Biological Conservation 153 (2012) 219–226

Contents lists available at SciVerse ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

A collaborative approach for estimating terrestrial wildlife abundance

Jason I. Ransom [a,*], Petra Kaczensky [b], Bruce C. Lubow [c], Oyunsaikhan Ganbaatar [d,e], Nanjid Altansukh [d]

[a] US Geological Survey, Fort Collins Science Center, 2150 Centre Avenue, Building C, Fort Collins, CO 80526, USA
[b] Research Institute of Wildlife Ecology, University of Veterinary Medicine, Savoyenstrasse 1, A-1160 Vienna, Austria
[c] Natural Resource Ecology Laboratory, Colorado State University, Fort Collins, CO 80523, USA
[d] Great Gobi B Strictly Protected Area, Mongolia
[e] International Takhi Group, Switzerland

ARTICLE INFO

Article history:
Received 17 January 2012
Received in revised form 1 May 2012
Accepted 12 May 2012

Keywords:
Asiatic wild ass
Distance sampling
Equus
Gazelle
Gobi
Khulan
Mongolia
Point count
Population estimation

ABSTRACT

Accurately estimating abundance of wildlife is critical for establishing effective conservation and management strategies. Aerial methodologies for estimating abundance are common in developed countries, but they are often impractical for remote areas of developing countries where many of the world's endangered and threatened fauna exist. The alternative terrestrial methodologies can be constrained by limitations on access, technology, and human resources, and have rarely been comprehensively conducted for large terrestrial mammals at landscape scales. We attempted to overcome these problems by incorporating local peoples into a simultaneous point count of Asiatic wild ass (*Equus hemionus*) and goitered gazelle (*Gazella subgutturosa*) across the Great Gobi B Strictly Protected Area, Mongolia. Paired observers collected abundance and covariate metrics at 50 observation points and we estimated population sizes using distance sampling theory, but also assessed individual observer error to examine potential bias introduced by the large number of minimally trained observers. We estimated 5671 (95% CI = 3611–8907) wild asses and 5909 (95% CI = 3762–9279) gazelle inhabited the 11,027 km^2 study area at the time of our survey and found that the methodology developed was robust at absorbing the logistical challenges and wide range of observer abilities. This initiative serves as a functional model for estimating terrestrial wildlife abundance while integrating local people into scientific and conservation projects. This, in turn, creates vested interest in conservation by the people who are most influential in, and most affected by, the outcomes.

Published by Elsevier Ltd.

1. Introduction

Estimating abundance is one of the most important prerequisites for the conservation and management of wildlife because it defines the need and scope of human action. Aerial surveys are often used to sample large mammal populations and generate statistical estimates of abundance (Caughley, 1977; Melville et al., 2008). While managers and practitioners in developed countries often have access to aircraft and technology to help accomplish this task, many of the world's endangered and threatened fauna exist in remote areas of developing countries where terrestrial access, technology, aircraft availability, and skilled human resources are extremely limited. Attempts at surveying wildlife abundance in such areas may be further complicated by the effects of low density on estimators (Barnes, 2002). Wildlife can thus decline rapidly without detection and the needed conservation actions may be implemented too late, if at all (Karanth et al., 2003).

Statistical sampling techniques have been used to estimate animal abundance for decades (Schwarz and Seber, 1999; Williams et al., 2002). The most developed, and best understood, methods include variations of double sampling, mark-resight (batch-marked animals), mark-recapture (uniquely-marked animals), sightability bias correction models, and distance sampling (Barker, 2008). Recently, researchers have begun to combine these techniques to create synergistically more effective methods (Laake et al., 2008; Lubow and Ransom, 2009), but even in light of such statistical advances the logistical problem of surveying remote areas with constrained resources has not been well-addressed.

Estimating Asiatic wild ass (*Equus hemionus*) and goitered gazelle (*Gazella subgutturosa*) abundance across the vast expanse of the Great Gobi B Strictly Protected Area (SPA), Mongolia, exemplifies this problem. Animals are distributed across the entire area, reliable aircraft are unavailable, and access is limited in the park (Kaczensky et al., 2008). Asiatic wild ass are now listed as endangered (IUCN, 2010) and anecdotal and scientific evidence suggest that abundance has declined globally by more than 50% over the past two decades. The Gobi region has long been a stronghold for the wild ass, though the species has disappeared from the vast

* Corresponding author. Address: National Park Service, 1201 Oakridge Drive, Suite 200, Fort Collins, CO 80525, USA. Tel.: +1 9702253584; fax: +1 9702253585.
E-mail address: Jason_I_Ransom@nps.gov (J.I. Ransom).

0006-3207/$ - see front matter Published by Elsevier Ltd.
http://dx.doi.org/10.1016/j.biocon.2012.05.006

majority of its historic range (Feh et al., 2001; Reading et al., 2001; Kaczensky et al., 2011). Goitered gazelles are classified as a vulnerable species by IUCN (2010) and while little is known about current populations, it is believed that their numbers are declining and Mongolia may contain the majority of the global population (Reading et al., 1999). Well-informed abundance estimates are needed to direct conservation plans and prompt action for the remaining populations of both species.

Conservation of species such as Asiatic wild ass and goitered gazelle can be challenging, even when protected areas are designated. Indigenous peoples often rely heavily on ecosystem services, and when national parks and protected areas exclude participation of adjacent indigenous communities from resource management decisions, conservation efforts may be undermined (McNeely et al., 1990; Adams et al., 2004; Corbera et al., 2007). Land use between native wildlife and pastoralists overlaps across most of Mongolia. Interviews of pastoral families in the Gobi region indicated that while some people regularly utilize wild asses for food and others consider them only as competition with livestock, many are interested in pursuit of conservation efforts (Kaczensky et al., 2006). We embraced this perspective to develop a community-based initiative for estimating wildlife abundance in the Great Gobi B SPA using a large-scale simultaneous point count across the entire area, and subsequently modeled the count data to generate estimates of abundance. This initiative illustrates a functional model for integrating local people into scientific and conservation projects by bringing them into protected areas, incorporating them directly into the science, and exposing them first-hand to the value of resource conservation. This collaboration in turn can create vested interest in conservation by the people who are most influential in, and most affected by, the outcomes (Danielsen et al., 2008; Reed, 2008).

2. Study area

The Great Gobi B SPA consists of 9265 km^2 desert and steppe biomes and our study area incorporated an additional 1762 km^2 of adjacent lands where wild asses have been known to roam (Feh et al., 2001; Kaczensky et al., 2008, 2011). Plains dominate the east and rolling hills populate the west. Elevations range from 1000 to 2840 m above sea level, with the Altai Mountains forming a northern boundary to the park and several mountain ranges forming the southern border with China. Desert environments are dominated by saxaul (*Haloxylon ammodendron*), which in places can be large enough to obscure views of asses or gazelles from observers. Steppe environments are dominated by Poaceae such as *Stipa* spp. and *Ptilagrostis* spp. Sympatric indigenous ungulates in this ecosystem are wild horse (*Equus ferus przewalskii*) on the plains, and argali (*Ovis ammon*), and Siberian ibex (*Capra sibirica*) in the mountains.

3. Methods

3.1. Field methodology

A combination of mark-resight and distance sampling techniques, similar to that described by Kissling and Garton (2006), was employed at observation points across the entire study area. We conducted this simultaneous point count using pairs of observers at 25 observation points in the eastern half of the park on 5–6 August, 2010, and then relocated the teams to count from an additional 25 observation points in the western half of the park on 7–8 August, 2010 (Fig. 1). The team was comprised of 4 organizers (2 Mongolian, 1 American, 1 Austrian), 24 local pastoralists, 7 park staff, 3 park rangers from nearby Shargen Gobi Saiga Reserve, and 12 university students and instructors (9 Mongolian, 3 German). Everyone was trained in equipment use and data collection protocols in the days preceding the survey. This training involved a classroom overview of survey history, project design, and data collection by the organizers, followed by a day of field practice where observers used compasses and rangefinders to measure targets at known distances. For field deployment, each pair of observers was equipped with a watch, binoculars, a customized optical rangefinder (see Ransom, 2011), standard map compass, pencils, and datasheets, as well as food and water.

Each observer at each point was instructed to collect data independently, with the first observer conducting a complete 360° survey and then passing the equipment to the second observer who subsequently conducted another complete 360° survey. Observers were instructed not to share datasheets or communicate between observations. Surveys from all points were conducted simultaneously at 20:00 h, after which observers slept at their observation points and then conducted surveys again at 07:00, 09:00, 11:00, 13:00, and 15:00 h for a total of 6 complete surveys at each point. All observers rendezvoused at a central point upon completion of the eastern 25 points to provision and review data collection efforts, and then were re-deployed to the remaining 25 observation points in the west.

Data collected at each observation included time, species, number of adults, number of offspring, vegetation type (shrub or open), behavior (laying, standing, running), discrete distance category (0–100 m, 101–500 m, 501–1000 m, 1001–2000 m, 2001–5000 m, 5001–7000 m), and compass bearing. Because discernment of adults versus offspring was inconsistent at long distances, we used only total count of individuals for analyses. Rangefinder capability was limited to 2500 m and the farthest distance categories were visually estimated. A single compass bearing was recorded at the center of small groups or a range of bearings was recorded for the endpoints of large dispersed groups. Covariate data for sun effect was calculated a posteriori as described in Ransom (2012) using data consisting of time of observation, compass bearing, observation latitude and longitude, and solar position information from the National Oceanic and Atmospheric Administration solar calculator (http://www.srrb.noaa.gov/highlights/sunrise/sunrise.html, accessed August 24, 2010).

3.2. Geographic information system (GIS) data

Observation points were chosen using a stratified random sample by overlaying a 15 km by 15 km grid across the study area and randomly selecting one elevated point in each cell. This allowed us to maximize the field of view and we defined the maximum viewing distance as 7000 m. The visible area from each observation point was calculated using the surface analysis option "viewshed" of the Spatial Analyst extension in ArcGIS 9.3 (Environmental Systems Research Institute, Redlands, California, USA). We used a digital elevation model (DEM) at 90 m spatial resolution obtained from the Shuttle Radar Topography Mission tiles for Mongolia and northern China (http://glcf.umiacs.umd.edu) for these analyses.

We anticipated that delimiting high and low density wild ass areas within the study area would decrease the encounter rate variance attributed to gregarious behavior; therefore, we attempted to stratify wild ass data by modeling habitat selection as a function of elevation, slope, vegetation type, distance from water, and normalized difference vegetation index (NDVI). We used linear regression to model these effects for detected groups and 1000 random points (within the visible radius of the 50 observation points). A group was defined as one or more animals in close proximity to each another. Elevation, slope, and distance from water for each location were calculated using the GIS data. Main vegetation types were classified from satellite imagery by von Wherden et al. (2006). NDVI data was derived from a Moderate

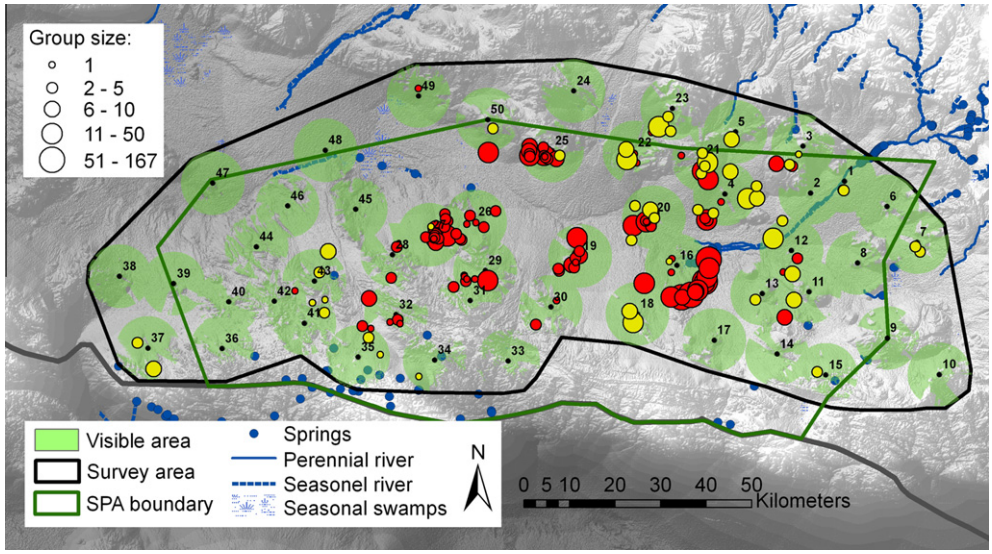

Fig. 1. Location of 50 observation points and viewsheds for an abundance survey of Asiatic wild ass (red: *Equus hemionus*) and goitered gazelle (yellow: *Gazella subgutturosa*) in the Great Gobi B Strictly Protected Area, Mongolia, during a survey at 09:00 h, August, 2010. Each point is located on an elevated area and contains a 7 km radius sampling area.

Resolution Imaging Spectroradiometer (MODIS) scene for 27 July–08 August 2010 and made available by the National Aeronautics and Space Administration (http://modis.gsfc.nasa.gov/data). We did not attempt to delimit high and low density gazelle areas because the animals have historically been observed widely, but in small numbers, across the entire study area, and we anticipated that sample size would be too small to model habitat selection meaningfully.

3.3. Statistical analyses

Regressions for habitat stratification and summary statistics were conducted using R version 2.12.1 (The R Foundation for Statistical Computing, 2010). Count data were analyzed in Program Distance version 6.0 (Thomas et al., 2010) using the conventional distance sample option and the total study area size of 11,027 km^2. We pooled data across all 6 surveys for the purpose of fitting the detection function; we had no a priori reason to expect that the detection function would vary systematically by time of day and separate detection functions would have been fitted with insufficient observations to be reliable. We tested pooled and unpooled normal probability distribution models for cluster size and encounter rate and compared them using AIC$_c$ (Burnham and Anderson, 2002). We weighted the data by number of survey occasions.

Because the presence of an observer could have displaced animals away from the observation point ($g(0)$), we combined the 0–100 m and 100–500 m categories into 0–500 m, assuming that animals were not systematically displaced beyond that distance. We assumed no animals were missed at zero distance ($g(0) = 1$) due to the relatively large body size, lack of tall vegetation, and typical behavior of the species. We fit detection functions to 3 alternatives for the remaining distance bins: (1) all 5 recorded bins: 0–500 m, 500–1000 m, 1000–2000 m, 2000–5000 m, 5000–7000 m; (2) 4 bins with observations between 2000 and 7000 m pooled; and (3) 4 bins with observations >5000 m dropped (right truncation).

We considered both half normal and hazard rate key functions with cosine and simple polynomial adjustment terms; however, we limited the number of adjustment terms to allow at least 1° of freedom for estimating the χ^2 goodness-of-fit (GOF) test. With 5 distance bins, all models had $\leqslant$3 parameters (hazard rate plus $\leqslant$1 adjustment term or half normal plus $\leqslant$2 adjustment terms) and for 4 bins all had $\leqslant$2 parameters (hazard rate with no adjustments terms or half normal with $\leqslant$1 adjustment term). When regression for detection $g(x)$ of different size groups (clusters) of animals was significant at $P = 0.15$, we used the regression ln(cluster size) against the estimated $g(x)$; otherwise, we used the mean cluster size.

We evaluated individual observer error (missed or detected groups known from paired independent observations) using mixed-effect logistic regression to model detection probability as a function of group size, behavior, vegetation type, sun effect (position of the sun in relation to the observer), and status (wildlife professional or not), with individual observer as a random effect on the model intercept to account for repeated measures. This was conducted using the lme4 package of R version 2.12.1. Model fit was evaluated by calculating area under the receiver operating curve (AUC) with function somers2 in R package Hmisc, using the fixed effect predictions while holding random effects at zero. Observers in two pairs collected data cooperatively instead of independently and one observer counted alone, so those records were omitted from of the individual observer detection probability analyses. Matching observation records was achieved by comparing compass bearing, distance, and group size data: when group size differed slightly between observations, we used the larger of the two counts under the assumption that one observer could have missed some individuals, but the other observer could not have counted individuals that weren't present.

4. Results

4.1. Surveys and stratification

Across the 300 possible survey occasions (6 surveys at each of 50 points), we completed 296, with 4 missed (1 at each of 4 points) due to transportation failures. We detected 432 wild ass groups and 148 goitered gazelle groups across all surveys. These sums include only unique groups per survey and exclude duplicate observations within observer pairs. Wild asses were not distributed equally across the study area, and central regions of the study area appeared most densely populated while areas in the west were

Table 1
Summary statistics of direct observations of Asiatic wild ass (*Equus heminous*) and goitered gazelle (*Gazella subgutturosa*) during 6 sequential surveys from 20:00 to 15:00 h at 50 observation points in the Great Gobi B Strictly Protected Area, Mongolia, August 2010.

	Survey time (hours)					
	20:00	7:00	9:00	11:00	13:00	15:00
Asiatic wild ass						
Total observed	1210	654	1038	1140	1141	1140
Number of groups	73	73	106	67	62	51
Mean group size	16.56	8.96	9.79	17.02	18.4	22.35
Standard error of mean	4.51	3.07	2.19	5.12	7.39	15.35
Minimum group size	1	1	1	1	1	1
Maximum group size	300	210	167	236	439	786
Encounter rate (groups/km^2)	1.46	2.12	1.34	1.24	1.02	1.52
Goitered gazelle						
Total observed	82	212	275	84	34	29
Number of groups	21	36	48	25	10	8
Mean group size	3.91	5.89	5.73	3.36	3.4	3.63
Standard error of mean	0.669	1.22	0.806	0.483	0.702	0.8
Minimum group size	1	1	1	1	1	1
Maximum group size	12	37	29	11	8	7
Encounter rate (groups/km^2)	0.72	0.96	0.50	0.20	0.16	0.40

noticeably vacant (Fig. 1). Regression analyses of wild ass abundance as a function of slope ($t = 0.476$, $P = 0.634$), elevation ($t = -0.568$, $P = 0.570$), distance to water ($t = 1.484$, $P = 0.138$), vegetation type ($t = -0.094$, $P = 0.925$), and NDVI ($t = 0.883$, $P = 0.377$) produced no clear evidence that wild asses were selecting habitat based on these factors at the time of the survey; consequently, we analyzed density of the entire study area with no stratification.

Viewshed calculations indicated that up to 29.13% of the total area across all observation points may have been unavailable due to topographic obstructions. Because this primarily affected available survey area in the distant categories rather than at 0–500 m, was too fragmented to practically delineate areas as unavailable, and the obstructions were primarily mountainous terrain where asses and gazelle were unlikely to be, we chose the conservative approach of including the entire area in the modeling effort rather than removing large radial wedges from the observation circle (Buckland et al., 1993). This could have inflated the variance considerably because of drastically reduced sample size and resulted in less informative abundance estimates.

4.2. Asiatic wild ass abundance

Wild ass group size ranged 1–786 animals and encounter rate ranged 1.02–2.12 groups/km, with the highest direct count occurring just before sunset and the lowest direct count occurring just after sunrise (Table 1). Nevertheless, a single average group size estimate across surveys was strongly favoured over separate estimates for each survey (AIC_c evidence ratio = 28.0). A single mean encounter rate for wild ass groups across the 6 surveys was preferred to separate estimates (AIC_c evidence ratio = 22.9); consequently, we used pooled data weighted by survey effort for wild ass to estimate group size, encounter rate, and detection function.

Distance data were obtained for all 432 wild ass groups detected during the 6 surveys, but only 297 groups were detected at distances <5000 m. With 5 distance bins, none of the models fit adequately ($P < 0.001$ for all detection function shapes; Fig. 2). With the outermost distance bins pooled, model fit improved slightly, but adequate fit was still rejected for all detection function shapes ($P = 0.394$ for the best fitting model). However, with data

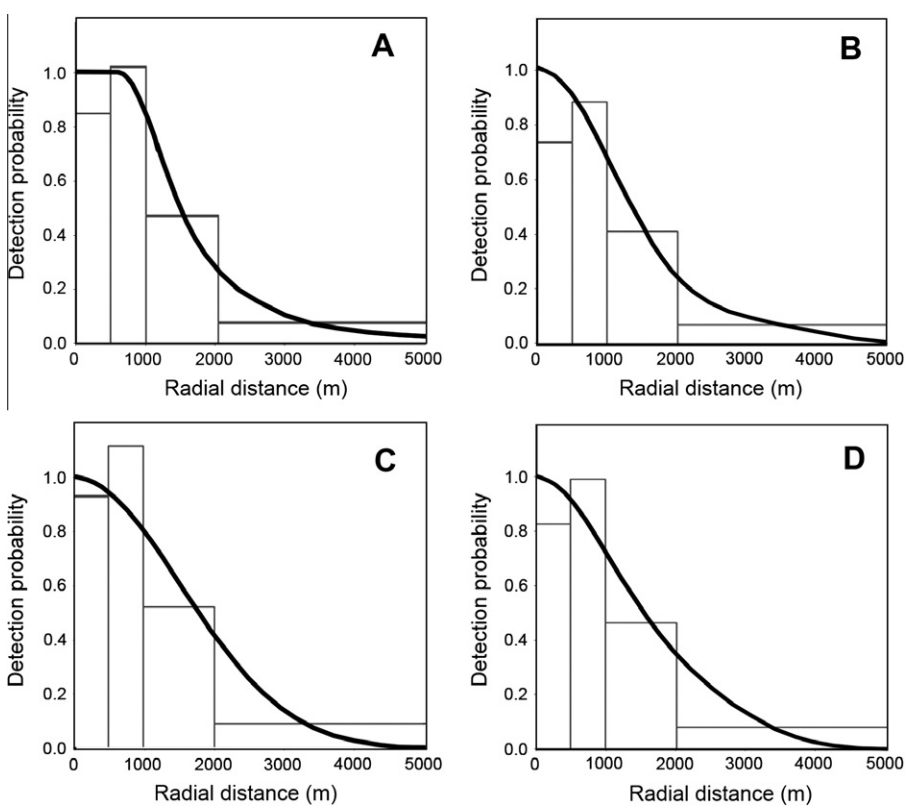

Fig. 2. Detection functions (bold lines) fit to Asiatic wild ass (*Equus hemionus*) data from a point count in the Great Gobi B Strictly Protected Area, Mongolia, August 2010, shown in order of descending AIC_c model weight: hazard rate (A), half normal with cosine adjustment (B), half normal (C), and half normal with simple polynomial adjustment (D).

Table 2
Model ranking and estimates of Asiatic wild ass (*Equus heminous*) abundance from a point count in the Great Gobi B Strictly Protected Area, Mongolia, August 2010. Models are ranked by change in corrected Akaike's Information Criteria (AIC_c; Δ_i) and AIC_c weight among all candidate models (w_i). Goodness of Fit (GOF) is shown as probability (*P*).

Detection function	Δ_i	w_i	Estimate	SE	CV	GOF *P*
Hazard rate, No. adjustments	0.00	44.1	5505	1145	20.8	0.404
Half normal, cosine adjustments	1.08	25.7	6368	1318	20.7	0.189
Half Normal, No. adjustments	2.02	16.1	5026	869	17.3	0.084
Half normal, polynomial adjustments	2.29	14.0	5657	1816	32.1	0.079
Model weighted		100.0	5671	1324	23.3	

truncated at 5000 m, all 4 detection function shapes fit adequately and each received some support from the data (Table 2); consequently, we use model-weighted averaging of the 4 models with truncation at 5000 m to estimate the final population abundance as 5671 wild asses (95% CI = 3611–8907) with CV = 23.3%.

In the most strongly supported model (unadjusted hazard rate), the overall detection probability was just 18.4% (7.8% CV) and effective detection radius was 2142 m (3.9% CV). Mean encounter rate was 1.00 groups/km (10.2% CV). After truncation at 5000 m, cluster size regression was not supported ($P = 0.559$); therefore we used the estimated mean cluster size of 6.5 (11.7% CV). Uncertainty in the abundance estimate was mostly due to estimation uncertainty in the cluster size (45.5% of the variance), followed by the encounter rate (34.4%), and the detection function (20.1%).

4.3. Goitered gazelle abundance

Gazelle group size ranged 8–48 animals and encounter rate ranged 0.16–0.96 groups/km (Table 1). There was strong evidence for differences in both group size and encounter rate by survey occasion. The temporal pattern for both parameters confirmed field observations that gazelle were typically active in the cool morning hours and more difficult to observe while bedded during hot afternoon hours (Table 1). Imperfect visibility at even the closest distance would invalidate the assumptions of distance sampling and could produce negatively biased estimates of group size and encounter rate. The evidence ratios supporting the use of 2 separate means (2 morning surveys at 0700 h and 0900 h; versus the other 4 surveys) for encounter rate was preferred over 6 individual means (AIC_c evidence ratio = 3.41) and over a single mean (AIC_c evidence ratio = 5915). Two means were preferred for group size over 6 separate means (AIC_c evidence ratio = 68.86) and over a single mean (AIC_c evidence ratio = 11.07). Given the observed behavior pattern and statistical evidence, we estimated group size and encounter rate using pooled data for the 2 occasions during morning survey periods (mean group size = 5.16 and encounter rate = 0.84).

Of the 148 gazelle groups detected, 84 occurred during the 2 morning survey occasions and 71 of these were at distances <5000 m. For the 3 alternative ways of handling the farthest distance categories, both the hazard rate detection function and the half normal with a cosine adjustment term fit adequately, but the remaining 2 detection function shapes did not (Table 3; Fig. 3). Consequently, we used model averaging for the top 2 right-truncated models to arrive at our best estimate of gazelle abundance with an overall detection probability of 8.9% (CV = 29.6%). Effective detection radius was 1488 m (CV = 14.8%). The cluster size regression was not significant ($P = 0.778$), so mean cluster size of 5.7 (CV = 13.4%) was used in the abundance computation. Mean encounter rate was 0.72 gazelle groups/km (CV = 2.7%). Most of the variance in the abundance estimate was due to the detection probability estimate (82.3%); cluster size contributed 17.0% and encounter rate merely 0.7% of the variance. Our best model-weighted estimate of abundance was 5909 gazelle (95% CI = 3762–9279) with CV = 31.8%.

4.4. Observer bias

Of 336 known wild ass groups detected, 23.2% were missed by the first observers and 25.0% were missed by the second observers, with an average effect of 24.1% more groups being detected by having two observers at each point. Likewise, of the 130 known gazelle groups detected independently, 37.7% of known gazelle groups were missed by the first observers and 25.4% were missed by the second observers, with an average effect of 31.6% more groups being detected by having two observers at each point.

Mixed-effect logistic regression of detection probability by individual observers (AUC = 0.804) indicated group size was an important factor in their ability to detect wild asses ($z = 3.524$, $P < 0.001$), which supports the 45.5% variance attributed to uncertainty in group size reported above. The poorest observer detected 66.6% (95% CI = 66.1–67.1) of 3-ass groups (median group size) and the best observer detected 98.3% (95% CI = 98.3–98.3) of 3-ass groups; however, detection probability for all observers increased with group size and nearly all large groups (>40) were seen (Fig. 4). There was no difference in detection of wild asses in open or shrub vegetation ($z = -0.016$, $P = 0.987$), exhibiting lying, standing or running behavior ($z = 0.018$, $P = 0.985$), or due to angle of the sun in relation to the observation direction ($z = -0.337$, $P = 0.706$). Group size was not a factor in detection of gazelles ($z = -0.450$, $P = 0.652$), which is reflected in the 0.7% of variance reported above; likewise, there were no statistical differences in gazelle detection in open or shrub vegetation ($z = 0.796$, $P = 0.426$), exhibiting lying, standing or running behavior ($z = 0.140$, $P = 0.889$), or due to angle of the sun in relation to the observation direction ($z = -0.098$, $P = 0.921$). There were no cases of shrub cover at

Table 3
Model ranking and estimates of goitered gazelle (*Gazella subgutturosa*) abundance from a point count in the Great Gobi B Strictly Protected Area, Mongolia, August 2010. Models are ranked by change in corrected Akaike's Information Criteria (AIC_c; Δ_i) and AIC_c weight among all candidate models (w_i). Goodness of Fit (GOF) is shown as probability (*P*).

Detection function	Δ_i	w_i	Estimate	SE	CV	GOF *P*
Hazard rate, No. adjustments	0.00	58.5	6519	2125	32.6	0.193
Half normal, cosine adjustments	0.69	41.5	5047	1124	22.3	0.108
Half normal, No. adjustments[a]	4.06		4090	1107	27.1	0.010
Half normal, polynomial adjustments[a]	4.52		3590	640	17.8	0.008
Model weighted		100.0	5909	1882	31.8	

[a] Not included in model weighted average results due to poor fit and $AIC_c > 4.0$.

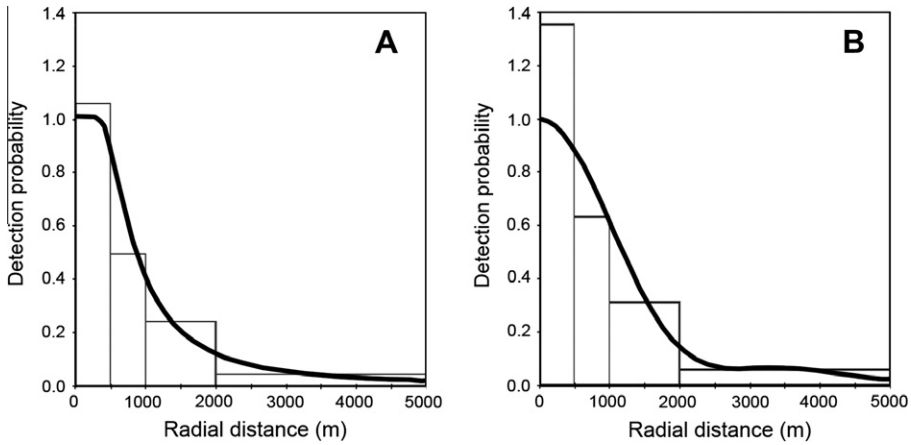

Fig. 3. Detection functions (bold lines) fit to goitered gazelle (*Gazella subgutturosa*) data from a point count in the Great Gobi B Strictly Protected Area, Mongolia, August 2010, shown in order of descending AIC_c model weight: hazard rate (A), half normal with cosine adjustment (B).

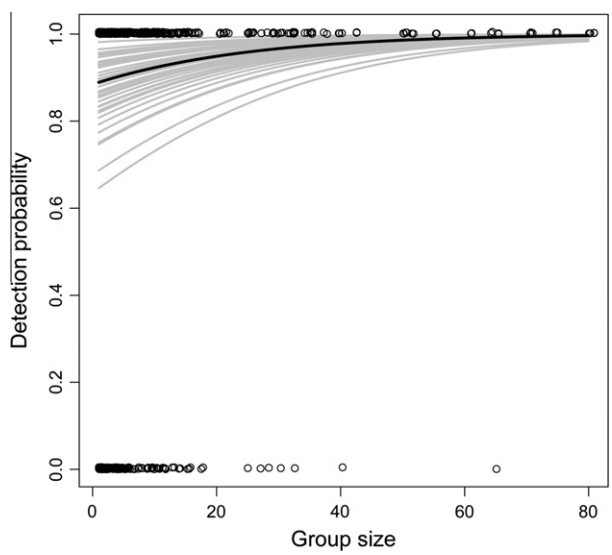

Fig. 4. Detection probability as a function of Asiatic wild ass (*Equus hemionus*) group size ($N = 336$ groups) estimated by mixed-effect logistic regression (black line) of 45 independent observers (gray lines) in a survey of the Great Gobi B Strictly Protected Area of Mongolia. Groups (○) are offset by a small random value to help visually distinguish points. Eleven groups of 92–786 asses are included in the model, but are too large to appear in the figure.

$g(0)$, indicating that while 46.1% of wild ass groups and 43.3% of gazelle groups were observed in shrub vegetation, any effect of obscuring vegetation was incorporated into the detection function. The status of observer as either a wildlife professional or not had no influence on detection probability for either species (wild ass: $z = 1.274$, $P = 0.203$; gazelle: $z = -0.262$, $P = 0.793$).

5. Discussion

Estimating wildlife abundance using terrestrial-based methods is challenging and fraught with logistical constraints that often produce poor estimates. This can result from an insufficient proportion of the inference area being sampled, poor access resulting in nonrandom transect placement, high variability in group size and encounter rate, wildlife movement prior to detection, and a number of factors influencing observation error. Such problems have been evident in previous surveys of wild ass and goitered gazelle in the Gobi (Feh et al., 2001; Reading et al., 2001; Kaczensky et al., 2007; Lkhagvasuren, 2007; P.K., unpublished data). We overcame some of these challenges by using a community-based large-scale point survey across the Great Gobi B SPA and our best estimate of these populations was 5671 (95% CI = 3611–8907) wild ass and 5909 (95% CI = 3762–9279) goitered gazelle. The coefficient of variation for both estimates was still somewhat higher than desired (23.3% for asses, 31.8% for gazelle), but was more precise for asses than many previous attempts to estimate this population (P.K., unpublished data).

Terrestrial-based distance sampling, especially in the point-count form, has historically been used for estimating abundance of avian fauna (Buckland, 2006). Terrestrial applications in line transect form have been applied to large mammal species ranging from primates (Plumptre, 2000) to deer (Marques et al., 2001) to elephants (Barnes, 2002), but most surveys have been conducted using few observers traversing fixed transects along roads and trials. The difficulty in adequately sampling from large spatial areas can be a limitation for terrestrial-based surveys, but we demonstrate here that it is feasible and can be a useful tool for estimating large mammal abundance across vast terrestrial areas. We also demonstrate that the point-count form can overcome some of the problems previously experienced with terrestrial distance sampling.

Examples of large, collaborative, terrestrial wildlife surveys are scarce in the literature, but are undoubtedly more common in practice. Jachmann (2002) and Msoffe et al. (2009) both compared smaller-scale terrestrial surveys with aerial surveys and reported higher precision in terrestrial applications. Barnes (2002) also demonstrated advantages of terrestrial counts over aerial counts for rare species. We could find few examples of landscape-scale, community-based, large terrestrial mammal abundance surveys. The Great Mara Count, which incorporated 84 people directly counting 43 species over the 2212 km^2 area at Maasai Mara Reserve, Kenya (Reid et al., 2003), and the Zambezi Valley, Zimbabwe surveys that incorporated indigenous peoples to perform line transect surveys across 2044 km^2 (Gaidet et al., 2003), were monumental efforts that addressed areas only one-fifth of the size of Great Gobi B SPA. The Ndoki-Likouala Conservation Landscape survey for elephants, gorillas, and chimpanzees across 28,000 km^2 of the Congo, incorporated nearly 100 observers to successfully collect line transect data in difficult forest habitat (Stokes et al., 2010).

Traditional distance sampling methodology relies on the assumption that detection probability is entirely a function of distance from the observer to the animal, and disregards many other sources of heterogeneity (Buckland et al., 1993). Such heterogeneity can inflate variance, and thus it is not uncommon to stratify the

data in some meaningful way, such as modeling habitat selection. This can partially mitigate the encounter rate variance problems that would result from assuming density is constant across space. Unfortunately, we could find no statistical explanation for distribution of wild asses in our study at the time of our survey. This is likely a common problem in assessing abundance of gregarious ungulates because their distribution may be behaviorally influenced by conspecifics rather than discrete functions of the environment, at least on a short temporal scale. However, as more surveys occur it may be possible to use past survey data to stratify a priori for new surveys and thus improve the variance attributed to encounter rate.

Observer error can be an important source of bias and the sampling method we present here increases the likelihood of this because it incorporates a large number of observers with unknown and potentially widely varying abilities. Empirical data on observer bias arising from stakeholder participation in such data collection is scarce (Reed, 2008). Our analyses found a 31.7% gap in detection probability between the worst and best observers at median wild ass group size and 19.1% at median gazelle group size. The paired approach we used overcame some limitations of individual observers and increased our sample size, though none of the covariates we investigated, aside from group size for wild asses, quantified the heterogeneity present. The lack of difference in detection probabilities between wildlife professionals and local observers is unsurprising because while the professionals may have been better trained and had more experience in wildlife surveys, the local pastoralists likely had equivalent experience looking carefully at livestock across vast distances.

Reactivity of animals to observer presence has been a common problem for terrestrial-based distance sampling surveys. Koenen et al. (2002) experienced disturbance of deer due to presence of observers and Southwell (1994) reported disparity between macropod populations, with considerable evasive behavior among animals in areas not conditioned to human presence. Among the past wild ass counts, Feh et al. (2001), Lkhagvasuren (2007), and P.K. (unpublished data), all reported evasive behavior of wild asses to vehicles and observer presence. We also experienced this as we drove through the park, but observers did not report asses detecting and evading them at the observation points. We attempted to minimize this problem in our survey by keeping observers in place overnight and for multiple surveys during daylight hours. Observers only recorded 6.8% of gazelles and 3.3% of wild asses running, whereas during previous line transects 71% of gazelles and 57% of wild asses were observed running (P.K., unpublished data). Evasive behavior was not noted by any of the observers, and although the detections for wild ass at 0–500 m were lower than for 500–1000 m, the difference was not enough to reject the adequacy of the model fit. The steep detection function for gazelle supports the assumption that this species also did not avoid observers; however, it cannot rule out the possibility of attraction to the observers. Such behavior was not observed or expected.

While our study addresses the larger problem of how to estimate animal abundance in remote areas, it also specifically aimed to determine wild ass and gazelle abundance in the Great Gobi B SPA, due to Mongolia's importance for the survival of both species. From a line transect survey in 2003, Lkhagvasuren (2007) reports an estimated 2095 ± 110 asses in Khovd aimag, within which Great Gobi B SPA is the only population. This was a single transect survey conducted from a road with perpendicular distances used to determine the strip width, but few groups were encountered. Asses may have systematically moved away from the transect, which would create a strong negative bias on the estimate (Buckland et al., 1993) or the single track could have missed a large portion of the population. The most comprehensive data for these ungulate populations consists of 33 counts conducted from systematic road surveys of the entire park in 2003–2010, which detected an average of 1262 wild asses and 410 gazelle per survey; however, estimates varied widely, ranging 1707–45,040 asses (average CV = 50.3%) and 2 564–10,766 gazelle (average CV = 26.8%) suggesting unmeasured bias, such as due to evasive behavior (P.K., unpublished data).

Our important improvement over these previous surveys is that we were able to adequately meet the statistical assumptions of distance sampling theory by overcoming the problem of movement prior to detection, and facilitated the use of customized rangefinders that could accurately measure distance. Our estimates are conservative, however, because while distance sampling theory accounts for the numerous and largely unknown sources of heterogeneity that may influence detection as distance increases from the observer, we also know that 29.1% of the available survey area may not truly have been available to observers. Although groups missed due to obstacles, such as those obscured by vegetation or rock outcroppings, would be accounted for by the measured detection function, the variation among points in the visible area would, in theory, increase the variance in the detection rate and inflate our variance estimates. However, the contribution to the total variance from the encounter rate was a modest portion of the total variance for wild asses and very small for gazelle, so the effect appears to be modest in our survey. Variance might be reduced by eliminating all data in wedge-shaped portions of each circle where an obstacle prevented visibility to the maximum distance; however, this would eliminate large numbers of observations that occur inside those wedges but at distances closer than the obstacles. The increase in variance from the reduction in sample size would offset the improvements resulting from controlling for differences in visible area among points.

Further improvements in the precision of these surveys could be made by reducing the uncertainty in the probability of detection for gazelle and mean group size for wild asses by increasing the number of groups seen. In addition, increasing the average detection probability within each circle would improve the detection function component of variance. Decreasing the survey radius negatively impacts the first goal, while improving the second. However, both objectives could be met by surveying a larger number of smaller circles. Based on the best-fitting detection function for wild asses, reducing the survey radius to 3000 m would increase the average detection probability by a factor of 2.16 and be more conducive to meeting rangefinder constraints. Surveyed area per circle would be decreased by a factor of 0.36, but this survey area could be doubled by doubling the number of survey points. The estimated effect on the total number of wild ass groups seen would therefore be 1.56. In other words, this design change would increase the sample size by 56% (53% for gazelle), while reducing variance in the estimated detection function by dropping more distant observations with low detection probabilities. Increasing the number of distance categories to six 500 m-wide bins would permit more adjustment terms to be fitted, potentially improving the precision further.

6. Conclusions

The need for improved sampling and analytical techniques for estimating wildlife abundance is critical to addressing conservation and management issues (Elphick, 2008). We have demonstrated that large community-based distance sampling surveys can be effective at generating informed estimates of animal abundance, despite the wide range of experience, knowledge, and capabilities of the local observers, and the lack of technical equipment. While such a large number of observers creates opportunity for observation and data collection error, this technique was robust at absorbing such errors and allowed for plasticity in analyses because we used paired observers, a large number of observation points, and multiple surveys per point. Perhaps the most important aspect of

our study is that it actively engaged the people whose livelihoods are inextricably tied to the area of interest with the science behind conserving the resources that exist there. Accurately estimating abundance is an essential step toward developing and implementing species conservation plans, mitigating human-wildlife conflict, and allowing sustainable harvest. The relationship between extensive pastoral land-use and conservation of an endangered and a vulnerable species in the Great Gobi B SPA provided an opportunity to engage local pastoralists as partners in conservation and to develop a tool that has far-reaching implications for large mammal conservation. Community participation in this single survey is not likely to measurably increase conservation action, but using the technique repeatedly over time to generate regular population estimates can provide a sustainable critical framework for integrating local people into management and conservation initiatives.

Acknowledgments

This project was funded by the International Takhi Group (ITG), Research Institute of Wildlife Ecology (FIWI) of the University of Veterinary Medicine, Vienna, Colorado State University's Center for Collaborative Conservation, US Geological Survey, Instituto OIKOS, and the Regione Lombardia, Italy. Special thanks to the German Academic Exchange Service Summer School Programm "Deutscher Hochschulen im Ausland 2010" organized by H. Ansorge and W. Xylander of the Senkenberg Museum Görlitz, Germany and R. Samjaa and D. Lkhagvasuren of the National University of Mongolia. Enormous thanks to the Great Gobi B SPA rangers and staff, Shargen Gobi Saiga Reserve rangers, and the local people from Bij, Bugat, Altansoyombo, Darvi and Altai of Khovd. Thank you to the supply team for their truly herculean task of provisioning 50 people in the middle of the Gobi for 5 days! Also, thanks to N. Enksaikhan and B. Sukhbaatar at the ITG office in Ulaanbaatar for logistical support and urban navigation. S.R.B. King and 3 anonymous reviewers provided useful insights into development of this manuscript. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the US Government or any of the institutions funding this project.

References

Adams, W.M., Aveling, R., Brockington, D., Dickson, B., Elliott, J., Hutton, J., Roe, D., Vira, B., Wolmer, W., 2004. Biodiversity conservation and the eradication of poverty. Science 306, 1146–1149.

Barker, R., 2008. Theory and application of mark-recapture and related techniques to aerial surveys of wildlife. Wildlife Res. 35, 268–274.

Barnes, R.F.W., 2002. The problem of precision and trend detection posed by small elephant populations in West Africa. Afr. J. Ecol. 40, 179–185.

Buckland, S.T., 2006. Point-transect surveys for songbirds: robust methodologies. Auk 123, 345–357.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., 1993. Distance Sampling: Estimating Abundance of Biological Populations. Chapman and Hall, London, United Kingdom.

Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach, second ed. Springer-Verlag, New York, USA.

Caughley, G., 1977. Sampling in aerial survey. J. Wildlife Manage. 41, 605–615.

Corbera, E., Kosoy, N., Tuna, M.M., 2007. Equity implications of marketing ecosystem services in protected areas and rural communities – case studies from Meso-America. Global Environ. Chang. 17, 365–380.

Danielsen, F., Burgess, N.D., Balmford, A., Donald, P.F., funder, M., Jones, J.P.G., Alviola, P., Balete, D.S., Blomley, T., Brashares, J., Child, B., Enghoff, M., Fjeldsa, J., Holt, S., Hübertz, H., Jensen, A.E., Jensen, P.M., Massao, J., Mendoza, M.M., Ngaga, Y., Poulsen, M.K., Rueda, R., Sam, M., Skielboe, T., Stuart-Hill, G., Topp-Jorgensen, E., Yonten, D., 2008. Local participation in natural resource monitoring – a characterization of approaches. Conserv. Biol. 23, 31–42.

Elphick, C.S., 2008. How you count counts: the importance of methods research in applied ecology. J. Appl. Ecol. 45, 1313–1320.

Feh, C., Munkhtuya, B., Enkbold, S., Sukhbaatar, T., 2001. Ecology and social structure of the Gobi khulan *Equus hemionus* subsp. in the Gobi B national park. Mongolia. Biol. Conserv. 101, 51–61.

Gaidet, N., Fritz, H., Nyahuma, C., 2003. A participatory counting method to monitor populations of large mammals in non-protected areas: a case study of bicycle counts in the Zambezi Valley. Zimbabwe. Biodivers. Conserv. 12, 1571–1585.

International Union of Conservation and Nature (IUCN), 2010. The Red List of Endangered Species, Version 2010.4. <http://www.iucnredlist.org/> (accessed 01.17.12).

Jachmann, H., 2002. Comparison of aerial counts with ground counts for large African herbivores. J. Appl. Ecol. 38, 841–852.

Kaczensky, P., Sheehy, D.P., Walzer, C., Johnson, D.E., Lhkagvasuren, Sheehy, C.M., 2006. Room to roam? The threat to khulan (wild ass) from human intrusion. Mongolia Discussion Papers, East Asia and Pacific Environment and Social Development Department, Washington DC, World Bank.

Kaczensky, P., Enkhsaikhan, N., Ganbaatar, O., Walzer, C., 2007. Identification of herder-wild equid conflicts in the great Gobi B strictly protected area in SW Mongolia. Explor. Biol. Resour. Mongolia 10, 99–116.

Kaczensky, P., Ganbaatar, O., von Wehrden, H., Walzer, C., 2008. Resource selection by sympatric wild equids in the Mongolian Gobi. J. Appl. Ecol. 45, 1762–1769.

Kaczensky, P., Kuehn, R., Lhagvasuren, B., Pietsch, S., Yang, W., Walzer, C., 2011. Connectivity of the Asiatic wild ass population in the Mongolian Gobi. Biol. Conserv. 144, 920–929.

Karanth, K.U., Nichols, J.D., Seidensticker, J., Dinerstein, E., David Smith, J.L., McDougal, C., Johnsingh, A.J.T., Chundawat, R.S., Thapar, V., 2003. Science deficiency in conservation practice – the monitoring of tiger populations in India. Anim. Conserv. 6, 141–146.

Kissling, M.L., Garton, E.O., 2006. Estimating detection probability and density from point-count surveys: a combination of distance and double-observer sampling. Auk 123, 735–752.

Koenen, K.K.G., DeStefano, S., Krausman, P.R., 2002. Using distance sampling to estimate seasonal densities of desert mule deer in a semidesert grassland. Wildlife Soc. B. 30, 53–63.

Laake, J., Dawson, M.J., Hone, J., 2008. Visibility bias in aerial survey: mark-recapture, line-transect or both? Wildlife Res. 35, 299–309.

Lkhagvasuren, B., 2007. Population assessment of khulan (Equus hemionus) in Mongolia. Explor. Biol. Resour. Mongolia 10, 45–48.

Lubow, B.C., Ransom, J.I., 2009. Validating aerial photographic mark-recapture for naturally marked feral horses. J. Wildlife Manage. 73, 1420–1429.

Marques, F.F.C., Buckland, S.T., Goffin, D., Dixon, C.E., Borchers, D.L., Mayle, B.A., Peace, A.J., 2001. Estimating deer abundance from line transect surveys of dung – sika deer in southern Scotland. J. Appl. Ecol. 38, 349–363.

McNeely, J.A., Miller, K.R., Reid, W.V., Mittermeier, R.A., Werner, T.B., 1990. Conserving the World's Biodiversity. International Union of Conservation and Nature, Gland, Switzerland.

Melville, G.J., Tracey, J.P., Fleming, P.J.S., Lukins, B.S., 2008. Aerial surveys of multiple species: critical assumptions and sources of bias in distance and mark-recapture estimators. Wildlife Res. 35, 310–319.

Msoffe, F.U., Ogutu, J.O., Kaaya, J., Bedelian, C., Said, M.Y., Kifugo, S.C., Reid, R.S., Neselle, M., van Gardingen, P., Thirgood, S., 2009. Participatory wildlife surveys in communal lands: a case study from Simanjiro. Tanzania. Afr. J. Ecol. 48, 727–735.

Plumptre, A.J., 2000. Monitoring mammal populations with line transect techniques in African forests. J. Appl. Ecol. 37, 356–368.

Ransom, J.I., 2011. Customizing a rangefinder for community-based large animal surveys. Biodivers. Conserv. 20, 1603–1609.

Ransom, J.I., 2012. Detection probability in aerial surveys of feral horses. J. Wildlife Manage. 76, 299–307.

Reading, R.R., Mix, H.M., Lhagvasuren, B., Blumer, E.S., 1999. Status of wild bactrain camels and other large ungulates in south-western Mongolia. Oryx 33, 247–255.

Reading, R.R., Mix, H.M., Lhagvasuren, B., Feh, C., Kane, D.P., Dulamtseren, S., Enkhbold, S., 2001. Status and distribution of khulan (*Equus hemionus*) in Mongolia. J. Zool. Soc. Lond. 254, 381–389.

Reed, M., 2008. Stakeholder participation for environmental management – a literature review. Biol. Conserv. 141, 2417–2431.

Reid, R.S., Rainy, M., Ogutu, J., Kruska, R.L., Kimani, K., Nyabenge, M., McCartney, M., Kshatriya, M., Worden, J., Ng'ang'a, L., Owuor, J., Kinoti, J., Njuguna, E., Wilson, C.J., Lamprey, R., 2003. People, Wildlife and Livestock in the Mara Ecosystem: the Mara Count 2002. International Livestock Research Institute, Nairobi, Kenya.

Schwarz, C., Seber, G.A.F., 1999. Estimating animal abundance: review III. Stat. Sci. 14, 427–456.

Stokes, E.J., Strindberg, S., Bakabana, P.C., Elkan, P.W., Iyenguet, F.C., Madzoke, B., Malanda, G.A.F., Mowawa, B.S., Moukoumbou, C., Ouakabadio, F.K., Rainey, H.J., 2010. Monitoring great ape and elephant abundance at large spatial scales – measuring effectiveness of a conservation landscape. PLoS One 5, e10294.

Thomas, L., Buckland, S.T., Rexstad, E.A., Laake, J.L., Strindberg, S., Hedley, S.L., Bishop, J.R.B., Marques, T.A., Burnham, K.P., 2010. Distance software: design and analysis of distance sampling surveys for estimating population size. J Appl. Ecol. 47, 5–14.

von Wherden, H., Hilbig, W., Wesche, K., 2006. Plant communities of the Mongolian transaltay Gobi. Feddes Rep. 7, 536–570.

Williams, B.K., Nichols, J.D., Conroy, M.J., 2002. Analysis and Management of Animal Populations – Modeling, Estimation, and Decision Making. Academic Press, San Diego, California.