or mammals. Mackenzie *et al.* (2006) argue that this assumption can be relaxed if movement in and out of sampling sites is non-Markovian, or random, throughout the survey period. If movement is random – no permanent immigration or emigration of a species occurs among surveys within a single season – then occupancy models should be robust to closure violation, although resulting

estimates of probability of “occupancy” must be interpreted as probability of “occurrence” or “use” (Mackenzie *et al.* 2006: 105-106). The sensitivity of occupancy models to closure violation is an area of active research (*e.g.* Rota *et al.* 2009), and the framework has recently been extended to estimate occupancy at multiple scales (Nichols *et al.* 2008; Mordecai *et al.* 2011), and to accommodate non-random (Markovian) movements (Hines *et al.* 2010). The issue of closure has yet to be addressed explicitly in the context of IRC surveys, so this remains a key avenue for future research.

Nonetheless, occupancy is increasingly being used as a state variable since it is easier to quantify on large scales than are most demographic metrics (Thompson 2004; Mackenzie *et al.* 2006; Long *et al.* 2008). Occupancy is also quite flexible in its application. Mackenzie *et al.* (2003) describe how occupancy dynamics through time can be modelled to provide estimates of local patch extinction and colonization. Together these can be used to estimate rates in occupancy change through time, a landscape-scale analog to population growth rates. Mackenzie *et al.* (2004) discuss how occupancy models can be used to investigate co-occurrence of different species at a site; this analysis is useful for multispecies datasets where the presence of one species is expected to influence the presence, or detection, of another species. Multispecies extensions of occupancy models are also being used to assess community dynamics, including the probability of undetected species (Royle and Dorazio 2008; Zipkin *et al.* 2010; Burton *et al.* 2011). The robust nature of occupancy models, their flexibility, ever-increasing adaptability, and transparent estimation of detectability make occupancy a highly desirable state variable for IRC studies (O’Connell and Bailey 2010).

#### 4.1.2. Abundance

Estimating changes in abundance through time is often a key objective in monitoring studies (Williams *et al.* 2002). Indices of abundance (*i.e.*, “relative” abundance), such as detections per unit effort, are often used to track population changes (Johnson 2008), but have been criticized for failing to adequately account for potential heterogeneity in detection probability (Anderson 2001; Pollock *et al.* 2002;

Conn *et al.* 2004). In IRC studies, some authors have suggested that photographic rates (number of camera days per photograph of a species) are suitable indices of species density (Carbone *et al.* 2001, 2002; Rovero & Marshall 2009) but this approach has been similarly criticized when it fails to reliably calibrate the relationship between index and abundance (Jennelle *et al.* 2002). Mackenzie and Kendall (2002) illustrate how detection probabilities can be used to adjust estimates of relative abundance among populations, useful when each population has different probabilities of detection. Mackenzie *et al.* (2005) further describe how occupancy modelling can provide estimates of detection probability that can then be used to adjust population estimates.

Camera-trap data can be used for density estimation using capture-recapture techniques for species where individuals are uniquely marked (Foster and Harmsten 2012). Estimating absolute abundance (or density) typically requires a “capture” or sighting history of individually identifiable or marked individuals, which IRC data can provide for species with natural markings such as tigers (Karanth 1995; Karanth *et al.* 2004), wolverines (Royle *et al.* 2011), bobcats (Larrucea *et al.* 2007b), and possibly cougars (Kelly *et al.* 2008). IRC capture-recapture studies typically use a species-specific sampling design with cameras placed to identify markings and stations deployed at roughly the home-range scale. Individual capture histories are constructed across consecutive trap-days and modelled in a mark-recapture framework.

Aside from the requirement for individual identification, a second notable challenge in estimating density is in defining the effective sampling area. The usual approach is to buffer the trapping array by half a home range diameter or the mean maximum distance moved between captures of an individual (Williams *et al.* 2002), but this approach is fairly arbitrary and only weakly supported by ecological or statistical theory (Gardner *et al.* 2009). New approaches have emerged to estimate density based on spatially explicit hierarchical models of the distribution of individuals and their exposure to traps (Royle *et al.* 2009; Efford *et al.* 2009; Gardner *et al.* 2010).

#### 4.1.3. Density from presence-absence data

For most mammalian species, including most targeted by the ABMI program, individuals are not readily or reliably identified from natural markings. However, density estimates can still be derived from presence-absence data in some situations. Royle and Nichols (2003) developed a density estimation model that assumes that the greatest source of heterogeneity affecting occupancy is variation in animal abundance, such that occupancy scales with abundance. They use finite mixture models to derive estimates of abundance from occupancy data. However this approach requires large volumes of data and is based on restrictive assumptions. Chandler and Royle (2011) developed a method of density estimation based on repeated detections where individuals are not identifiable, using a similar hierarchical Bayesian approach as in Royle *et al.* (2009), and this model could be applied to IRC survey data.

In a very different approach, Rowcliffe *et al.* (2008) developed a model to estimate densities from camera data without individually identifying or marking individuals. Their approach models probabilities of random contact with a camera's detection cone as a function of animal movement rates and group size. However, it requires a large number of assumptions, only some of which have been empirically tested (*e.g.* Rowcliffe *et al.* 2011). Notably, the "gas" model assumes that contact with an IRC is random, not targeted, making it inappropriate for baited or lured sites. This is a challenge when lure is being used to maximise detection probability, as may be required for mammal monitoring in Alberta.

#### 4.2. Multispecies variables

The ABMI mammal monitoring program is designed to simultaneously track multiple species, so multispecies indices should also be considered as state variables. Many different ways have been proposed for combining data across multiple species into a composite index, including measures of species richness or diversity (Lande 1996; Gotelli and Colwell 2001; Lamb *et al.* 2009). Species richness may be an important state variable in monitoring programs aimed at assessing the effects of anthropogenic

landscape change on ecosystems (Yoccoz *et al.* 2001; Tobler *et al.* 2008; O'Brien 2008). At its simplest, richness is a tabulation of presence-absence data across individual species for a particular site or region; however, as for single species metrics, imperfect detection can introduce significant bias so detectability should be addressed (Mackenzie *et al.* 2006; Lamb *et al.* 2009). Approaches to estimating the probability of undetected species, and thus more robust measures of species richness, have been proposed within occupancy modelling and capture-recapture frameworks (Mackenzie *et al.* 2006: chapter 9; Williams *et al.* 2002: chapter 20). Recently developed hierarchical multispecies occupancy models provide an integrated framework for simultaneously modelling the dynamics of individual species and the communities (or assemblages) they represent (Royle and Dorazio 2008; Zipkin *et al.* 2010). As for single-species occupancy models, the analytical framework uses repeated surveys within a season “closed” to changes in occupancy, and is thus well-suited to camera-trap detection data (Burton *et al.* 2011; Kéry 2011).

Other composite indicators of the status of multiple species may be useful in an IRC mammal monitoring program. The ABMI currently focuses on “biodiversity intactness” as a framework for assessing and reporting changes in species and assemblages (Nielsen *et al.* 2007; Lamb *et al.* 2009; ABMI 2011). The method uses empirically derived reference conditions to scale species’ responses to anthropogenic disturbance, and could be applied to single-species, site-level variables such as occupancy. Other occupancy-based composite indices have recently been proposed specifically for IRC-based mammal monitoring. The Wildlife Picture Index (WPI; O'Brien *et al.* 2010) is based on the geometric mean of scaled, species-specific occupancy estimates from landscape-scale camera trap sampling, and represents one of the few robust, standardized approaches proposed for global monitoring of medium and large-sized terrestrial fauna. The Tropical Ecology Assessment and Monitoring Network (TEAM, [teamnetwork.org](http://teamnetwork.org)) also uses occupancy estimates from camera trap sampling to derive multispecies metrics of status and change in mammal communities (*e.g.*, species and functional diversity, community structure; Ahumada *et al.* 2011).

### **4.3. Recommendations for state variables**

Occurrence data are readily obtainable for a broad range of mammal species from IRC surveys, with no need for individual identification. They are flexibly transformed from temporally continuous datasets to discreet repeat surveys, facilitating their use within an occupancy modelling framework. These data can be used to generate robust estimates of occurrence probability accounting for imperfect detection, and can be used to monitor the dynamics of species as their populations change across space and time. For certain species it may be also be reasonable to derive density estimates from occupancy data. Furthermore, an occupancy framework can be used to assess community-level changes through integrated modeling of multiple species and robust estimation of species richness when some species may go undetected. Occupancy estimates are also suitable for use in other composite, multispecies monitoring indicators, such as biodiversity intactness or the Wildlife Picture Index. For these and other reasons, occupancy is being used as the target state variable by an increasing number of broad-scale monitoring programs (Bailey *et al.* 2007; DeWan and Zipkin 2010). We therefore recommend that occupancy be the target state variable of an IRC-based Alberta mammalian monitoring program. Specifically, we recommend that IRC data be used within the repeated sampling framework to generate occupancy estimates that explicitly account for detection probability.

## 5. TARGET SPECIES

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There are twelve families of non-microtine, non-volant terrestrial mammals in Alberta (Table 2). Of those families with large and mid-size species, most are readily detectable with IRC surveys. Species that are rare or clustered, such as swift fox and pronghorn, will have lower detectability than common or dispersed species, since detectability varies with abundance (Mackenzie *et al.* 2005). Fisher *et al.* (2011b) showed that a stratified experimental design resulted in higher estimates of detection probability ( $p$ ) than did a systematic design, even for more common species. Maximising  $p$  is a key objective, since greater  $p$  provides greater power to detect change (Kendall *et al.* 1992). However, the conceptual foundation for the ABMI is of a systematic monitoring system, not a targeted stratified system. Given this reasonable constraint, two main issues remain: (1) which season in which to sample, and (2) which mammalian families to target.

Species' phenology obviously varies seasonally. Bears hibernate so are not available for detection in winter. Ungulates "yard up" in winter, becoming more clumped in distribution, and therefore less detectable across large areas. Small mammals (mice and voles) are restricted to the subnivean layer for long periods. In contrast, most carnivores are easier to detect in winter, since they are nutritionally limited then and can be more easily baited into a sampling site. Ungulates may also be nutritionally stressed in winter, and thus attracted to a baited site, although (depending on the attractant used) they may be less likely than carnivores to move through energetically demanding winter snowpack.

Species' detectability also varies markedly among body sizes. Remote camera surveys are most useful for surveys of large and medium-sized mammals, > *ca.* 0.5 kg (*e.g.* O'Connell *et al.* 2006; Fisher *et al.* 2011a,b). Smaller mammals (< 0.5 kg) are detected much less frequently in IRC surveys (Fisher *et al.* 2011a,b; Fisher *et al.* unpublished data). Microtine rodents have been rarely detected in IRC studies, but then survey designs have not focussed on these species, so they could potentially be sampled with IRC surveys (Kays and Slauson 2008).

**Table 2. Probabilities of detection ( $p$ ) for camera trap surveys of terrestrial mammals found in Alberta.** Detectability varies with abundance and density, trapping duration and intensity, habitat, camera type, bait, human persecution, *etc.*, so the listed values are meant only as general guidelines rather than rate parameters. Where data are available, detection probabilities are based on six, week-long camera sampling occasions in western Alberta (Fisher *et al.* 2011b); otherwise, estimates are based on 128 camera-weeks of sampling in Cape Cod, Massachusetts (O’Connell *et al.* 2006). Sampling or site covariates affecting detectability are listed where supported by occupancy model comparison.

Family	Species	Max. $p$ *	Covariate**	Source / comment
Ursidae	<i>Ursus arctos</i>	0.42	time	Fisher <i>et al.</i> 2011b
	<i>Ursus americanus</i>	.		detectable
Canidae	<i>Canis lupus</i>	0.65	stratified	Fisher <i>et al.</i> 2011b
	<i>Canis latrans</i>	0.20		O’Connell <i>et al.</i> 2006 <sup>†</sup>
	<i>Vulpes vulpes</i>	0.41	stratified	Fisher <i>et al.</i> 2011b
	<i>Vulpes velox</i>	.		very rare
Felidae	<i>Puma concolor</i>	.		higher $p$ at baited winter sites
	<i>Lynx canadensis</i>	.		detectable
	<i>Lynx rufus</i>	.		rare / elusive
Mustelidae	<i>Gulo gulo</i>	0.57	time	Fisher <i>et al.</i> in review <sup>†</sup>
	<i>Martes pennanti</i>	.		higher $p$ at baited winter sites
	<i>Martes americana</i>	0.45	stratified	Fisher <i>et al.</i> 2011b
	<i>Taxidea taxus</i>	.		rare / clustered
	<i>Neovison vison</i>	.		rare / clustered
	<i>Mustela spp.</i>	.		varies among species
Cervidae	<i>Alces alces</i>	0.17	none	Fisher <i>et al.</i> 2011b
	<i>Rangifer tarandus</i>	.		rare / clustered
	<i>Odocoileus virginianus</i>	0.63	time	Fisher <i>et al.</i> 2011b
	<i>Odocoileus hemionus</i>	.		detectable
	<i>Cervus elaphus</i>	.		detectable
Bovidae	<i>Oreamnos americanus</i>	0.35	stratified	modelled together;
	<i>Ovis canadensis</i>			Fisher <i>et al.</i> 2011b
	<i>Bison bison</i>	.		rare / clustered
Antilocapridae	<i>Antilocapra americana</i>	.		rare / clustered
Leporidae	<i>Sylvilagus nuttalli</i>	.		rare
	<i>Lepus townsendii</i>	.		rare
	<i>Lepus americanus</i>	.		higher $p$ at baited winter sites
Sciuridae	<i>Tamiasciurus hudsonicus</i>	0.35	stratified	Fisher <i>et al.</i> 2011b
	<i>Glaucomys sabrinus</i>	.		detectable
	<i>Neotamias spp.</i>	.		small / rare
	<i>Ictidomys</i>	.		small / rare
	<i>(Spermophilus) spp.</i>	.		likely varies among species
	<i>Marmota spp.</i>	.		detectable in summer
Erethizontidae	<i>Erethizon dorsatum</i>	.		detectable
Procyonidae	<i>Procyon lotor</i>	0.39		O’Connell <i>et al.</i> 2006 <sup>†</sup>
Mephitidae	<i>Mephitis mephitis</i>	0.21		O’Connell <i>et al.</i> 2006 <sup>†</sup>

\* No data = “.”

\*\* “Time” indicates  $p$  changed among surveys, typically decreasing. “Stratified” indicates  $p$  varied among habitat types and was maximal in a habitat-based stratified design. <sup>†</sup> Winter sampling. All others are summer sampling.

### 5.1. Recommendations for target species

All twelve of the mammalian families listed in Table 2 can be targeted with a provincial-scale mammalian monitoring program. It would be too costly to focus such a program on the rarest species; for example, swift fox, bison, and bobcat may not be sufficiently sampled to allow for estimation of trends in  $\psi$  or density within a standardised program (but could be targeted with additional stratified sampling efforts as required on a regional basis). Conversely, most common species should be easily sampled, so the design should try to capture the maximum number of species possible at a level of effort sufficient to achieve statistically useful sample sizes for the least detectable of the “common” species. We suggest that sampling during summer will provide the best opportunity for maximising the diversity of surveyed mammals, including bears which are of great management interest but currently not surveyed by ABMI’s winter snow-tracking program. Notably, camera trapping may also provide data on occurrence of domestic livestock and humans, which may be useful for modelling anthropogenic impacts and footprint.

The lowest observed  $p$  for mammal species at lure-baited sites in summer is approximately 0.20 within a week-long survey (Fisher *et al.* 2011b), meaning there is a 20% probability of detecting these species given that they occur. However, in Fisher’s survey, some species had occurrence rates too low to estimate occupancy, even though they are fairly common (*e.g.* black bear, fishers). Therefore we recommend the monitoring program assume that  $p \sim 0.10$  per camera-week for these species, and design the sampling program accordingly (*q.v.*). Targeting all mammal families will require double-method sampling: one method that targets large and mid-size mammals ( $> 0.05$  kg), and one that targets small mammals ( $< 0.05$  kg) such as Microtines.

Where possible, we recommend obtaining data on detection rates from other camera trap studies in Alberta to further inform sampling design. For example, data should be available from the Athabasca Oil Sands Wildlife Habitat Effectiveness and Connectivity (WHEC) Project (Corey de la Mare and Holger Spaedtke, pers. comm.) and the Alberta Boreal Deer Project (J.T. Fisher, AITF) in northeast Alberta, the Willmore

Wolverine and East Slopes Predator Projects in the central Rockies

(<http://albertawolverine.com>; <http://willmoreresearch.ca>; J.T. Fisher, AITF), and possibly other programs such as Parks Canada camera trap monitoring in Banff and Waterton National Parks (*e.g.*, Ford *et al.* 2009; Gibeau and McTavish 2009; [www.pc.gc.ca/pn-np/ab/banff/plan/faune-wildlife/plan1.aspx](http://www.pc.gc.ca/pn-np/ab/banff/plan/faune-wildlife/plan1.aspx); [www.pc.gc.ca/pn-np/ab/waterton/ne/ne5.aspx](http://www.pc.gc.ca/pn-np/ab/waterton/ne/ne5.aspx)).

Many questions about species detectability in relation to sampling effort and design could be asked by mining these existing data, and the answers will help inform the design of an ABMI pilot study.

## 6. SAMPLING DESIGN

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Monitoring programs designed to estimate occupancy for multiple target species could adopt one of several sampling design options, such as “standard” designs with uniform effort, double-sampling designs, removal designs, and rotating panel designs (see Mackenzie and Royle 2005, MacKenzie *et al.* 2006 for review). In general, all seek to optimise the trade-off between spatial and temporal replication, or specifically the number of sites sampled vs. number of within-season surveys at each site (Mackenzie and Royle 2005; Bailey *et al.* 2007). For a province-wide systematic monitoring program such as the ABMI, spatial replication is fixed or determined by more strategic factors that govern annual prioritization of survey effort. Therefore, the primary design challenge is to optimise survey effort to:

1. Minimize the bias and variance of the occupancy estimator ( $\Psi$ ), to achieve a desired level of precision in temporal trends for minimal total survey effort;
2. Maximize  $p$  – the probability of detecting a species given it occupies the site at the time of sampling.

For camera traps, there are two main sources of sampling error that reduce  $p$ : the species may “occupy” but be temporarily absent from a patch, or the species may be present within a patch but not enter the detection zone of the camera trap. Temporary absence from a site is obviously a particular problem for wide-ranging, vagile species such as grizzly bears and wolverines. Missed detections are a more difficult problem to control. This error can arise from phenology; for example, a denning mother may not be available for detection, or an ungulate occupied at rutting or calving grounds may not encounter a camera trap. Missed detections can also be caused by elusive or risk-averse behaviour (Thompson 2004); this is a known problem with wolves (Fisher *et al.* unpublished data; Gibeau and McTavish 2009) and coyotes (Larrucea *et al.* 2007a). Finally, missed detections could also arise from sampling error, *i.e.* movement within the patch relative to the camera, particularly when the zone of detection is small relative to the area of interest (*i.e.*, the “site” for inference). The latter should be less

problematic as it is unbiased with respect to the sampling, and overall detection probability increases with sampling duration.

Both of these sources of error are tied to the assumption of closure of sampling sites, or at least of random movement into and out of sites. Occupancy estimates may become biased if the closure/random movement assumption is violated; temporary emigration from a site can become confused with permanent emigration, thus inflating occupancy estimates (Rota *et al.* 2009). Closure violation also increases variance in occupancy estimates, since variable detectability introduced by temporary and permanent emigration leads to imprecise model parameters. Low probability of detection likewise leads to imprecise parameter estimates (Rota *et al.* 2009). An effective sampling design for an IRC-based mammal monitoring program should try to maximise  $p$  by manipulating survey duration, and maximise precision of  $\psi$  by modelling and accounting for closure violation. Ideally, a pilot IRC monitoring program could be combined with complementary research to assess animal movements relative to camera stations (*e.g.*, telemetry study), thereby adding important insight to issues of site closure and species detectability.

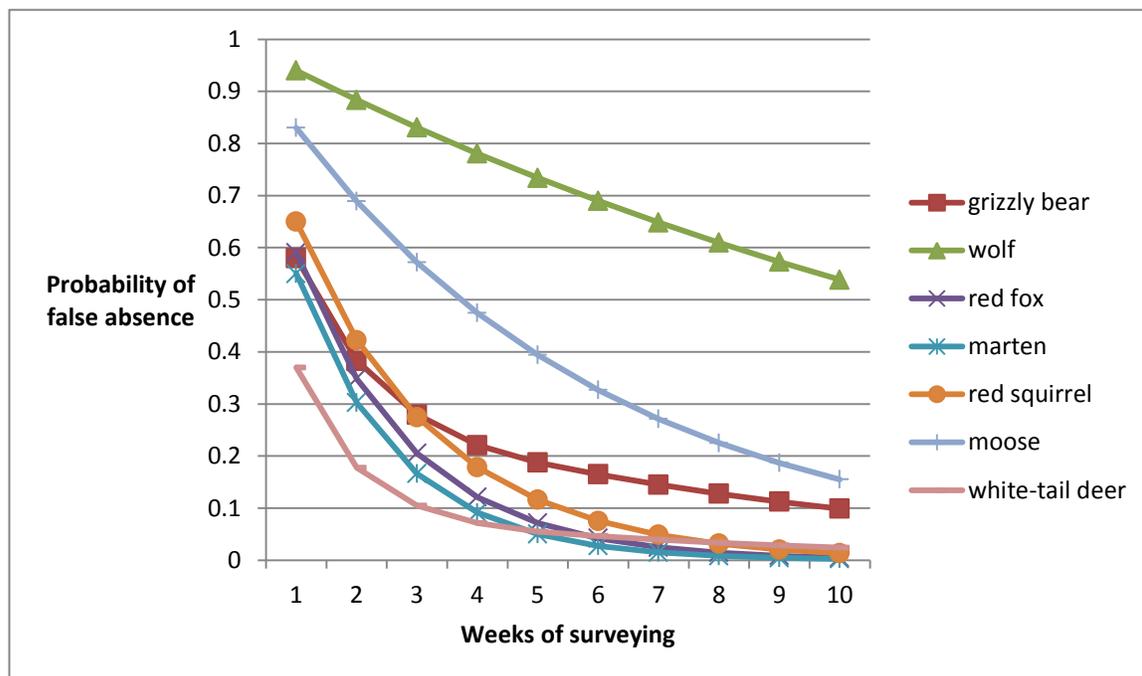
### 6.1 Survey duration

A suitably long sampling duration is required to minimise error associated with temporary absence and missed detections. Determining what is “suitable” is a challenge but can be informed by existing data. From per-survey probabilities of detection ( $p$ , Table 2) we can calculate the probability of false absence ( $pfa$ ) for a given survey duration as  $[1-p]^k$ , where  $k$  = number of independent sampling occasions. Limiting  $pfa$  to 0.05 – 0.15 is a recommended goal for a monitoring program (Field *et al.* 2005; Long and Zielinski 2008).

We used the estimates of occupancy and detection from Fisher *et al.* (2011b) in Table 2 to calculate  $pfa$  for the subset of species for which  $p$  was estimable. We used estimates of  $p$  from systematic surveys where these differed from stratified surveys (to match the ABMI framework), and we used survey-specific estimates of  $p$  where  $p$

declined over time (*i.e.* grizzly bears, white-tailed deer). We extrapolated beyond the six-week sampling interval used by Fisher *et al.* (2011b) using the lowest observed  $p$  for the species (Figure 1). Of the seven species examined, five had an estimated  $pfa < 0.1$  after six weeks of sampling; all but wolves had an estimated  $pfa < 0.2$  after 9 weeks of sampling. More generally, a weekly survey  $p = 0.10$  would require 18 weeks of sampling to obtain a  $pfa = 0.15$ .

A sampling design can compensate for low  $p$  by increasing effort; for example, 20% detectability over sampling effort  $N$  means an effort of  $(5 \times N)$  is required to approach 100% (O’Connell *et al.* 2006: 1630). At minimum, a summer survey using lure-baited sites should sample for 6-8 weeks. A pilot program aimed at guiding future monitoring efforts should sample for longer (*e.g.*,  $> 18$  weeks); the data gathered therein should be used to examine latency to detection and  $pfa$  over time to inform the optimal survey duration.



**Figure 1.** Probability of false absence for mammal species in a camera-trapping program, based on lured camera sites surveyed weekly for 6 weeks in the Rocky Mountains of Alberta, Canada (data from Fisher *et al.* 2011b).

## 6.2 Sampling unit

Validity of the assumption of site closure is difficult to assess in IRC surveys, as the definition of “closure” depends on the definition of the size of the sampling unit. IRC surveys use a point-sampling method to survey “occupancy” of a “site” by animals that are often vagile and wide-ranging. Conceptually, probability of occupancy can in these situations be interpreted as probability of “occurrence” at, or “use” of, a site (MacKenzie *et al.* 2006: 105-106). MacKenzie *et al.* (2006) suggest that as long as a species’ movements (*i.e.*, those of all local individuals of that species) into and out of a site are random then the resulting occupancy estimates are unbiased; however, Rota *et al.* (2009) suggest this may not be true, and that closure violations may decrease accuracy and precision in  $\psi$  estimates.

Recently it has been proposed that sampling at multiple units within a “site” can provide information on occupancy at multiple scales; that is, occupancy at each unit (*e.g.*, camera station) and within the site as a whole, defined by the spatial extent of the multiple units (Nichols *et al.* 2008; Mordecai *et al.* 2011). This multi-scale, multi-method sampling design (and corresponding analytical model) is based on Pollock’s robust design and provides information about  $p$  at each unit within a site, improving estimation of site-scale occupancy by integrating this detection information across units. In an IRC survey for mammals, this could be accomplished by deploying an array of >1 cameras (*e.g.*, 2-4) at each site, analogous to the ABMI approach of replicating bird point counts within a site (ABMI 2010).

## 6.3 Attractants to increase detection probability

The use of an attractant can markedly increase detectability of elusive mammals in both winter (Fisher *et al.* unpublished data) and summer (Fisher *et al.* 2011b) by capitalising on novelty-investigation behaviours (Doty 1986) . On the other hand, the use of bait or lure could decrease detection rates for certain species (Kays and Slauson

2008). Controlled studies are needed to better understand the influence of natural and artificial attractants in camera trap surveys targeting multiple species (Schlexer 2008), and this could be part of an ABMI pilot mammal monitoring program (see section 7.2 below). We recommend that maximizing detection probability be a key objective and thus an integral component of the pilot phase of an IRC-based mammal-monitoring program in Alberta.

#### **6.4 Recommendations for sampling design**

A camera trapping design for use in an occupancy modelling framework should seek to (1) ensure the assumption of site closure is met, to the degree possible with vagile animals; (2) provide data to model the degree to which the closure assumption is violated; and (3) provide data to examine how estimates of detectability may vary with survey duration, number of replicate sampling occasions, and spatial and temporal dispersion of sampling units. Experimental designs can be informed by analytical and simulation modelling of estimates of  $\Psi$  and  $p$  derived from pilot data, for instance using program GENPRES (Bailey *et al.* 2007). However, given the wide variety of taxa targeted by the ABMI multi-mammal monitoring program, and the high variance among estimates of  $p$  for these taxa (Table 2), finding an optimal design may prove difficult. We recommend a pilot sampling design focused on maximizing detection probability for target species by using an attractant and sampling for at least 18 weeks per site. Resulting data can be used to examine how the estimated probabilities of false absence decline over time, and thereby identify an optimal sampling duration that maximizes the reliability of inference across multiple mammal species. Further, we recommend a design that includes four cameras at each sampling unit (subject to budget limitations) in order to facilitate assessment of the site closure assumption and improve inference via multi-scale/multi-method occupancy analysis (Nichols *et al.* 2008). Analysis of these pilot data will inform the trade-off between allocating multiple cameras at a site vs. spreading them out at additional sites.

## 7. SAMPLING LOGISTICS

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There are many important practical considerations for designing an effective camera trapping program (Kays and Slauson 2008). Logistical details will ultimately be dependent on monitoring objectives, sampling design, and funding availability; we discuss them briefly here under general themes of equipment and materials, staffing and budget, and data management.

### 7.1 Camera equipment

A central decision in IRC surveys is what make and model of camera trap to use, as there are many options available that vary widely in price and performance. Key considerations include: cost, trigger sensitivity and speed, detection zone, power supply, data storage, flash type and range, durability, and security. Given that performance can vary markedly across camera types, the same type would ideally be used across a monitoring program to control this potential source of heterogeneity in detectability. Since camera-trap technology will continue to change rapidly, and given the broad spatial and temporal scale of ABMI monitoring, it may be necessary to change camera make or model to some degree. In that case, it would be important to standardize with respect to a set of key specifications (*e.g.*, passive infrared, trigger speed/sensitivity, image resolution and storage capacity, battery life) and ensure random deployment of camera types with respect to sampling locations. To further guard against potential bias, camera type could be included as a covariate on detection probability in occupancy modeling of resulting data. Ideally, performance differences could be calibrated across different camera types using a standardized “control” environment (*e.g.*, Swann *et al.* 2004; analogous to calibration of recording devices for ABMI/BAM bird surveys).

Decisions on camera make and model should be made based on the most up-to-date information. The website [trailcampro.com](http://trailcampro.com) contains useful performance reviews of many different camera types, along with pricing information, etc. There is also an email listserv widely used for discussion and advice by many scientific experts in camera trap

methodology (Camera Trap Information Exchange - cameratraps@yahoo.co.uk). Reconyx infrared digital camera traps have become a leading brand for wildlife surveys, with a reputation for high quality performance. Older Reconyx models have been successfully used to survey mammals in Alberta (*e.g.*, PM30 and PM85 models used in Fisher *et al.* 2011; see also other studies noted in section 5.1 above). Current Reconyx HyperFire models feature no- or low-glow infrared illumination (to minimize animal disturbance) and include “professional” models (PC900 - \$650, PC800 - \$550) and “scouting” models (HC600 - \$550, HC500 - \$450; details at reconyx.com).

Equipment needs associated with camera units include: batteries (or other power supply), data storage (*i.e.*, memory cards), attachment devices (*e.g.*, brackets, straps, T-bars, posts), security (*e.g.*, lock, case), and possibly weather protection (*e.g.*, dessicant). For example, recommended accessories and associated prices listed at reconyx.com for the PC900 model include:

- 12 AA batteries (NiMH rechargeable or 1.5 volt lithium; rated to run for 1 year or up to 40,000 images; \$35).
- Secure Digital memory card (up to 32GB; 4 GB rated to hold ~10,000 images; \$30).
- Python cable lock (\$30).
- C-bracket mounting kit (\$25).

This would translate into a per-unit cost of ~\$770 (not including shipping, taxes, etc, although noting that more economical options and bulk discounts are probable). Costs may also vary with differing sampling logistics in different parts of the province; for example, camera mounting and security structures would likely be relatively more important in agricultural or more densely inhabited regions of Alberta (*i.e.*, less trees and/or greater chance of theft).

The number of camera units required depends on the sampling design. Assuming the ABMI “full implementation” objective of sampling 330 sites per year, with 4 units per site plus an additional 10% as replacement units, there would be a need for ~1450 camera units. This would translate into a high-end, coarse estimate of >\$1,000,000 in

initial camera equipment costs. Using the same inputs, a pilot study at 30 sites might entail a start-up cost on the order of \$100,000. Costs would be reduced with less cameras deployed per site, and/or if cameras were moved between sites during a sampling season (*e.g.*, 2 sets of 165 sites or 3 sets of 100 sites, provided sampling duration at each site was sufficient and order was randomized to prevent confounding phonological bias). The cost of IRC-based monitoring decreases considerably after initial camera equipment is purchased, although costs associated with periodic replacement and maintenance of cameras must be factored in (particularly for a long-term program like ABMI's, where the life-span of monitoring activities is expected to be much greater than the life-span of cameras).

## 7.2 Attractant

We recommend the use, or at least testing, of an attractant to increase detection rates at camera stations. There are a great number of types of attractants that have been used in wildlife studies—including food baits, scent lures, visual lures, and natural attractants (*e.g.*, rub trees, latrine sites)—and a useful review is provided by Schlexer (2008). Some IRC studies have sought to maximize detectability by using wildlife trails as an “attractant” (*e.g.* Muhly *et al.* 2011). Unfortunately, few systematic studies have assessed the effectiveness of different attractants or wildlife trails at maximising  $p$  across a range of target mammal species (but see Kays *et al.* 2011). As with camera types, it would be important to apply a consistent, standardized methodology for the use of attractant, and to ensure that there is no methodological bias with respect to sampling locations (*e.g.*, different attractants used in different regions of the province). This might be difficult to implement if trails are used as an “attractant”, since their density, distribution and nature (*i.e.*, human vs. animal) will vary with the landscape being surveyed. In addition, the effect of trail-based sampling on the inference space of probabilistic experimental design remains unknown – can on-trail estimates be extrapolated to off-trail areas? For these reasons, we focus on biological attractants,

though the use of trails warrants consideration (and it is noted that current ABMI snow tracking protocols make use of trails for mammal monitoring; ABMI 2010).

While carcass-baited sites have been used successfully in IRC studies (*e.g.*, beaver carcasses in Fisher *et al.* 2011, and Fisher *et al.* in review), the logistics of using carcasses across the large spatio-temporal scale of the ABMI program do not seem realistic. Other multi-species mammal surveys have used commercial scent lures (*e.g.*, Gusto, Zielinski *et al.* 2005; O’Gorman’s LDC Extra and Summer Special, Fisher *et al.* 2011b) and readily available food items (*e.g.*, chicken, cat food, apple, grain, salt; Zielinski *et al.* 2005; B. Furnas, California Dept. of Fish and Game, personal communication). Considerations for choosing an appropriate attractant include cost; availability; ease of storage, transport and application; longevity; safety; and documented performance in attracting focal species. Another important consideration may be the willingness of land owners to accept an attractant at sites located on private land. More research into options is warranted (see *e.g.*, Schlexer 2008 and references therein), and a test of different attractants (including natural attractants) would be a useful component of a pilot study.

### *7.3 Staffing and budget*

Staffing requirements and associated costs would be comparable to those of the other ABMI terrestrial protocols, so we do not provide a detailed breakdown here. Camera units could likely be set at a site by a single individual, although teams of two are recommended for safety and to facilitate carrying of equipment and setting/testing cameras (a possible exception would be if camera deployment was done in conjunction with other ABMI protocols, *e.g.*, site establishment, plant/tree surveys, ABMI 2010). The number of teams required would be dependent on the accessibility of sites and travel logistics, as with the other terrestrial protocols. Deployment of four cameras at a site should not take more than a few hours, dependent on proper equipment performance and particular site characteristics (*e.g.*, trees for mounting vs. posts, the need for

manipulating vegetation or extra security precautions. Note that all camera units should be tested for basic performance before deployment to the field).

An important difference between a camera protocol and that for winter snow-tracking is the need for a second site visit to retrieve cameras. This could represent a significant expense in terms of travel, etc., although camera retrieval can be done relatively quickly and could perhaps be combined with other site visits (*e.g.*, with summer protocol if sufficient time has elapsed since deployment). Despite the need for two site visits, camera trapping should provide significant savings over winter snow tracking in terms of total staffing costs since it eliminates the need to maintain staff on stand-by while waiting for suitable snow conditions. Future technological advancements may also allow remote downloading of camera data after initial deployment (*e.g.*, through satellite or cellular phone networks; Kays *et al.* 2011).

Other than camera equipment, attractants, and image processing (see next section), budget items associated with IRC-based mammal monitoring would be similar to other ABMI protocols (*e.g.*, standard field equipment—see ABMI 2010).

#### *7.4 Data management*

In addition to standard considerations for maintaining field data quality (*e.g.*, ABMI 2010), it is critical in IRC-based monitoring to establish an efficient system for labeling, storing, and processing digital images. A single unit can generate thousands of images over a sampling season, and a first key consideration is to ensure cameras are equipped with sufficiently large memory cards to store the anticipated number of photos (at the desired resolution). It is also critical to make sure every camera unit (and memory card) deployed is appropriately labelled with a unique identification linking it to the sampling site, season, year, GPS coordinates, etc. Reconyx (and other) units allow for the programming of a camera identifying label that will be included on each resulting image, and it is also important to take “test” photos with unique identifiers (*e.g.*, dated signs) at deployment and collection of cameras. Before being deployed, cameras should be checked to ensure that they are properly recording the date and time of each captured

image (in addition to ensuring other features are set appropriately, *e.g.*, sensitivity, image resolution, delay). Upon camera retrieval, it should be immediately ensured that images are properly labelled and backed up. Sufficient staff time (and expertise) needs to be allotted for the processing of images for animal identifications. The time required to identify species from camera data is very small relative to field costs; for example, the identification of photos from Fisher *et al.* (2011b) averaged approximately \$6.00 /site / survey-week. Automated or semi-automated image analysis techniques also have the potential to improve the efficiency of camera-trap data processing in the future (Kays *et al.* 2011).

Several software packages exist for image and data management. Notably, the software Timelapse is being employed by Parks Canada, Alberta Parks, and AITF (<http://grouplab.cpsc.ucalgary.ca/cookbook/index.php/Demos/TimelapseCoder/>). Timelapse allows customization of the data entry interface, links images in folders to data, and exports data into Microsoft Access for analysis. Other relevant software programs include DeskTEAM (Fegraus *et al.* 2011), PhotoSpread ([www.ericabelson.com/photospread](http://www.ericabelson.com/photospread)), Camera Base ([www.atrium-biodiversity.org/tools/camerabase](http://www.atrium-biodiversity.org/tools/camerabase)) and Picasa/Exif (Sundaresan *et al.* 2011; see also Harris *et al.* 2010 and the Camera Trap Information Exchange listserv for useful discussion of this topic). Whatever software is adopted, resulting databases should link specific images to their associated data files. Images should also be archived in a similar manner to museum specimens to facilitate independent review and/or future research (*e.g.* Botello *et al.* 2007).

### **7.5 Recommendations for sampling logistics**

We recommend that a standard make and model of camera trap be used for IRC-based mammal monitoring program in Alberta. More research may be needed to identify the best options currently available, but Reconyx Hyperfire units are an industry leader. Should it be necessary to use different types of camera traps, we recommend that they be standardized with respect to key specifications (*e.g.*, passive infrared, trigger

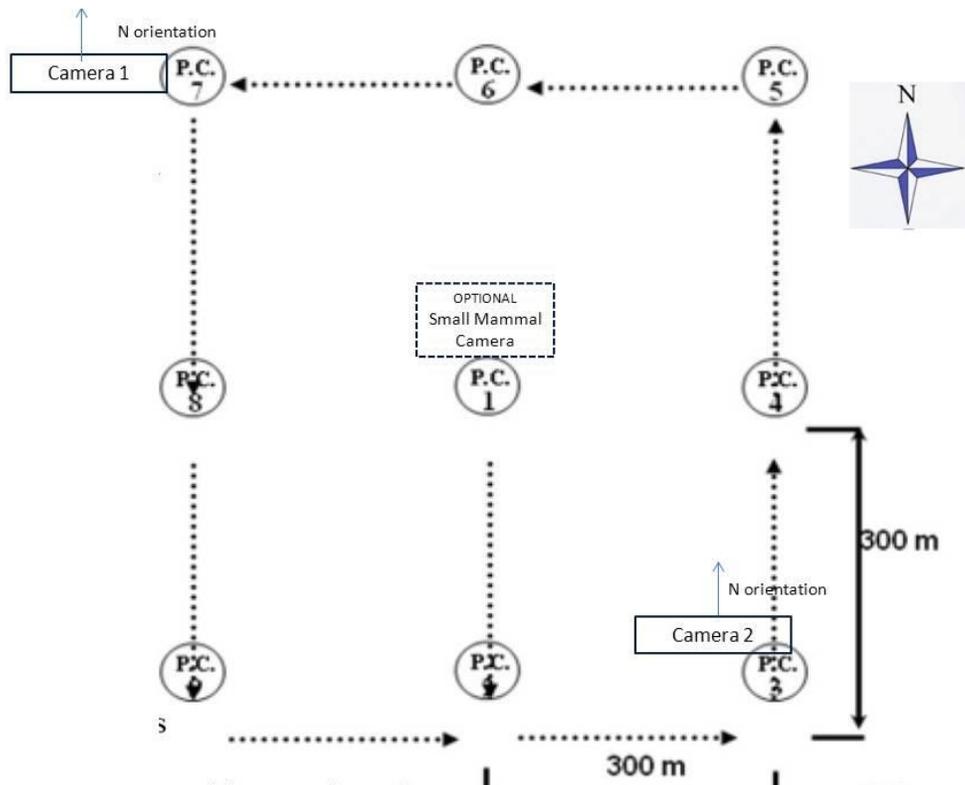
speed/sensitivity, image resolution and storage capacity, battery life, flash) and deployed randomly, and that “camera type” is included as a covariate on detection probability. Additional camera-related equipment must be factored in during budget preparation (*e.g.*, batteries, memory cards, locks, mounting equipment). We recommend use of a standardized attractant, such as a commercial scent lure, to increase detection probability, although we suggest that testing attractant effectiveness be part of a pilot study. The logistics and costs of staffing, travel, site access, etc., for IRC monitoring should be similar to those for other ABMI terrestrial protocols, and we recommend that opportunities for coordination be sought to maximize efficiency (*e.g.* camera setup during site preparation and/or retrieval during summer protocol). A standardized protocol for labelling, storing and processing an abundance of digital images is an essential component of an IRC monitoring program.

## 8. PROPOSED PROTOCOLS AND PILOT DESIGN

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Based on our review of the literature and available data, we recommend a pilot IRC-based mammal monitoring design with these primary components:

1. **Sampling units are based on the systematic grid of ABMI terrestrial monitoring sites.** This will capitalise on available site-level habitat and physical data that can serve as site and sampling covariates in the data analysis, and should also facilitate integration across multi-taxa within the broader program.
2. **Multiple cameras are deployed at each site.** The number will ultimately depend on pilot results and available budget resources, but we provide an initial recommendation of 2-4. In addition, a camera dedicated to small mammals may be considered.
3. **Cameras are deployed in a standardized spatial array around site centre.** The ABMI bird point count plots provide known reference points and a reasonable basis for within-site replication. We recommend placing cameras at the far ends of the grid to maximize the distance between them (*e.g.* PC 3, 5, 7, 9; Figure 2). Should a camera targeting small mammals be deployed, it could be located at the centre point count (PC1).
4. **Cameras are baited with an attractant such as scent lure.** Alternatively, a pilot protocol may wish to examine the effects of scent lure by baiting some sites and not others and examining the effect on detection probability across species. In the absence of this experiment, an attractant is recommended to minimize risk of insufficient detections for reliable inference.



**Figure 2.** Proposed layout of camera traps within the ABMI terrestrial bird point count grid. Two camera stations are shown (at PC 3 and 7) as well as an optional camera at site centre (PC1) targeting small mammals. Additional cameras could be set at PC 5 and 9 (opposite corners to maximize separation). Camera units should be set in a consistent manner to minimize confounding detection heterogeneity within and across sites. For example, cameras should face north to minimize image problems related to solar flare, and should be set at a consistent height, angle, and setback distance relative to the target capture area (*e.g.*, lure or trail). The visibility of cameras should be minimized to reduce risk of animal avoidance or theft, although vegetation that could interfere with image capture should be removed (*e.g.*, branches or tall grass that could obscure animals or cause false triggers).

5. **Cameras should be deployed for a minimum of 6-8 weeks.** Ideally, a pilot study should deploy cameras for at least 18 weeks, and the resulting data used to examine trends in estimated probabilities of false absence across species to ascertain optimum survey duration.
  
6. **Surveys should be standardised by season.** Winter surveys will yield different data than summer surveys due to phenological and behavioural differences affecting detection probabilities (*e.g.* hibernation, greater search intensity for limited food resources in winter). We recommend surveying during spring/summer as it will likely yield more diverse community data (including data on high-profile grizzly and black bears) and facilitate greater logistical and analytical coordination with other ABMI protocols. However, a pilot study in winter would also be recommended to facilitate calibration of winter snow-tracking data to winter camera trap data, and then winter to summer camera data.

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