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Tools and Technology

Comparing the Costs and Detectability of Bobcat Using Scat-Detecting Dog and Remote Camera Surveys in Central Wisconsin

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ABSTRACT Determining cost-effective field methods for detecting carnivores is critical for effective survey and monitoring studies. As the bobcat (*Lynx rufus*) undergoes range expansion in the northern and eastern United States, field methods may be useful for informing revisions in population management. We paired 2 scat detection-dog teams and 16 remote cameras at 4 survey sites within central Wisconsin, during summer 2011, and compared detection totals, detection probabilities, and costs between methods. Laboratory expenditures are an additional cost for scat collection, and we modeled the probability that a collected scat was genetically confirmed as bobcat as a function of dog, handler, site, and the strength of the dog's behavior. We estimated that detection-dog surveys required only 2 days to achieve a 90% probability of detecting a bobcat in a 4-km^2 area, while a single camera station would require 7–8 weeks. But a month of detection-dog surveys cost 33% more than a 4-month camera survey, with projected cost differences increasing annually. There were dog-specific differences in collection rate, and the probability that a collected scat was genetically confirmed as bobcat was best predicted by the individual dog associated with collection and the survey area, rather than the handler or the dog's observed response. We recommend cameras as a generally more cost-efficient bobcat survey method, and we advise against relying on the strength of an individual dog's response as a means of screening samples for genetic analysis. However, the most appropriate survey method is likely to be goal-dependent, and we recommend that detection-dog contractors both advertise and match the strengths and weaknesses of specific dogs with the needs of clientele.

KEY WORDS bobcat, detection probability, *Lynx rufus*, non-invasive sampling, scat-detecting dogs, Wisconsin.

Although, the bobcat (*Lynx rufus*) is ubiquitous and relatively abundant across the continental United States, it exists at low density throughout the northern part of its range where trends suggest ongoing range expansion and population growth (Anderson and Lovallo 2003, Roberts and Crimmins 2010). In response, several states have either recently implemented or are exploring revisions of harvest geography (e.g., Linde et al. 2012, New York State Department of Environmental Conservation 2012, Pennsylvania Game Commission 2012). Harvest indices, the primary technique currently employed for monitoring (Roberts and Crimmins 2010) have little value in unharvested areas.

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Previous research identified assessing alternative methods to detect and monitor bobcats as an important research need more than a decade ago (Anderson and Lovallo 2003). Since that time, alternative monitoring remains sporadically practiced and the most common non-harvest techniques are incidental detections reported by the public, track stations or surveys, and hunter survey data (Roberts and Crimmins 2010). These methods are generally inexpensive but reliant on suitable weather conditions or assumptions of constant detection. Furthermore, such methods are limited to presence–absence data that may suffer false positives (McKelvey et al. 2008).

Capture–recapture (Otis et al. 1978) is the most widely used analysis for estimating carnivore population parameters. Non-invasive techniques such as scat-surveys or remote cameras have shown promise as methods to generate estimates of abundance in the southern United States by allowing identification of individuals (e.g., Heilbrun et al. 2006, Ruell et al. 2009) with far less effort than directly capturing animals. However, non-invasive efforts in New England and the Great Lakes region have had mixed

success detecting bobcat (e.g., Gompper et al. 2006, Long et al. 2007*a*, Adams 2009), with only a single example of survey-based bobcat population estimation in the northern part of its range (Stricker et al. 2012). Hence, managers in northern regions most interested in generating empirical abundance estimates have little guidance on how to efficiently acquire it.

Prior to a larger scale survey designed to estimate bobcat abundance across central Wisconsin, USA (Clare 2013), we sought to compare the viability of scat-detection dogs and remote cameras as tools for bobcat detection and monitoring effort in central Wisconsin. Because scat-detection-dog surveys remain nascent, we also wanted to validate previous assertions of their efficiency (Harrison 2006, Long et al. 2007*b*). Detectability strongly influences the precision of state parameter estimates, so our first objective was to determine the relative usefulness of the 2 techniques in terms of total bobcat detections and estimates of detection probability. Because both cameras and dogs are expensive, we also sought to quantify gross cost differences between techniques and compare relative cost-efficiency.

Genetic analyses represent an additional expense for scat surveys, and individual identification using microsatellites can represent a significant cost. Previous studies have attempted to reduce laboratory costs by relating probability of genetic confirmation to the detection dog's behavior when targeting a scat (Long et al. 2007*a*). Though scat-detection rates have been observed to vary with specific dogs and environmental factors (Smith et al. 2003, Reed et al. 2011), influences on the accuracy of scat collection are poorly understood. Thus, our final objective was to determine what factors (e.g., the individual dog or associated handler) might best explain whether collected scats were genetically confirmed as bobcat or non-target species.

STUDY AREA

Because we sought to compare the relative efficacy of techniques, we sampled locations with anticipated bobcat presence based upon public sightings. Given available equipment and survey time, we selected 4 sites as sampling arrays during summer 2011: Mead State Wildlife Area (MSWA), Navarino State Wildlife Area (NSWA), Necedah National Wildlife Refuge (NNWR), and Clark County Forest (CCF; Fig. 1). Central Wisconsin was defined ecologically by diverse vegetation resulting from its location along a tension zone between northern mixed forests and southern deciduous forest or prairie. Upland communities were typified by mixed oaks (*Quercus* spp.) and pines (*Pinus* spp.), with hardwood stands dominated by maples (*Acer* spp.) at mesic sites. Predominant lowland species included speckled alder (*Alnus incana rugosa*) and tamarack (*Larix laricina*). Though central Wisconsin was an equitable mixture of cropland (35%) and forest (37%) with patchy concentrations of wetlands (7%), the study sites were largely forested (26–78%, $\bar{x} = 49\%$) with interspersed wetland (9–29%, $\bar{x} = 18\%$) and very limited crop presence (0–19%, $\bar{x} = 9.5\%$). Monthly high temperatures ranged from an average of 28° C in July to 7° C in November, and average precipitation was 37.6 cm from 1 July to 31 October (National Oceanic and Atmospheric Administration 2013).

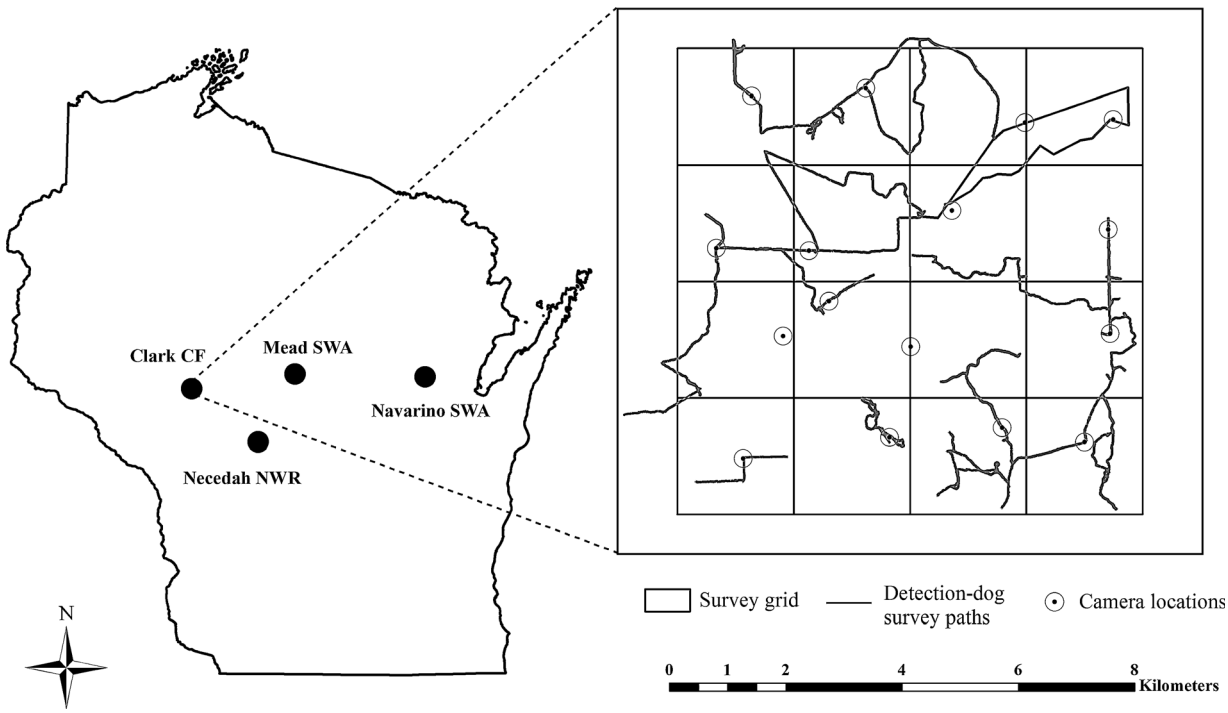

Figure 1. Location of survey sites and configuration of sampling arrays for bobcat with camera locations and detection-dog transect routes in during surveys in central Wisconsin, USA, in 2011. Mead State Wildlife Area (SWA), Navarino State Wildlife Area (SWA), Necedah National Wildlife Refuge (NWR), and Clark County Forest (CF).

METHODS

Sample Collection and Processing

We gridded each site into a square 4 × 4 array of 16 2 × 2-km cells. Camera sampling ran from 27 July through 15 November 2011. Within each grid-cell, we placed 1 unbaited PC800® camera (Reconyx, Inc., Weston, WI) along a linear feature or expected travel path such as a dirt road or game trail to increase rates of detection (Negroes et al. 2010). Though bobcat home range size in the region was unknown, summer (15 May–14 Oct) male and female home ranges in northwestern Wisconsin were 39 km^2 and 19 km^2, respectively (Lovallo and Anderson 1996). Thus, we assume the survey effort met recommended capture–recapture protocols of ≥4 detectors/home range (Otis et al. 1978) for both male and female bobcats, though the spatial extent of the survey grids was too small for formal capture–recapture analysis.

Cameras were secured to trees using cable-locks and were set to fire 3 times/triggering event with no subsequent delay between triggers. Depending upon tree proximity to the path being sampled and the path's width (0.5–6 m), camera height (50–150 cm), vertical angle (flat to 15° downward), and perpendicularity (60°–90°) varied. For example, cameras set closer to a path faced the path at an angle more parallel than cameras further away to provide adequate time for the camera to trigger and fire. We extensively crawl-tested all locations to ensure that a bobcat moving along the target path at all distances from the camera would fall within the detection zone. We kept each array active for between 6 weeks and 8 weeks to meet assumptions of closure (Otis et al. 1978, Nielsen and Woolf 2002). Two arrays were checked every 2 weeks, and 2 were checked only once after 2 weeks of deployment.

From 9 August through 24 September 2011, we contracted 2 teams (dog and human handler) of scat-detecting dogs from the University of Washington's Conservation Canine program (http://conservationbiology.uw.edu/conservation-canines/). Both detection-dog teams surveyed for ≥5 total days within each array, predominantly along unpaved roads or walking trails. Though teams were required to survey each cell, survey paths were not predetermined to allow the dogs to maximize survey distance, and survey effort varied across cells (e.g., Russell et al. 2012, Thompson et al. 2012). At all scat samples targeted by dogs (indicated by a sitting behavior) or judged to be morphologically consistent with bobcat scat, human handlers took a GPS coordinate. Handlers subjectively interpreted the strength of the dog's response as none, low, medium, or high based upon the trained behavior and handler familiarity with the dog's baseline behavior and body language (e.g., a partial sit might be interpreted as a low-strength response for a more exuberant dog or a medium-strength response for lethargic dog). Handlers collected scat portions and stored them in a 50-mL conical tube with silica desiccant; moist samples were air-dried in a paper bag before storage. Dogs were rewarded with play if the targeted sample was judged to be morphologically consistent with bobcat scat. Roughly halfway through the sampling period (survey-day 9 out of 24), the 2 handlers switched dogs.

Molecular Laboratory Procedures

We extracted DNA from the edges of scat samples (Stenglein et al. 2010) within 2 weeks of collection using QIAamp® DNA Stool Mini Kit (Qiagen, Inc., Valencia, CA). We followed manufacturer's instructions except when a sample resulted in poor amplifications. In these cases we re-extracted the scat sample and decreased final elution from 200 μL to 50 μL. We used polymerase chain reaction (PCR)-restriction fragment length polymorphism on a portion of the mitochondrial cytochrome *b* (cyt-*b*) gene to determine species (Bidlack et al. 2007) rather than the commonly used 16S loop sequence (Mills et al. 2000) because preliminary analyses showed greater amplification efficiency. We amplified cyt-*b* fragments in reactions with 25–100 ng DNA template, 0.2 mM dNTPs, 1.5 mM $MgCl_2$, 1× PCR buffer (Fisher PCR Buffer B; ThermoFisher Scientific, Waltham, MA), 40 pM forward and reverse primers, 0.5× preCES II enhancer mix (Ralser et al. 2006), and 0.25 U *Taq* polymerase (New England Biolabs, Ipswich, MA). Thermal cycling parameters were an initial 30 s at 94° C, followed by 40 cycles of 94° C, 54° C, and 72° C for 30 s each, and a final extension at 72° C for 15 min. Amplified products were restricted in 6-μL reactions with 4 μL PCR product, 0.5 μL molecular-grade water, 0.25 μL *Dde*I and *Hpa*II (New England Biolabs; Bidlack et al. 2007), and 1 μL buffer for 4 hr at 37° C. The restricted product was visualized on a 2.5% agarose gel with ethidium bromide under ultraviolet light. We replicated all samples that amplified but apparently failed to digest (indicative of canid species) 3 times. All molecular work was performed at the College of Natural Resources-Molecular Conservation Genetics Laboratory at the University of Wisconsin-Stevens Point.

Comparing Detection Totals and Probability

We tested for differences in the number of detection events between methods and between dogs using Wilcoxon's paired-sample test (Zar 1999) using sites as replicates, with $\alpha = 0.10$ given small sample size. We assumed that spatial correlation between camera and scat detections would indicate an equal proportion of detections, so we compared presence–absence via camera and scats at each grid cell using McNemar's Chi-square test (Zar 1999). Because the spatial grain of grid cells was coarse and dog survey effort was not uniformly spaced within grid cells, it was possible for camera and scat detections to be spatially correlated even if occurring within different cells. To account for this, we also used a paired *t*-test to compare the distance between scat samples and nearest-neighbor cameras with or without bobcat detections.

We used a single-season (closed) occupancy framework (MacKenzie et al. 2002) to estimate probability of detection (*P*). We considered each grid cell a unit of replication, and subdivided camera data into weeklong sampling occasions and dog transects into 1-km segments because it provided a comparable number of sampling sessions between methods. Although we assumed that bobcat occurrence in adjacent grid cells was spatially dependent, introducing a condition-

ally autoregressive error term (e.g., Latimer et al. 2006) would not have altered our estimate of P because no covariates were considered. We censured portions of dog transects that fell outside of grid cell boundaries, and in 8 cases where extra cameras allowed 2 stations within a cell, we randomly selected 1 station for analysis.

Markov Chain Monte Carlo simulation was used for estimation in WinBUGS v 1.4.3 (Spiegelhalter et al. 2003) through the R2WinBUGS package (Sturtz et al. 2005) in Program R (R Development Core Team 2013). Each simulation consisted of 3 chains with a burn-in of 2,000 iterations apiece, and 8,000 iterations (thinning rate = 8) used for posterior estimation. Prior distributions for detection and presence were distributed uniformly from 0 to 1. We assessed convergence using Gelman and Rubin's (1992) diagnostic, and assumed convergence if $\hat{R} < 1.01$. The observation process for surveys with non-random spatial replication can exhibit Markovian dependence upon observation in a previous segment (Hines et al. 2010, Karanth et al. 2011). However, our dog survey segments were often non-contiguous within cells, because teams left and re-entered cells along different paths, and exploratory likelihood-based consideration of this model suggested it was not competitive with the standard framework (Δ deviance >2).

To project the cumulative detection probability P^*, we extrapolated session-specific P for each method such that $P^* = 1 - (1 - P)^{\#\text{sessions}}$ (MacKenzie et al. 2006). We also derived a daily detection probability for dog surveys where 1 day was equal to the mean daily distance traveled by the team.

Cost Consideration

We summed total direct purchase or contract expenses and on-site logistical expenses (gas, vehicle rental, housing for dog teams) associated with both methods for our survey season. Hours associated with the lead author's time performing genetic analyses and in-field camera support were not tallied, so we used a US$38/sample cost for genetic identification alone based upon current genetic contracting charges (K. Pilgrim, United States Forest Service Rocky Mountain Research Station, personal communication), and doubled the calculated cost of technician assistance with camera checks and processing data at US$10/hr. We used these values to estimate cost per naive detection event. Because many survey efforts span multiple years, we extrapolated associated costs/detection over a 5-year period, assuming a 3% inflation rate for all costs. We assumed a 10% replacement rate for camera equipment annually based upon observed costs associated with subsequent camera surveys (J. D. J. Clare, unpublished data).

Determining Associations With Collection Accuracy

After scat samples were genetically confirmed as coming from bobcat or other species, we considered 12 candidate generalized linear models to explain successful collection using a logit link in R. We hypothesized the probability that a putative sample was genetically confirmed as bobcat might be related to the dog detecting the sample (Smith et al. 2003), the handler working with the dog, or the strength of the dog's reaction to the sample (Long et al. 2007*a*). We also considered the specific area in which the scat was collected because we hypothesized that differences in dietary overlap with co-occurring carnivores or bobcat density might influence the detection dogs' ability to differentiate between depositing species, or result in dog frustration (MacKay et al. 2008) that altered targeting behavior. These were all included as potential factorial covariates, with interactive and additive combination of dog × site, dog × handler, dog × response, and handler × response. We ranked models using Akaike's Information Criterion corrected for small sample size (AIC_c), and calculated the Akaike weight (w_i) for each model in order to infer its relative support (Burnham and Anderson 2002).

RESULTS

Comparing Detection Rates and Probability

Over 3,346 camera-trap-nights ($\bar{x} = 53$/station and 836/array), we recorded 129 detection events (3.8/100 trap-nights), for an average of 32 detections/array (SE = 11.3). Dogs surveyed 388 km over 44 survey-days ($\bar{x} = 8.8$ km/day) and collected 94 scat samples. Of these samples, 92 (98%) amplified sufficiently to determine the species of origin. We confirmed 59 samples (64%) as bobcat (1.34 samples/survey-day), for an average of 14.75 detections/array (SE = 3.3). One dog collected far more scat samples ($n = 71$ vs. $n = 23$), and more bobcat scat samples ($n = 39$ vs. 20, $T_+ = 0$, $P = 0.090$), though dog-specific survey effort was equitable (188 km vs. 200 km).

There was no significant difference between total detections for each method ($T_+ = 1$, $P = 0.140$; Table 1). Remote cameras and dogs detected bobcat in virtually the same proportion of grid cells (32 vs. 31, respectively; McNemar's $\chi^2 = 0.040$, df = 1, $P = 0.850$). Scat-detections were located roughly 3 times closer to cameras (792 m vs. 2,029 m) with bobcat detections than cameras without detections ($t = -6.751$, $P < 0.001$), though we excluded Navarino State Wildlife Area from this specific test because there were no camera detections to pair.

We estimated $\hat{p} = 0.311$ (95% CRI = 0.247–0.378)/week using cameras, and $\hat{p} = 0.135$ (95% CRI = 0.096–0.185)/km using dogs. Detection dogs surveyed an average of 8.8 km/day, and so we estimated $\hat{p}_{day} = 0.721$. These estimates suggested that it would require nearly 2 dog survey-days, 16 km of dog transect, or 7–8 weeks of camera deployment to achieve

Table 1. The total number of putative bobcat scats collected by scat-collecting dogs, the total number of samples genetically confirmed, and the number of bobcat photographic sequences recorded by remote cameras in at 4 sites during 2011 in central Wisconsin, USA.

Site	Scats collected	Scats confirmed	Camera detections
Clark County Forest	12	9	20
Mead State Wildlife Area	19	16	55
Navarino State Wildlife Area	30	8	0
Necedah National Wildlife Refuge	32	26	54

$P^* = 0.90$ if a bobcat was present, and roughly 4–5 weeks of camera deployment to exceed the detection probability of one dog survey-day.

Cost Considerations

Total costs associated with a single season of 2-dog surveys were 33% greater than those required by a camera survey, and subsequent annual costs for detection dogs were >3× greater than camera costs (Table 2). The predominant expense for both methods was upfront purchase or contract costs. Our observed cost per bobcat detection was US$606 using scat surveys and US$200/detection using cameras. Assuming constant detection rates over a 5-year period, the ratio in annual costs per detection by method doubled (US$682 for dogs, US$93 for cameras).

Determining Associations With Collection Accuracy

Of the 92 scat samples identified to species, 6 had to be censured from analysis because there was no information regarding the dog's response. The most supported model ($w_i = 0.93$) was an additive combination of the dog present and the study site; the only other model within 7 ΔAIC_c was an interaction between dog and site (Table 3). Within the top model, there were only 2 β parameters indicating differences between factorial covariates: one dog was more accurate than the other ($Z = 2.70$), and both dogs were less accurate at NSWA, where camera surveys failed to detect bobcats ($Z = -3.10$).

Table 3. The number of estimated parameters (K), second-order Akaike's Information Criterion score (AIC_c), and Akaike weight (w_i) for models of detection-dog scat-collection accuracy for bobcat at 4 64-km^2 sites in central Wisconsin, USA, in 2011.

Model	K	AIC_c	ΔAIC_c	w_i
Dog + site	5	92.82	0	0.93
Dog × site	8	98.74	5.92	0.05
Site	4	100.67	7.85	0.02
Dog	2	106.21	13.39	0.00
Dog + handler	3	106.94	14.12	0.00
Dog × handler	4	108.8	15.98	0.00
Dog + response	5	110.55	17.73	0.00
Dog × response	8	111.63	18.81	0.00
Handler	2	114.75	21.93	0.00
Handler + response	5	120.71	27.89	0.00
Response	4	121.59	28.77	0.00
Handler × response	8	123.01	30.19	0.00

DISCUSSION

In contrast to previous comparisons between detection dogs and cameras to survey bobcats (Harrison 2006, Long et al. 2007*b*), cameras detected more bobcat occurrences and were more cost-effective than detection dogs. Although both methods showed similar spatial patterns of bobcat detection, it is unclear whether differences in detection totals resulted from different numbers of individual bobcats detected or differences in individual detectability. Although we acknowledge that the length of our camera surveys led to field effort over distinct phenological seasons (Lovallo and Anderson 1996) and may weaken direct comparison, camera-detection rates were greater in mid-summer when dogs were surveying.

Despite Wisconsin's comparatively low bobcat density (Roberts and Crimmins 2010), we found comparatively high rates and probability of camera-based detections. Observed camera-detection rates were equal to or greater than southwestern U.S. surveys where cameras were placed along dry creek beds (3.57 detections/100 trap-nights; Harrison 2006) or linear features (0.57–1.57/100 trap-nights; Larrucea et al. 2007). These studies used film-based cameras, and differences in detection rates may partially be due to improvements in digital equipment, such as greater image-storing capacity, larger detection zones within which animals could trigger the camera, and faster trigger recovery times. Many felid species are far more detectable to cameras on-trail (Sollman et al. 2011, Mohamed et al. 2013). Thus, our placement of cameras along travel paths rather than baited sites off-trail (e.g., Gompper et al. 2006) may have also improved detection rates and the technique's comparative value. For example, our estimate of detection probability was more than double those produced by baited camera surveys in comparable latitudes (Moruzzi et al. 2002, Long et al. 2007*b*). However, these studies were also conducted during months when prey was more available. Baited surveys may be more effective in winter when space use is naturally more diffuse and prey availability is more limiting (e.g., Stricker et al. 2012).

Table 2. Annual costs (US$) associated with detection-dog and camera surveys for bobcat at 4 64-km^2 sites in central Wisconsin, USA, in 2011. Costs are projected over a 5-year sampling period assuming 3% inflation and 10% annual camera replacement.

Year	1		2		3		4		5	
Method	Scat	Camera	Scat	Camera	Scat	Camera	Scat	Camera	Scat	Camera
Purchase	27,539[a]	18,828[b]	28,365	1,939	29,216	1,997	30,093	2,057	30,995	2,119
Logistical support[c]	4,653	1,981	4,793	2,040	4,936	2,102	5,084	2,165	5,237	2,230
Lab costs	3,572	0	3,679	0	3,789	0	3,903	0	4,020	0
Field labor[d] ($10/hr)	0	6,000	0	6,180	0	6,366	0	6,566	0	6,754
Total	35,764	26,809	36,837	10,159	37,941	10,465	39,080	10,788	40,252	11,103

[a] Cost for contracting dogs, hourly wage for handlers, training costs at organization headquarters, transport to site, and overhead.
[b] Cost of remote cameras, cable locks, Secure Digital cards, and 6 camera security boxes.
[c] On-site costs including gas, and housing and rental vehicles for detection-dog teams.
[d] Labor costs associated with student field assistants.

Although the low density of bobcats in the study area is a presumed cause of our comparatively low scat-collection rates (Long et al. 2007*a*), differences in scat persistence may also be a major factor. Harrison (2006) collected >10 times as many bobcat scat samples per km (1.73 vs. our observed 0.17) in New Mexico, USA, and Vynne et al. (2010) collected low-density puma (*Felis concolor*) and jaguar (*Panthera onca*) scats in the Brazilian Cerrado at a comparable rate (0.09 samples/km and 0.18 samples/km). Scat collection per km and per day was roughly 92% and 75% lower than scat surveys conducted by humans for snow leopard (*Uncia uncia*; Janecka et al. 2011). Our study area's relatively moist climate in conjunction with heavy rain in July 2011 (18 cm) may have accelerated scat decomposition (Reed et al. 2011).

Sampling design may have also limited scat detection. Our point estimate of detection probability per km was 30% less than a study based around off-trail visits in a similar climatic region (Long et al. 2007*a*). Although felid species seem to preferentially travel along linear features, their defecation locations may be dictated more by territorial boundaries (MacDonald 1980), and collection rates on and off trail can be equivocal (Vynne et al. 2010). Vehicular traffic may have further removed samples, because the site with the smallest sample size (Clark County Forest) was the only site allowing all-terrain vehicle use.

Determining Associations With Collection Accuracy

We found that the probability that a collected scat was confirmed as bobcat was most influenced by the dog present at collection and whether the sample was collected at one site where we failed to detect bobcats using cameras. Dogs can become frustrated when rarely rewarded (MacKay et al. 2008), and it appears that the density of the target species or the rate of scat decomposition influence both the collection rate and the accuracy of collected samples. Genetic results were poorly predicted by handler confidence in the dog's response; therefore, we warn that *in situ* screening or validation measures (e.g., Harrison 2006, Long et al. 2007*a*) may not be particularly useful, particularly if the dog's behavior is purely motivated by reward (MacKay et al. 2008). If a detection dog's drive for reward causes false-indicating behavior in the absence of target species, the technique may be more suitable for cryptic species existing at high density rather than low density.

Because there were clear differences in collection totals and accuracy between dogs, we recommend that organizations contracting dogs provide information on the characteristics of specific animals. Different attributes may be desirable for different survey objectives, locations, or constraints. Assuming minimal inter-year variance, an extremely accurate dog might be more useful when attempting to ascertain presence if effort and laboratory costs need to be minimized, while a dog with greater collection rates would be more useful for capture–recapture analysis for surveys with greater budgets. However, understanding the consistency of dog-specific attributes across separate projects remains a research need.

Cost Considerations

On a temporal basis, detection dogs were far more efficient than cameras. The 8 weeks estimated to generate a 90% detection probability of bobcats with cameras may violate assumptions of closure (Otis et al. 1978), and this requires great upfront equipment costs in order to generate adequate spatial coverage for any survey effort. In contrast, scat surveys sample backward in time (MacKay et al. 2008). This may be one reason that other studies with shorter camera-survey durations may have found detection dogs more cost-efficient on a 'per survey' basis (Harrison 2006, Long et al. 2007*b*). Detection dogs also offer other survey advantages. They can be useful when species have short detection windows (e.g., Duggan et al. 2011), or are otherwise only detectable using bait (e.g., Thompson et al. 2012). Finally, the information contained in a scat sample can be used to test diverse objectives (Wasser et al. 2004).

Yet the trade-offs between detection-dog efficiency and their cost (e.g., Long et al. 2007*b*) may be disproportionate. The functional difference between camera and detection-dog expenses are that the large initial investment associated with the former is much reduced in subsequent years, while contracted dogs require a larger constant investment annually. Camera cost structure enables an investigator to make up for the initial purchase with longer seasonal deployment and multiple field seasons. Furthermore, the cost of camera equipment varies widely, and many models can be purchased for less than half of the unit cost we paid. Although theft and vandalism remain risks for camera surveys, investigators considering security when selecting sites and requisite protection mechanisms can reduce these risks (e.g., Clarin et al. 2014).

In contrast, despite minor differences in expense categories, the seasonal cost of contracting detection-dog teams was essentially fixed between all organizations we sought to contract. This has 2 practical consequences. First, the ongoing rental cost of detection-dog teams makes surveys over several seasons very expensive (>US$30,000 annually for 4 weeks with 2 teams). This cost may be difficult to justify if dogs are not targeting multiple species (e.g., Long et al. 2007*a*, Vynne et al. 2010) and is more expensive than leasing a dog and training handlers (Long et al. 2007*b*). Secondly, the cost makes it very difficult to balance sampling return with experimentation. Although we found our contractors very knowledgeable about the environments and designs in which detection dogs are most useful (H. Smith, Center for Conservation Biology, University of Washington, personal communication), there is little quantitative peer-reviewed information about dog performance under a wide range of real survey or environmental conditions.

Contracting detection-dog surveys may be a qualified risk when applied to novel organisms or survey designs. Renting only dogs themselves may alleviate expenses, and purchasing dogs may be the best investment for scat surveys (Long et al. 2007*a*), but dog-specific variation remains an investment risk. We encourage users of detection dogs to continue reporting dog-specific collection data, and expect

that survey efficacy parameters will become more transparent as detection dogs receive more use.

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