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Citizen science data facilitate monitoring of rare large carnivores in remote montane landscapes

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ABSTRACT

Population monitoring of large carnivores, particularly in remote montane landscapes, represents a considerable conservation challenge. Occupancy modeling using repeated detection/non-detection surveys offers a practical and robust tool for assessments of this type. Sign surveys or photographic detections have been the two primary survey methods to inform occupancy models. However, these approaches are expensive to implement and resource-intensive. Thus, their applicability for assessing the distribution of rare large carnivores residing in inaccessible landscapes is limited, particularly when large scale species monitoring is desired. Here, our intent was to predict the occupancy of the endangered Persian leopard (*Panthera pardus saxicolor*) inhabiting the rugged mountains of northeastern Iran. Using a Bayesian occupancy modeling framework, we compared patterns of leopard occupancy derived from standardized monitoring data implemented using spatially-replicated sign surveys to those informed by citizen scientist observations. We found that leopard occupancy probability was comparable between the two survey methods (sign survey = 0.92, 95% CI 0.85–1 and citizen science = 0.94, 95% CI 0.88–1) though detection probability varied (sign survey = 0.52, 95% CI 0.46–0.58 and citizen science = 0.25, 95% CI 0.18–0.32). The magnitude of effect among the environmental covariates that predicted leopard occupancy probability was also similar for the two methods. Thus, while yielding comparable predictions, the citizen science approaches were half the cost of sign surveys. The implementation of the effective citizen scientist data enabled us to expand by two-fold the monitored area while halving the costs in comparison to the area investigated via sign surveys. Our paper demonstrates that citizen science surveys represent a cost-effective, reliable, and surprisingly overlooked means to efficiently assess occupancy, particularly for rare large carnivores inhabiting mountainous landscapes.

1. Introduction

Mountainous ecosystems cover approximately 25% of global land surface area and support an estimated one-third of terrestrial biological diversity (Körner, 2004). These biodiversity hotspots also tend to have comparatively lower levels of human activity and anthropogenic disturbance (Tang et al., 2006; Myers et al., 2000). The conservation of large carnivores living in these landscapes represents a formidable challenge for conservationists and managers. For example, carnivores inhabiting mountainous landscapes tend to persist at lower densities than carnivores in lowland habitats (Bellemain et al., 2007; Alexander et al., 2015; Jiang et al., 2015). That rarity presents problems for accurate population estimation. Moreover, only one third of the current extant range of some large carnivores, such as big cats is projected to remain as suitable habitat in the next half century (Li et al., 2016; Ebrahimi et al., 2017), highlighting the vulnerability of large carnivores to demographic and environmental changes. Large carnivore rarity and vulnerability underscores the critical and time-sensitive need to develop efficient monitoring methods so that conservation plans have the greatest chance of success (Nichols and Williams, 2006; Nielsen et al., 2009).

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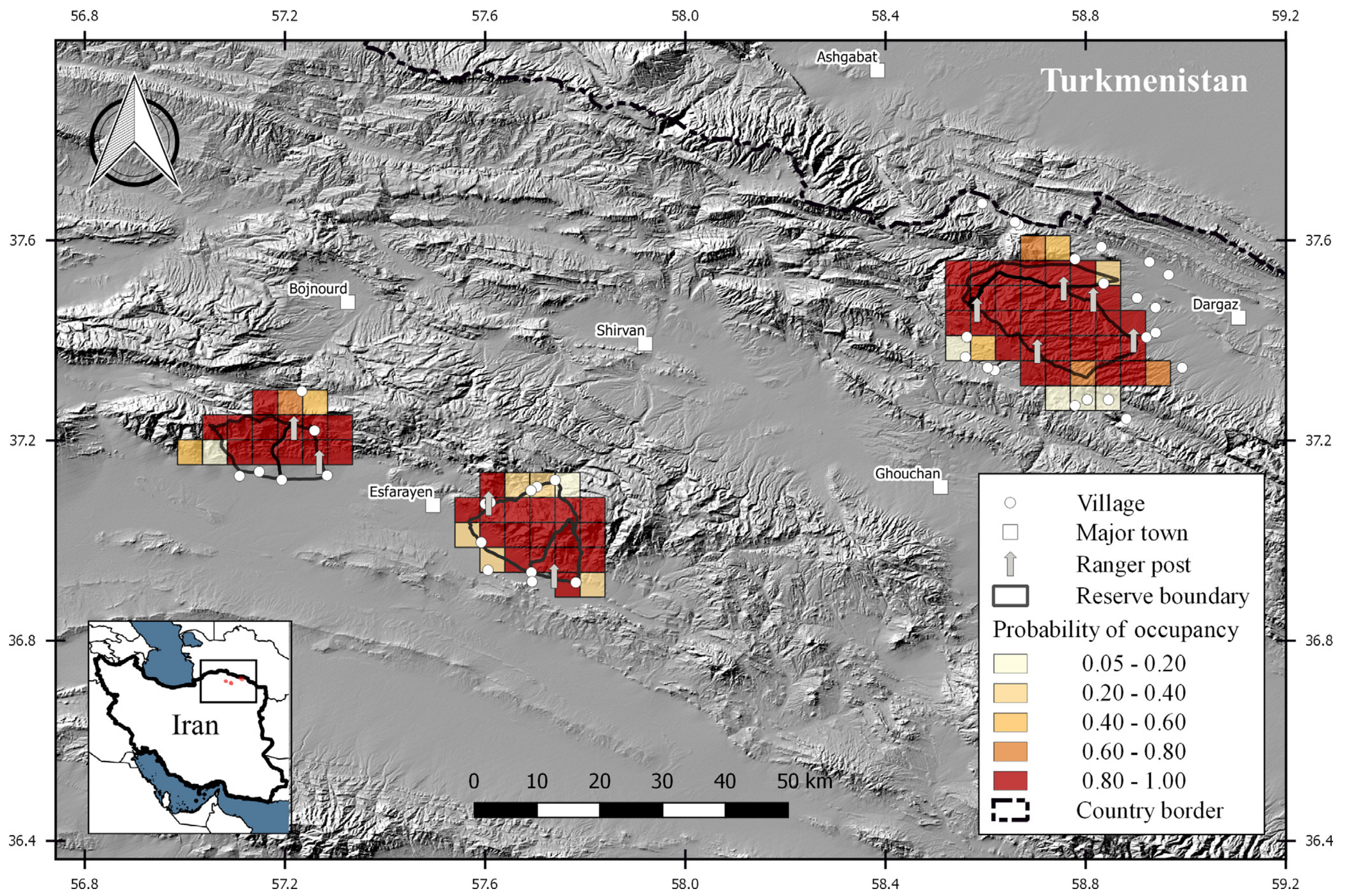

Fig. 1. The predicted relative probability of Persian leopard occupancy as calculated from models built using citizen science data in northeastern Iran. Each of 80 sites (cells) is depicted at a resolution of 25 km^2.

Conservation managers need reliable and cost-effective techniques for monitoring wildlife populations (Joseph et al., 2006). Occupancy modeling which accounts for imperfect detection, where a location is used by the species but is not detected, is a useful tool for monitoring rare and elusive species (MacKenzie et al., 2002; MacKenzie et al., 2006). This modeling framework develops predictions that can be interpreted as wildlife abundance or density (MacKenzie et al., 2006; Linden et al., 2017; Steenweg et al., 2018). In particular, temporal and spatial patterns in occupancy are often related to changes in animal abundance, and thereby provide insight into the probability of a species' occurrence (Noon et al., 2012). Occupancy modeling has been widely used for monitoring the population trends of rare large carnivores across time and space (Karanth et al., 2011; Henschel et al., 2016; Wibisono et al., 2011; Rich et al., 2017). Occupancy models can also be used to clarify habitat niche width of species on the generalist–specialist continuum (Moll et al., 2016), quantify species interactions (Steinmetz et al., 2013), evaluate large-scale species habitat-use (Petracca et al., 2018; Soofi et al., 2018), and improve the precision of abundance estimates in combination with capture–recapture methodologies (Blanc et al., 2014).

Sign and photographic detections surveys represent two common methods used to inform occupancy models for large carnivores (Khorozyan et al., 2010; Suryawanshi et al., 2013; Soofi et al., 2018; Alexander et al., 2016; Bischof et al., 2014; Steenweg et al., 2016). However, these techniques are both expensive and potentially time and resource intensive (Zeller et al., 2011; Miller et al., 2013; Soofi et al., 2018). These factors can diminish the applicability of these techniques, particularly in regions with poor funding, political instability, and difficult landscape accessibility. More recently, there has been a surge in interest in biogeographical studies based on data collected using 'citizen scientists' (Cooper et al., 2007). The application of citizen science approaches integrate public outreach and scientific data collection to supplement or substitute for other more expensive or intensive survey techniques (Dickinson et al., 2012; Strien et al., 2013). This field has been growing to include the monitoring of rare species (Zeller et al., 2011; Miller et al., 2013; Petracca et al., 2018; Shumba et al., 2018). Yet surprisingly, the potential application of citizen science approaches in quantifying the patterns of distribution and occupancy in large carnivores inhabiting mountainous regions has not been widely evaluated. If a citizen science approaches proved robust, it would provide an extremely cost-effective alternative to traditional methods used to study and monitor large carnivores in mountainous regions (e.g., using camera trap or sign surveys). Although previous work has shown that citizen science data can produce reliable estimates of distribution trends (Strien et al., 2013; Broman et al., 2014) and resource selection (Shumba et al., 2018), such data may also demonstrate a poor match with standardized monitoring data because of the lack of spatial and/or temporal non-randomness in sampling effort and decreased sensitivity to population changes (Kamp et al., 2016; Snäll et al., 2011). Therefore, citizen science data must be validated and their quality must be appropriately matched with research questions (Silvertown, 2009).

In this study, we critically evaluated the efficacy of using citizen scientist data in occupancy modeling of large carnivores inhabiting mountainous landscapes. We did so by deploying two data collection platforms to detect the endangered Persian leopard (*Panthera pardus saxicolor*) across multiple montane sites in northeastern Iran. First, we deployed the conventional standardized spatially-replicated sign surveys. Simultaneously, we conducted interviews with local villagers to access citizen scientist observations of leopard occurrence. We fitted occupancy models informed by both data collection formats using

Table 1
Summary of Persian leopard survey efforts during summer 2013 in northeastern Iran.

Study area	Area (km^2)	Sign survey				Citizen science			
		#Sites	#Sites with leopard signs	#Transects	≠Transects with leopard signs	#Sites	#Rangers	#Herders	#Sites with leopard sightings
Sarigol	280	11	8	110	41	23	7	14	16
Salouk	200	8	5	82	25	16	7	23	9
Tandoureh	450	20	20	172	97	41	9	44	28
Total	930	39	33	364	163	80	23	81	53

Bayesian occupancy modeling. To account for imperfect detection, we conducted multiple searches (i.e. sign transects or interviews) at each site. We compared occupancy patterns yielded by these two sampling schemes for the focal species. We discuss the implication of our findings for the estimation of occupancy for other rare animals persisting in montane landscapes.

2. Materials and methods

2.1. Study areas

The Kopet Dag and Aladagh Mountains in northeastern Iran contain a number of montane reserves, including Tandoureh National Park and Protected Area, Salouk National Park and Protected Area, and Sarigol National National Park and Protected Area (Fig. 1). These reserves exist at the eastern extreme of the Irano-Anatolian Biodiversity Hotspot (E57°15′ to E59°15′, N36° 20′ to N37°20′; Fig. 1 and Table 1). In total these reserves comprise 930 km^2 of rugged mountainous landscapes consisting of steep cliffs and deep valleys with elevations ranging between 1000 and 3000 m above sea level. The climate is temperate semi-arid with a mean annual precipitation of 200–300 mm and temperatures that range from −20 to 35 °C (Darvishsefat 2006). The main prey species for leopards include urial *Ovis orientalis*, bezoar goat *Capra aegagrus*, and wild pig *Sus scrofa*.

We positioned this study within three study sites each encompassing three different land management regimes. The National Parks experience greater law enforcement and livestock grazing is completely banned. The Protected Areas have lower levels of protection with less intense anti-poaching efforts. Finally, multi-use lands, surrounding the above two regimes, are multi-use areas where human settlements are located. Furthermore, nomadic pastoralists from surrounding settlements are permitted to graze their herds in Protected Areas during the summer months (May–August). Grazing herds are comprised largely of sheep (*O. aries*; 84% ± 2) with smaller numbers of goats (*C. hircus*).

2.2. Data collection

We used both sign and citizen science surveys to assess 39 sites across our three study areas. Of these sites, 27 (69.2%) were located in national parks versus 12 (30.8%) in protected areas. We also surveyed an additional 41 sites for the citizen science method which included multi-use lands. Sites had a spatial resolution of 25 km^2 which approximates a small resident female home range. This resolution was calculated based on a female/male home range ratio of 0.4 (du Preez et al., 2014) and the minimum convex polygon of a resident male leopard GPS-tracked in Tandoureh (63.3 km2; Farhadinia et al., 2018). Comparable spatial resolutions were similarly used in previous occupancy modeling attempts for leopards (Steinmetz et al., 2013; Burton et al., 2012; Soofi et al., 2018) which will enable us to interpret our findings in the context of species occupancy patterns.

2.3. Sign surveys

We walked 364 half-kilometer transects. Each transect was considered a spatial replicate (see Karanth et al., 2011). The number of spatial replicates per site (i.e. 0.5 km walked) was proportional to the percentage of leopard habitat (Karanth et al., 2011). Thus, we surveyed an average of 9.4 ± SE 0.6 transects (ranging 4–14) per site. We excluded non-mountainous areas from our survey effort given that these landscapes are seldom used by leopards (see Ebrahimi et al., 2017). Sites were mostly contiguous to overcome the accessibility challenges associated with this remote field work. Spatial replication without replacement does not induce bias in the occupancy estimation (Guillera-Arroita, 2011), particularly for mobile species because they are likely to occur at any potential spatial unit within an occupied site (Kendall and White, 2009).

We positioned our transects along ridgelines (34.3%), valley bases (21.7%) and slopes (44.0%). As we walked transects, we recorded a track and marked the spatial locations of sign using GPS receivers (Garmin GPSMAP 62 s, Olathe, Kansas, USA). Leopard signs consisted of both pug and scrape marks. Simultaneously, we recorded the presence of livestock and the primary species comprising leopard prey were also noted, both through direct sighting and/or signs.

When low-density, highly mobile species with home ranges larger than the sampling sites are targeted, there is a chance of the species moving among sites (MacKenzie and Royle, 2005). Therefore, we repeated our surveys to meet the assumption that survey sites experience a constant state of occupancy throughout the sampling season (i.e. the closure assumption; Rota et al., 2009). Therefore, we carried out all sign surveys for 23 days between June and September 2013, without any time gap between the surveys in each study area.

Variation in detection rates between observers is expected in any biological survey (Wintle et al., 2005). Such variation is particularly common in assessments of large, mountain-living carnivores because sign surveys are known to be subject to observer bias due to different levels of sign detectability. However, the presence of two trained field crews can eliminate such bias (McCarthy et al., 2008). Accordingly, all of our field excursions was conducted by a trained investigator (MSF) accompanied by an experienced game guard, both exclusively looking for leopard signs.

2.4. Citizen science survey

We considered two groups of local people to be citizen scientists. These included rangers and herders. Across a period of 13 days between August and September 2013, we collected data from herders living in villages located on the borders of the three study sites (n = 26, Table 1). Only one person associated with each herd was interviewed (typically the only person accompanying the herd in the pasture). We also recorded direct sightings made by 23 rangers working for ≥ 5 years within each study area (Table 1). We evaluated respondents' ability to identify carnivores by showing them photographs of different species known from the area (leopard, wolf and striped hyena). Those respondents familiar with species were asked for any interaction with leopards for the previous five years. We only accepted direct sightings of leopards. This process helped ensure a lack of species misidentification (Miller et al., 2011). In both citizen science surveys, repeated interviews with different respondents at the same site were treated as survey replicates for occupancy models (Zeller et al. ,2011).

Table 2
Predicted leopard response to covariates based on *a priori* hypotheses. The '+' signifies a positive effect on the response variable whereas an '−' signifies a negative effect on the response variable.

Covariates (unit)	Ψ	p
Distance to village (km)	+	
Distance to ranger post (km)	–	
Protection status	+	
Livestock grazing		–
Habitat*		+
Observer (ranger)		+

* Landscape feature shows where each transect was laid, including ridgeline, slope or valley bottom.

2.5. Sampling and environmental covariates

For sign surveys, we included two sampling covariates that we hypothesized could influence the likelihood of detection. These included landscape feature and the occurrence of grazing by livestock in each spatial replicate (Table 2). Presence of livestock can potentially destroy all signs, particularly pugmarks of leopards and other animals. Also leopards are expected to walk more along ridgeline or valley trails compared to slopes. For citizen science surveys, we included a single sampling covariate: observer type (herder or ranger; Table 2).

We also included three environmental covariates that we hypothesized to influence the occupancy of leopards target species. These included the Euclidean distance (m) of each transect center to the nearest active ranger post and main village, which served as surrogates for the wild prey abundance and human disturbance, respectively. We measured these two environmental covariates at the scale of transect where leopard occurrence are also detected, and then used them for modeling occupancy at the scale of site. We also included the protection status of each site as a categorical covariate (Table 2). The three categories of protection included national parks (established anti-poaching and overgrazing control), protected areas (overgrazing control, but with less efficient anti-poaching) and multi-use lands (without any efficient regulatory control). The latter, composed of villages, farmlands and pastures, was used only for citizen science.

To calculate the distance variables, we obtained the spatial location of human settlements (i.e. villages and ranger posts) using a handheld GPS receiver and then we visually confirmed village locations using Google Earth Pro 7.1.7.2606 (Google Inc., USA). We estimated all spatial metrics using Quantum GIS (QGIS Development Team, 2017).

2.6. Data analysis

Variance inflation factors of the covariates suggested a lack of multicollinearity (cutoff of 3.0; Zuur et al., 2010). We conducted two rounds of occupancy modelling analysis. We initially focused our analysis on the 39 sites that we surveyed using both survey methods to evaluate the reliability of citizen science data for predicting leopard occupancy in comparison to using sign survey data. This round was focused on only two land management regimes, i.e. national park and protected area. Below, we refer to this as *method comparison modeling*. Then, to estimate occupancy probability, detection, and the influence of environmental covariates, we modelled our data using the full set of 80 sites for which we collected citizen science data. These data encompassed all three land management regimes, i.e. national parks, protected areas and their surrounding multi-use lands. Below, we refer to this second round of analysis as *final modeling*.

We analyzed all leopard models in a hierarchical Bayesian framework (MacKenzie et al., 2002; Tyre et al., 2003). The method enables the estimation of two key parameters including the occupancy probability (Ψ) and detection probability (P). Here, Ψ represents the probability that a particular site is occupied by the target species whereas P is defined as the probability of species detection. Both of these processes can be affected by habitat covariates (MacKenzie et al., 2006; Karanth et al., 2011). We note that occupancy in this context is not interpreted as continuous occupancy, but rather as the use of a given site by our mobile focal species during the study period (MacKenzie et al., 2002; Mackenzie, 2006). Such an interpretation is a standard way of using the term *occupancy* in studies of mobile animals (e.g., see Linden et al., 2017).

We modeled site-occupancy as a Bernoulli-distributed latent variable (Z_i), which took a value of one when site i was used and zero otherwise. We modeled effect of covariates on the occupancy probability (Ψ_i) using a logit link. To facilitate comparison, the two survey types used the same environmental covariates. For both sign and citizen science survey data, the occupancy probability of the hierarchical model took the form:

$$\text{logit}(\Psi_i) = \alpha_0 + \alpha_k * \text{prot\_status}_i + \alpha_{village} * \text{dist\_village}_i + \alpha_{ranger} * \text{dist\_ranger}_i, \quad (1)$$

where α_0 is an intercept, α_k is the estimated effect of the kth protection status, $\alpha_{village}$ is the estimated effect of proximity to the nearest village, and α_{ranger} is the estimated effect of proximity to the nearest ranger post (Table 2). For the sign model, protection status took one of two levels (national park or protected area, with the latter as the reference level), whereas for the citizen science survey model it took one of three levels (national park, protected area, and multi-use land, with the multi-use land as the reference level; see description above).

We also used a logit link to model the effect of covariates on P at site i and replicate j. The detection level of the hierarchical sign model took the form:

$$\text{logit}(P_{i,j}) = \beta_0 + \beta_k * \text{topography}_{i,j} + \beta_{graze} * \text{grazing}_{i,j}, \quad (2)$$

where β_0 is an intercept, β_k is the estimated effect of the kth topography type and β_{graze} is the estimated effect of grazed compared to un-grazed replicates. Topography type took one of three levels (valley, slope, or ridge, with valley as the reference level). Similarly, the detection level of the hierarchical survey model took the form:

$$\text{logit}(P_{i,j}) = \beta_0 + \beta_{obs} * \text{observer}_{i,j}, \quad (3)$$

where β_0 is an intercept and β_{obs} is the estimated effect of ranger observers compared to herders.

We analyzed these models in a Bayesian framework using Markov Chain Monte Carlo (MCMC) simulations. We generated these simulations by interfacing R Studio version 1.0.136 (R Development Core Team, 2013) with JAGS (Plummer, 2003) via the package R2jags (Su and Yajima, 2012). For all models, we used non-informative priors that were uniformly distributed between −10 and 10. We generated posterior distributions of parameters by running three MCMC chains of 100,000 iterations each following a burn-in of 10,000 and we thinned chains by eight. We confirmed model convergence using R-hat statistics (i.e., all values were < 1.1; Gelman and Hill, 2007). Prior to model-fitting, we standardized covariates to have a mean of zero and a standard deviation of one (Kéry, 2010).

We assessed model goodness-of-fit using Bayesian p-values (Gelman et al., 1996). We calculated these values by computing the proportion of times that the summed chi-square deviance, between the model and the observed data, was greater than the summed chi-square deviance between the model and a simulated dataset generated by the model (Kéry and Royle, 2015). Bayesian p-values near 0.5 indicate good model fit (i.e., the simulated data generated by the model closely resembles the observed data), whereas extreme values (near zero or one) indicate poor model fit (Gelman et al., 1996; Kéry and Royle, 2015).

3. Results

We detected leopard signs in 44.8% (n = 163) of the spatial

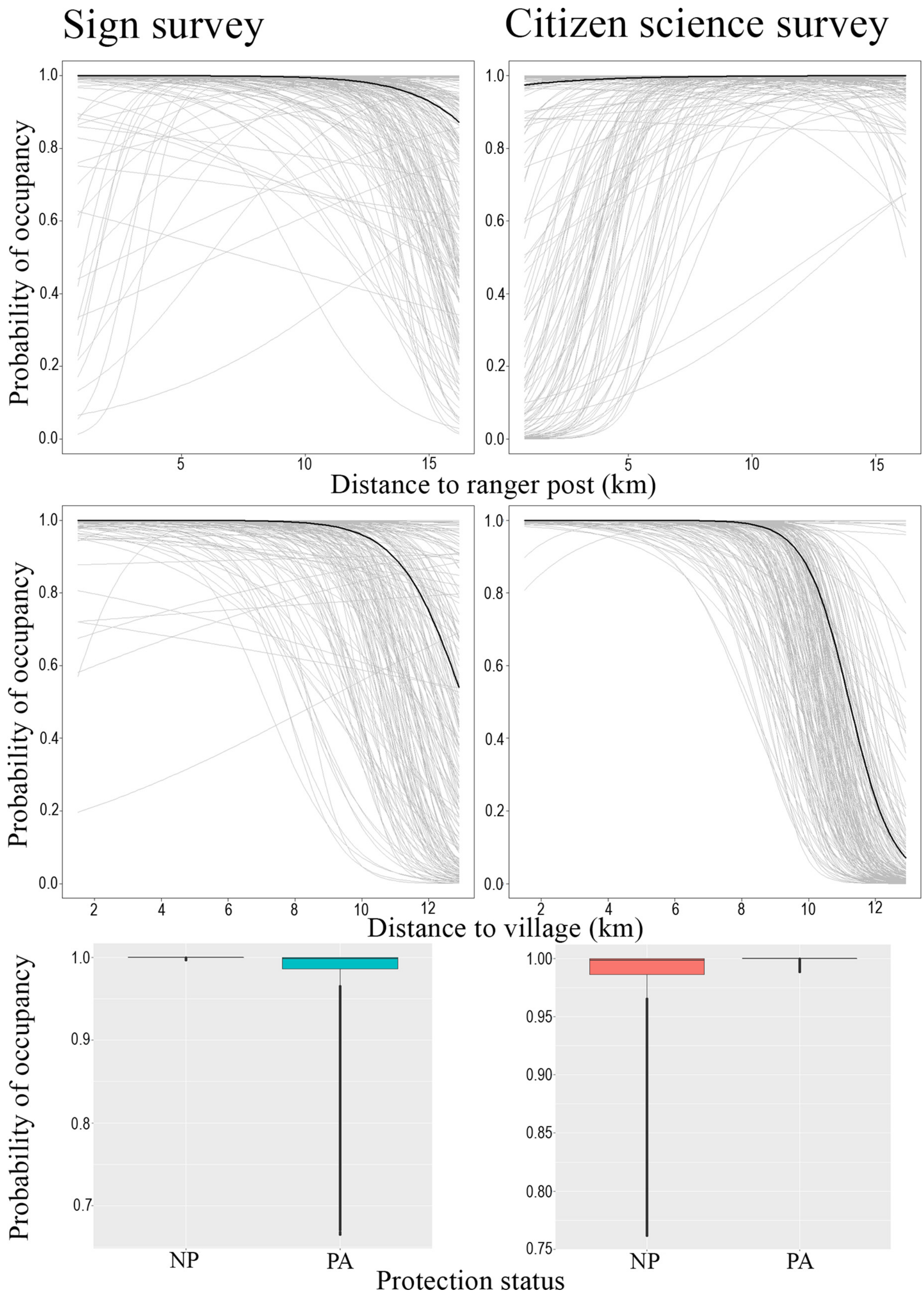

Fig. 2. Comparative associations between the probability of occupancy and environmental covariates for Persian leopard in northeastern Iran based on spatially-replicated sign survey and citizen science data collected at the same 39 sites. Black lines are model-averaged mean predictions and gray lines are model-averaged predictions from a random posterior sample of 200 iterations to depict uncertainty. The bottom row of panels depicts boxplots of parameter estimates within the 95% credible interval estimated by Bayesian model analysis. NP = National Park and PA = Protected Area.

replicates of our transect surveys, resulting in a high overall naïve site occupancy (0.85). We detected fresh leopard signs in all NP sites. We interviewed a total of 104 locals, with a mean of 6.8 ± 0.4 (range 2–15, median 7) persons per each site. 42.5% (n = 36) of sites for citizen science were on multi-use lands whereas the rest were either within national parks (31.2%) or protected areas (26.2%). The citizen science surveys provided naïve site occupancy rates of 74.0% (for 39 sites) or 57.5% (for 80 sites).

3.1. Method comparison modeling

Model-estimated occupancy probability (Ψ) was high for the 39 sites where both sign surveys [0.92, 95% credible interval (CI): 0.85.1.0] and citizen science surveys (0.94, 95% CI 0.88–1.0; Fig. 2; Table S1). There was no evidence that Ψ differed between the two survey methods ($t = -0.85$, df = 3, $p = 0.46$). For both survey methods, there was no evidence that the environmental covariates affected occupancy (Table S2), with the exception of level of protection. Occupancy probability was higher in national parks than in protected areas ($\alpha_{Protection} = 6.98$, 95% CI 1.19–9.9; Table S2).

Conversely, we found variation in the detection probability between the two survey methods (sign survey = 0.52, 95% CI 0.46–0.58 versus citizen science = 0.25 95% CI 0.18–0.32, Table S1). In the sign survey, detection probability was negatively affected by livestock grazing ($\beta_{Grazed} = -1.92$, 95% CI -2.53 to -1.33). In the citizen science survey, detection probability differed based on observer type ($\beta_{Observer} = 3.61$, 95% CI 2.95–4.31), with higher detection probabilities exhibited by rangers compared to herders (Fig. 3 and Table S2). The occupancy model was not a good fit for the sign survey data (Bayesian p-value = 1.00), perhaps due to relatively uninformative detection covariates, or very high raw occupancy of leopards (0.85). In contrast, the citizen science model fit was acceptable (Bayesian p-value = 0.67).

Table 3
Parameter estimates of occupancy (Ψ) and detection probabilities (P) generated by hierarchical Bayesian models based on citizen science data from 80 sites across three study areas for Persian leopard in northeastern Iran. Both $\alpha_{National\ Park}$ and $\alpha_{Protected\ Area}$ and their associated effects are compared to the reference category (multi-use lands).

Parameter	Mean (SD)	95% CI
$\Psi_{Sarigol}$	0.86 (0.05)	0.75, 0.98
Ψ_{Salouk}	0.82 (0.06)	0.73, 0.98
$\Psi_{Tandoureh}$	0.90 (0.04)	0.82, 0.99
$\Psi_{Overall}$	0.82 (0.05)	0.74, 0.93
Sites used (out of 80)	65.61 (3.42)	61.00, 74.00
$P_{Overall}$	0.20 (0.02)	0.15, 0.25
α_0	5.49 (2.12)	1.43, 9.48
$\alpha_{National\ Park}$	3.17 (4.00)	−4.43, 9.65
$\alpha_{Protected\ Area}$	6.17 (2.54)	0.56, 9.80
α_{Ranger}	−4.24 (2.21)	−8.21, 0.27
$\alpha_{Village}$	6.42 (2.66)	−0.43, 9.81
β_0	−1.52 (0.17)	−1.85, −1.21
$\beta_{Observer}$	3.84 (0.31)	3.25, 4.46

The overall estimates of occupancy probability and the effects of covariates on occupancy probability were very similar for both the sign survey and citizen science models (Fig. 2 and Table S2).

3.2. Final modeling

We implemented the final modeling using all 80 sites surveyed via citizen science method to estimate occupancy probability and effects associated with our covariates. Accounting for imperfect detection, the citizen science survey model estimated that ~66 (82.5%) out of 80 sites were occupied (95% CI 61–74; Table 3). Leopards had a low detection probability overall ($P = 0.25$ 95% CI 0.18–0.32), which was

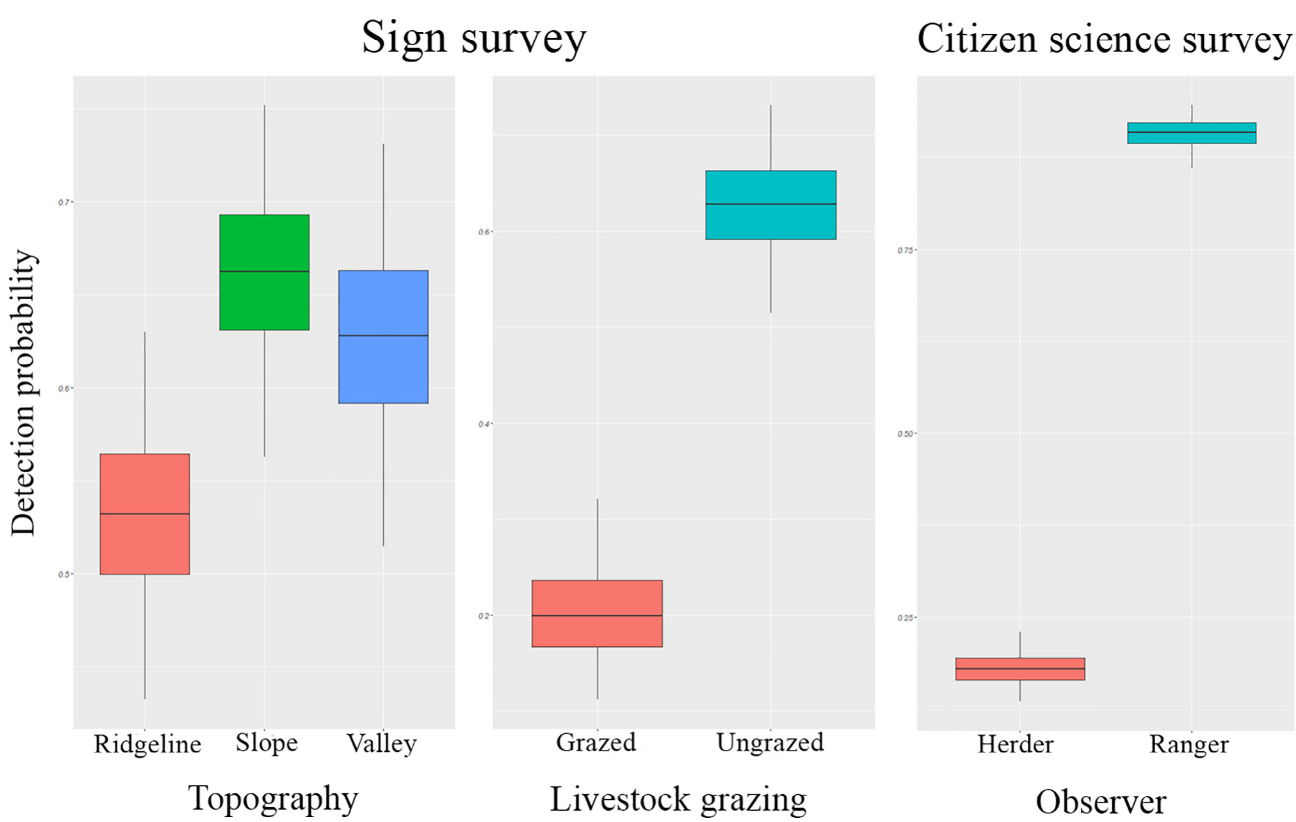

Fig. 3. Boxplots of detection probability of Persian leopards in northeastern Iran, given occurrence, for three sampling covariates and two different survey methods, i.e. sign survey (topography and livestock grazing) and citizen science (observer type). Boxplots based upon parameter estimates within the 95% credible interval estimated by Bayesian model analysis.

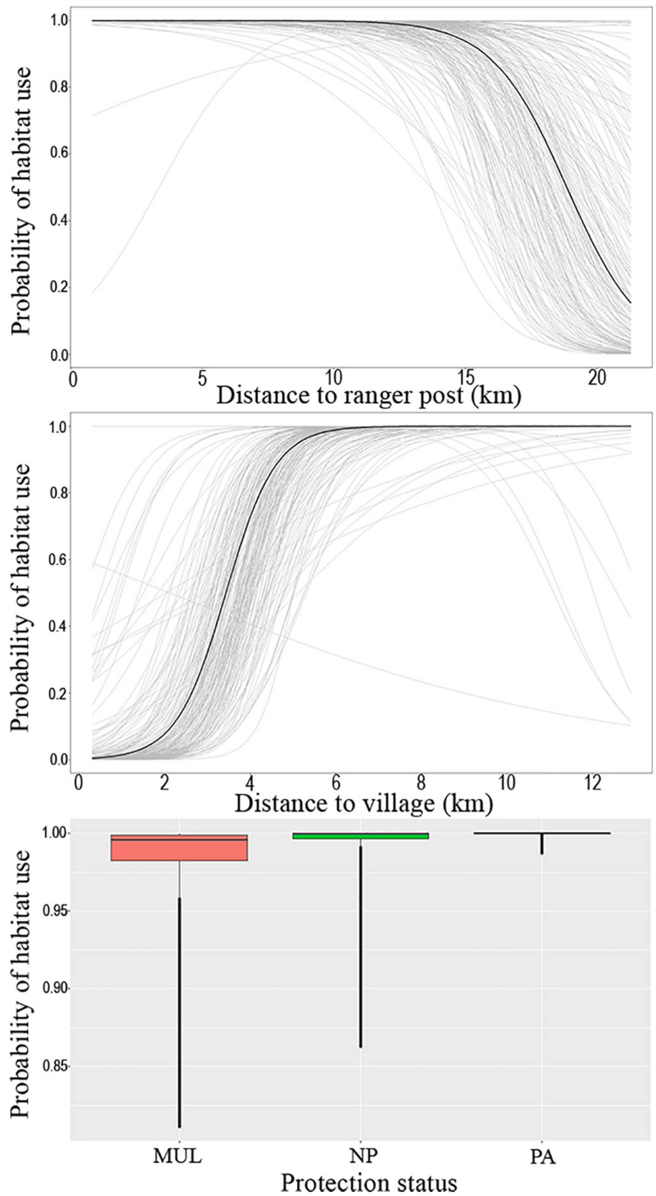

Fig. 4. Associations between the occupancy probability and environmental covariates for Persian leopard in northeastern Iran based on citizen science data in 80 sites. Black lines are model-averaged mean predictions and gray lines are model-averaged predictions from a random posterior sample of 200 iterations to depict uncertainty. The bottom plot depicts boxplots of parameter estimates within the 95% credible interval estimated by Bayesian model analysis. NP = National Park, PA = Protected Area and MUL = Multi-Use Lands.

significantly higher for rangers than herders ($\beta_{Observer}$ = 3.84, 95% CI 3.25–4.46; Fig. 4). There was no evidence that leopard occupancy was affected by any covariates (Table 3), except that it was higher in protected areas than in multi-use lands ($\alpha_{Protected\ Area}$ = 6.17, 95% CI 0.56–9.80).

4. Discussion

In this analysis we found that models fitted using citizen science approaches yielded comparable results for occupancy and the effect of environmental covariates to models developed from more traditional sign survey data. The application of citizen science approaches enabled us to monitor twice the area investigated for signs (n = 80 versus 39 sites) for almost half the cost and produced a model with a better fit. The citizen science-based modeling suggested no strong limiting factor for occupancy of leopards, except protection level.

Managers need reliable estimates of animal populations to track trends over time. Although occupancy modeling is widely adopted as a surrogate for abundance (MacKenzie et al., 2006), the nature of occupancy-abundance relationships depends on the sampling scales (Efford and Dawson, 2012; Steenweg et al., 2018). When the mean home range size is larger than sampling sites, occupancy probability most directly relates to site use during the survey rather than abundance (MacKenzie et al., 2006; Steenweg et al., 2018). Sampling scale was smaller than the mean home range of montane-living large carnivores in both this study and in previous research efforts (Suryawanshi et al., 2013; Ghoddousi et al., 2010; Soofi et al., 2018; Khorozyan et al., 2010; McCarthy et al., 2010; Alexander et al., 2016). Therefore, it is less likely that the findings from these studies represent the abundance for population monitoring. Application of resource-intensive survey methods (i.e. sign and photographic detection surveys) are primary constraints that has encouraged the selection of small scale sites by managers and conservationists (McCarthy et al., 2008). The large area encompassed by wide-ranging, mobile species such as the Persian leopard make it nearly impossible to truly investigate an entire sampling area by means of camera traps or sign surveys (Efford and Dawson, 2012). Thus, an achievable and reliable solution for population monitoring of large carnivores in rugged terrains is needed.

Our study demonstrated that citizen science-based occupancy modelling can offer a robust and efficient alternative to sign surveys for estimating trends in large carnivore populations in remote montane landscapes. The citizen science method used here has several highly desirable attributes, including its low cost and non-invasive nature (Zeller et al., 2011; Miller et al., 2013), the ability to cover large areas for monitoring rare elusive species (Petracca et al., 2018; Shumba et al., 2018), and the robustness of results when compared to traditional methods such as sign surveys (Table S2, Fig. 2). Given these desirable attributes, we encourage biologists working in remote, mountainous areas or with very wide-ranging species to adopt it as a reliable survey method for monitoring purposes. Establishing large-scale investigations often results in high heterogeneity in relevant spatial covariates, which is essential for good performance of occupancy models (MacKenzie et al., 2006) and helps clarify habitat associations for mobile species (Moll et al., 2016). Importantly, local communities can be seen as invaluable resources of information to launch collaborative monitoring programs, particularly for elusive large carnivores in rugged landscapes. Thus, the resulting ecological data can be viewed as a public good that is generated through increasingly collaborative tools and resources (Dickinson et al., 2012).

Nonetheless, the method has two major sources of bias. First, when compared with camera trap data, local inquiries have sometimes been viewed as unreliable for estimating species occurrence, particularly for smaller carnivores (Caruso et al., 2017; but see also Petracca et al., 2017). Second, misclassification (false positive identification of a species), can lead to overestimation of occupancy, particularly when species with similar body size or appearance are targeted (Miller et al., 2013; Petracca and Frair, 2018), unlike our study areas. Finally, citizen science approaches rely upon the availability of local informants.

The occupancy probability of the Persian leopard was not strongly predicted by any of the covariates, except protection level, indicating there was no factor that strongly limited leopard occupancy in our study area. Leopards' occupancy probability increases noticeably after almost two kilometers from surrounding villages. Stock loss to leopards in our study areas was low (0.9 domestic animal per herd per annum; Farhadinia et al., 2017) and the occupancy trend suggests that livestock depredation is more likely to occur when herds are away from the village, either on summer montane pastures or multi-use lands for the rest of year. The high probability of occupancy across all different land management regimes highlights the mosaic landscape of national parks as montane refugia and surrounding multi-use lands for persistence of large carnivores in Asian mountains.

5. Conclusion

Presence/absence surveys are useful for assigning IUCN Red List categories of threatened species, particularly when budgets are limited or elusive species are targeted (Joseph et al., 2006). Currently, there is substantial uncertainty associated with the actual status of large carnivores in remote landscapes, and such uncertainty hampers assessment of species extinction risk (e.g. Ale and Mishra, 2018; McCarthy et al., 2017). Citizen-science occupancy modelling at large spatial scales can be a solution for this problem. Our study showed that the citizen science approach can be used to investigate local-scale occupancy for a large carnivore, adding to an increasingly wide range of uses in biological studies.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecolind.2018.06.064.

References

Ale, S.B., Mishra, C., 2018. The snow leopard's questionable comeback. Science 359 (6380) p. 1110 LP-1110.

Alexander, J.S., et al., 2015. Face value: Towards robust estimates of snow leopard densities. PLoS One 10 (8), e0134815.

Alexander, J.S., et al., 2016. On the high trail: examining determinants of site use by the Endangered snow leopard *Panthera uncia* in Qilianshan. China. *Oryx* 50 (2), 231–238.

Bellemain, E., et al., 2007. Genetic tracking of the brown bear in northern Pakistan and implications for conservation. Biol. Conserv. 134 (4), 537–547.

Bischof, R., et al., 2014. Using time-to-event analysis to complement hierarchical methods when assessing determinants of photographic detectability during camera trapping. Methods Ecol. Evol. 5 (1), 44–53.

Blanc, L., et al., 2014. Improving abundance estimation by combining capture–recapture and occupancy data: example with a large carnivore. J. Appl. Ecol. 51 (6), 1733–1739.

Broman, D.J.A., et al., 2014. Modeling bobcat *Lynx rufus* habitat associations using telemetry locations and citizen-scientist observations: are the results comparable? Wildl. Biol. 20, 229–237.

Burton, A.C., et al., 2012. Hierarchical multi-species modeling of carnivore responses to hunting, habitat and prey in a West African protected area. PLoS One 7 (5), e38007.

Caruso, N., et al., 2017. Carnivore occurrence: do interview-based surveys produce unreliable results? Oryx 51 (2), 240–245.

Cooper, C., et al., 2007. Citizen science as a tool for conservation in residential ecosystems. Ecol. Soc. 12 (2).

Darvishsefat, A.A., 2006. Atlas of Protected Areas of Iran. Ravi, Tehran.

R Development Core Team, 2013. R: A language and environment for statistical computing.

Dickinson, J.L., et al., 2012. The current state of citizen science as a tool for ecological research and public engagement. Front. Ecol. Environ. 10 (6), 291–297.

du Preez, B.D., Loveridge, A.J., Macdonald, D.W., 2014. To bait or not to bait: a comparison of camera-trapping methods for estimating leopard (*Panthera pardus*) density. Biol. Conserv. 176, 153–161.

Ebrahimi, A., Farashi, A., Rashki, A., 2017. Habitat suitability of Persian leopard (*Panthera pardus saxicolor*) in Iran in future. Environ. Earth Sci. 76 (20), 697.

Efford, M.G., Dawson, D.K., 2012. Occupancy in continuous habitat. Ecosphere 3 (4), 1–15.

Farhadinia, M., et al., 2017. Wolves can suppress goodwill for leopards: Patterns of human-predator coexistence in northeastern Iran. Biol. Conserv. 213, 210–217.

Farhadinia, M.S., et al., 2018. Anchoring and adjusting amidst humans: ranging behavior of Persian leopards along the Iran-Turkmenistan borderland. PLoS One 13 (5), e0196602.

Gelman, A., Hill,, J., 2007. Data Analysis using Regression and Multilevel/Hierarchical Models. Cambridge University Press, New York.

Gelman, A., Meng, X.-L., Stern, H., 1996. Posterior predictive assessment of model fitness via realized discrepancies. Stat. Sin. 6 (4), 733–807.

Ghoddousi, A., et al., 2010. The status of the endangered Persian leopard *Panthera pardus saxicolor* in Bamu National Park, Iran. Oryx 44 (4), 551–557.

Guillera-Arroita, G., 2011. Impact of sampling with replacement in occupancy studies with spatial replication. Methods Ecol. Evol. 2 (4), 401–406.

Henschel, P., et al., 2016. Determinants of distribution patterns and management needs in a critically endangered lion *Panthera leo* population. Front. Ecol. Evol. 4, 110.

Jiang, G., et al., 2015. New hope for the survival of the Amur leopard in China. Sci. Rep. 5, 15475.

Joseph, L.N., et al., 2006. Presence-absence versus abundance data for monitoring threatened species. Conserv. Biol. 20 (6), 1679–1687.

Kamp, J., et al., 2016. Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark. Divers. Distrib. 22 (10), 1024–1035.

Karanth, K.U., et al., 2011. Monitoring carnivore populations at the landscape scale: occupancy modelling of tigers from sign surveys. J. Appl. Ecol. 48 (4), 1048–1056.

Kendall, W.L., White, G.C., 2009. A cautionary note on substituting spatial subunits for repeated temporal sampling in studies of site occupancy. J. Appl. Ecol. 46 (6), 1182–1188.

Kéry, M., 2010. Introduction to WinBUGS for ecologists: Bayesian approach to regression, ANOVA, mixed models and related analyses. Academic Press.

Kéry, M., Royle, J.A., 2015. Applied hierarchical modeling in ecology: analysis of distribution, abundance and species richness in R and BUGS. Prelude and Static Models. Academic Press.

Khorozyan, I., et al., 2010. Using Geographical Mapping and Occupancy Modeling to Study the Distribution of the Critically Endangered Leopard (*Panthera pardus*) Population in Armenia. In: Cushman, S.A., Huettmann, F. (Eds.), Spatial Complexity, Informatics, and Wildlife Conservation. Springer, pp. 331–347.

Körner, C., 2004. Mountain biodiversity, its causes and function. Ambio Spec. Rep. 13, 11–17.

Li, J., et al., 2016. Climate refugia of snow leopards in High Asia. Biol. Conserv. 203, 188–196.

Linden, D.W., et al., 2017. Examining the occupancy–density relationship for a low-density carnivore. J. Appl. Ecol. 54 (6), 2043–2052.

MacKenzie, D.I., et al., 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology 83 (8), 2248–2255.

Mackenzie, D.I., 2006. Modeling the probability of resource use: the effect of, and dealing with, detecting a species imperfectly. J. Wildl. Manage. 70 (2), 367–374.

MacKenzie, D.I. et al., 2006. Occupancy modeling and estimation.

MacKenzie, D.I., Royle, J.A., 2005. Designing occupancy studies: general advice and allocating survey effort. J. Appl. Ecol. 42, 1105–1114.

McCarthy, K., et al., 2008. Assessing estimators of snow leopard abundance. J. Wildl. Manage. 72 (8), 1826–1833.

McCarthy, T., et al., 2010. Preliminary results of a long-term study of snow leopards in South Gobi, Mongolia. Cat News 53, 15–19.

McCarthy, T. et al., 2017. *Panthera uncia*. The IUCN Red List of Threatened Species 2017: e.T22732A50664030. Available at: http://dx.doi.org/10.2305/IUCN.UK.2017-2.RLTS.T22732A50664030.en [Accessed February 9, 2018].

Miller, D.A., et al., 2011. Improving occupancy estimation when two types of observational error occur: Non-detection and species misidentification. Ecology 92 (7), 1422–1428.

Miller, D.A.W., et al., 2013. Determining occurrence dynamics when false positives occur: estimating the range dynamics of wolves from public survey data. PLoS One 8 (6), e65808.

Moll, R.J., et al., 2016. Clarifying habitat niche width using broad-scale, hierarchical occupancy models: a case study with a recovering mesocarnivore. J. Zool. 300 (3), 177–185.

Myers, N., et al., 2000. Biodiversity hotspots for conservation priorities. Nature 403, 853–858.

Nichols, J.D., Williams, B.K., 2006. Monitoring for conservation. Trends Ecol. Evol. 21 (12), 668–673.

Nielsen, S.E., et al., 2009. Capacity of large-scale, long-term biodiversity monitoring programmes to detect trends in species prevalence. Biodivers. Conserv. 18 (11), 2961–2978.

Noon, B.R., et al., 2012. Efficient species-level monitoring at the landscape scale. Conserv. Biol. 26 (3), 432–441.

Petracca, L.S., et al., 2018. Robust inference on large-scale species habitat use with interview data: the status of jaguars outside protected areas in Central America. J. Appl. Ecol. 55 (2), 723–734.

Petracca, L.S., Frair, J.L., 2017. When methodological flaws limit inference: a response to Caruso et al. Oryx 51 (2), 208.

Plummer, M., 2003. JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. In: Proceedings of the 3rd International Workshop on Distributed Statistical Computing. p. 124:1–8.

QGIS Development Team, 2017. QGIS Geographic Information System. Available at: http://qgis.osgeo.org.

Rich, L.N., et al., 2017. Assessing global patterns in mammalian carnivore occupancy and richness by integrating local camera trap surveys. Glob. Ecol. Biogeogr. 26 (8), 918–929.

Rota, C.T., et al., 2009. Occupancy estimation and the closure assumption. J. Appl. Ecol.

46 (6), 1173–1181.
Shumba, T., et al., 2018. African wild dog habitat use modelling using telemetry data and citizen scientist sightings: are the results comparable? Afr. J. Wildl. Res. 48 (1), 013002.
Silvertown, J., 2009. A new dawn for citizen science. Trends in ecology & evolution 24 (9), 467–471.
Snäll, T., et al., 2011. Evaluating citizen-based presence data for bird monitoring. Biol. Conserv. 144 (2), 804–810.
Soofi, M., et al., 2018. Livestock grazing in protected areas and its effects on large mammals in the Hyrcanian forest, Iran. Biol. Conserv. 217, 377–382.
Steenweg, R., et al., 2016. Camera-based occupancy monitoring at large scales: power to detect trends in grizzly bears across the Canadian Rockies. Biol. Conserv. 201, 192–200.
Steenweg, R., et al., 2018. Sampling scales define occupancy and underlying occupancy–abundance relationships in animals. Ecology 99 (1), 172–183.
Steinmetz, R., Seuaturien, N., Chutipong, W., 2013. Tigers, leopards, and dholes in a half-empty forest: assessing species interactions in a guild of threatened carnivores. Biol. Conserv. 163, 68–78.
Strien, A.J., Swaay, C.A.M., Termaat, T., 2013. Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. J. Appl. Ecol. 50 (6), 1450–1458.
Su, Y.S. & Yajima, M., 2012. R2jags: a package for running jags from R.
Suryawanshi, K.R., et al., 2013. People, predators and perceptions: patterns of livestock depredation by snow leopards and wolves. J. Appl. Ecol. 50 (3), 550–560.
Tang, Z., et al., 2006. Biodiversity in China's mountains. Front. Ecol. Environ. 4 (7), 347–352.
Tyre, A.J., et al., 2003. Improving precision and reducing bias in biological surveys: estimating false-negative error rates. Ecol. Appl. 13 (6), 1790–1801.
Wibisono, H.T., et al., 2011. Population status of a cryptic top predator: an island-wide assessment of tigers in Sumatran rainforests. PLoS One 6 (11).
Wintle, B.A., et al., 2005. Estimating and dealing with detectability in occupancy surveys for forest owls and arboreal marsupials. J. Wildl. Manage. 69 (3), 905–917.
Zeller, K.A., et al., 2011. Integrating occupancy modeling and interview data for corridor identification: a case study for jaguars in Nicaragua. Biol. Conserv. 144 (2011), 892–901.
Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. Methods Ecol. Evol. 1 (1), 3–14.