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Monitoring in the presence of species misidentification: the case of the Eurasian lynx in the Alps

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Abstract

Inferring the distribution and abundance of a species from field records must deal with false-negative and false-positive errors. False-negative errors occur if a species present goes undetected, while false-positive errors are typically a consequence of species misidentification. False-positive observations in studies of rare species may cause an overestimation of the distribution or abundance of the species and distort trend indices. We illustrate this issue with the monitoring of the Eurasian lynx in the Alps. We developed a three-level classification of field records according to their reliability as inferred from whether they were validated or not. The first category (C1) represents 'hard fact' data (e.g. dead lynx); the second category (C2) includes confirmed data (e.g. tracks verified by an expert); and the third category (C3) are unconfirmed data (e.g. any kind of direct visual observation). For lynx, which is a comparatively well-known species in the Alps, we use site-occupancy modelling to estimate its distribution and show that the inferred lynx distribution is highly sensitive to presence sign category: it is larger if based on C3 records compared with the more reliable C1 and C2 records. We believe that the reason for this is a fairly high frequency of false-positive errors among C3 records. This suggests that distribution records for many lesser-known species may be similarly unreliable, because they are mostly or exclusively based on unconfirmed and thus soft data. Nevertheless, such soft data form a considerable part of species assessments as presented, for example in the International Union for Conservation of Nature Red List. However, C3 records can often not be discarded because they may be the only information available. When inferring the distribution of rare carnivores, especially for species with an expanding or shrinking range, we recommend a rigorous discrimination between fully reliable and un- or only partly reliable data, in order to identify possible methodological problems in the distribution maps related to false-positive records.

Introduction

Informed species conservation and management must be based on reliable information about its distribution, abundance, population trends and possibly more detailed demographic information, such as survival probabilities and recruitment rates (Gaillard, Loison & Toigo, 2003; Haydon & Fryxell, 2004). To reliably infer distribution, abundance and population trends from field observations, two basic issues must be accounted for in the collection and analysis of data: the spatial variation of the quantities under study and observation errors in measuring them (Yoccoz, Nichols &

Boulinier, 2001). Field data are typically prone to two kinds of observation errors: false-negative and false-positive errors. In the context of species distributions, false-negative observations arise when a species is overlooked where in fact it occurs. False-positive observations arise when a species is recorded erroneously at a place where it does not occur, for instance, because another species is mistaken for the study species. Conservation biologists and wildlife managers must ensure that the presence of a species has been correctly determined.

Failure to accommodate false-negative errors in species distribution models can lead to considerable underestimation of the range of a species (Kéry, Gardner & Monnerat, 2010; Kéry, 2011). In addition, estimates of the relationship between occurrence and environmental variables will be biased low (Tyre *et al.*, 2003; Kéry & Schaub, 2011) and those for dynamic parameters of distributional change (such as patch survival, colonization and turnover) are all overestimated (Royle & Dorazio, 2008). Fortunately, a large number of protocols for animal abundance or distribution estimation provide different methods for estimation of detection probabilities for specific kinds of count or species distribution statistics (Buckland *et al.*, 2001; Borchers, Buckland & Zucchini, 2002; MacKenzie *et al.*, 2002, 2006; Nichols & Karanth, 2002; Williams, Nichols & Conroy, 2002; Royle & Dorazio, 2008; Kéry & Schaub, 2011). In contrast, the issue of misidentification and false-positive errors has been addressed much less (but see Royle & Link, 2006). This is worrisome because for many species false-positive errors may be frequent and they have the potential to greatly bias the perceived distribution and abundance, especially when adopting models that account for false-negative errors (Royle & Link, 2006).

Information about the distribution of elusive, forest-living species, for instance in the felid family, is often based on direct sightings and may easily be subject to misidentification. As an example, the fishing cat *Prionailurus viverrinus* was first described for Sumatra in 1833 and has since been reported regularly, including by some camera trapping pictures in recent years. Verification by several cat experts revealed that all pictures showed leopard cats *Prionailurus bengalensis*, and Sanderson (2009) claimed that the fishing cat in fact never occurred on Sumatra. As another example, the Chinese mountain cat *Felis bieti* was described to occur in the provinces of Qinghai, Sichuan, Gansu, Ningxia, Xinjiang and Inner Mongolia (e.g. Zhang, 1997). However, in a reassessment, He *et al.* (2004) concluded that many reports were unreliable and that even some museum specimens had been misidentified so that now, the species' recognized distribution area is restricted to eastern Qinghai and north-western Sichuan. As a final example, some 200 reports on the Eurasian lynx (*Lynx lynx*) were collected in Carinthia (Austrian Alps) from 1990 to 1995, suggesting that this species was occurring throughout that region (T. Huber, pers. comm.). However, a systematic field survey in the winter 1995/1996 confirmed its presence only in the southernmost mountains of Carinthia, and a proper re-evaluation of all reports concluded that most reports were probably erroneous (Huber & Kaczensky, 1998).

The reliability of ecological field data to infer distributional ranges depends, among other things, on the experience of the observers and varies with their training and education, interest and consciousness. Depending on the environmental conditions, however, species identification is often difficult even for experts (DeMatteo & Loiselle, 2008). If species identification through direct observation is sometimes difficult, identification by means of tracks or other indirect signs can be even more challenging. Animals do not always leave perfect tracks, and imprints can look vastly different on various substrates and distinct conditions. Despite these difficulties, much knowledge of species distribution and abundance is based on 'soft' data, that is data that cannot be or have not been verified. Examples for soft data include second-hand reports or signs that are difficult or even impossible to verify. Museum specimens allow reconsideration provided their geographical origin can be reliably checked, but ephemeral signs such as tracks, kills and above all, direct sightings, cannot later be confirmed. Camera traps have become an important monitoring tool for felids (Karanth & Nichols, 1998), reducing the possibility of misidentification. However, they are mainly used in smaller study areas in the range of 100–1000 km^2 (e.g. Treves *et al.*, 2010, but see Sharma *et al.*, 2010 and Sollmann *et al.*, 2011 for exceptions). Therefore at the population level, soft data, whether published or based on personal communication of experts, form a considerable part of species assessments as presented, for example in the International Union for Conservation of Nature (IUCN) Red List (http://www.iucnredlist.org).

We have been confronted with the problem of false species identification in the monitoring of the Eurasian lynx populations in the Alps. After brown bear (*Ursus arctos*) and wolf (*Canis lupus*), the lynx is the third largest terrestrial predator and the largest felid in Europe with long, prominent black ear tufts, and short black-tipped tails. The only other felid species occurring in the Alps are the domestic cat and in the south-eastern Alps the wildcat (*Felis silvestris*), both much smaller than the lynx. Lynx were reintroduced into the Alps in the 1970s, but even 40 years later less than 20% of the Alps are recolonized (Molinari-Jobin *et al.*, 2010). Lynx experts from the seven Alpine countries initiated the Status and Conservation of the Alpine Lynx Population (SCALP, Molinari-Jobin *et al.*, 2003) project. This initiative aims to coordinate and standardize Alpine lynx monitoring and conservation. An explicit objective of the pan-Alpine conservation strategy for the lynx is the recolonization by the lynx of the entire Alps (Molinari-Jobin *et al.*, 2003). This requires continuous monitoring of population size and distribution (e.g. occupancy probability) in order to robustly assess the population status and propose adequate management measures. Presence records based on signs were reported almost throughout the 200 000 km^2 range of the Alps (Fig. 1). This large-scale monitoring of lynx allowed us to uncover differences in the perceived distribution depending

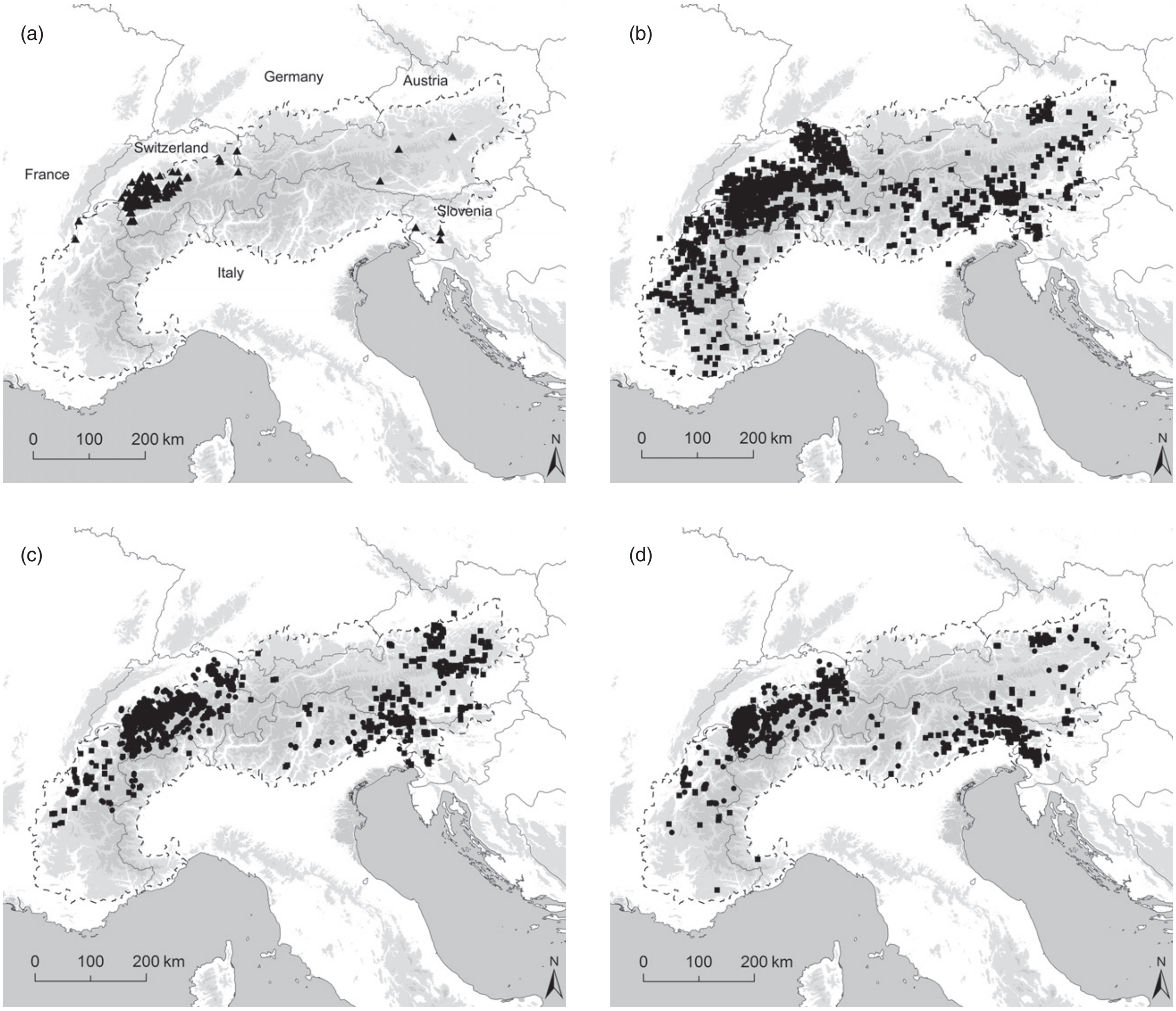

Figure 1 Distribution of lynx records compiled by the Status and Conservation of the Alpine Lynx Population network from 1995 to 2008 in the Alps (the dashed line outlines the area covered by the Alpine Convention). Adjacent ranges (e.g. Jura and Dinaric Mountains) are not considered. (a) Lynx mortalities; (b) direct sightings; (c) kills; and (d) tracks. C1 data is represented with a triangle, C2 data with a dot and C3 data with a square
(see methods chapter for further explanations).

on which types of presence records were used to describe the lynx distribution, for example reliable records such as lynx carcasses found, less reliable records such as direct observations and indirect signs such as tracks and kills (Fig. 1). Distinguishing genuine records of lynx presence from false-positives within this heterogeneous body of information is a challenge. The task at hand is to infer the real lynx distribution from a pool of data contaminated with false-positive observations. This is a widespread challenge for many species throughout the world.

In this paper, we describe and test a practical approach to disclose problems induced by varying reliability of, and different dangers and degrees of misinterpretation in various kinds of lynx observations. We hypothesized that

1 There are relatively constant proportions of different types of records (e.g. confirmed vs. soft data) in comparable parts of a landscape like the Alps;
2 Atypical proportions indicate a problem within the monitoring scheme (for instance, in a certain country);
3 Different kinds of direct or indirect signs of presence are the result of observation processes with different false-positive error rates; and
4 The establishment of a monitoring network and training of the people in this network should result in a decrease of the proportion of soft information over time.

These ideas are widely applicable when making inferences on the distribution and abundance of elusive animals from sparse and error-prone field data.

Methods

Data collection

The potential Alpine lynx population covers seven countries (France, Italy, Switzerland, Liechtenstein, Germany, Austria and Slovenia), and numerous administrative units, private organizations, scientists, hunters, naturalists and others are involved in the data collection to monitor lynx. Chance observations are continuously collected and compiled by a network of people trained to recognize and assess different signs of lynx presence and are annually unified in the SCALP database. Network members collect relevant observations made by themselves and by the general public throughout the year and forward them to their national centre in charge of the monitoring. Network members are game wardens, people from the forest service, hunters, naturalists and others trained in specific courses. The SCALP documents the distribution of the lynx over the entire Alps at the scale of a 10×10 km grid. Owing to the large number of people and organizations participating in the lynx monitoring in the Alps, we believe that no occupied cell has a zero probability of detection (see later). In this study, we use data collected across the Alps from 1995 to 2008. In addition, we contrast two countries, Switzerland and Italy. In Switzerland, specific training courses for game wardens started in 1983 already and the network covers the whole area of Switzerland, independently of presumed lynx presence or absence. In contrast, in Italy, the monitoring system has evolved from local to Alpine coverage from 1996 onwards only.

The SCALP classification of reliability of distributional records

We used a standardized interpretation key based on a categorization of possible presence records, where each record is evaluated retrospectively whether it can be and whether it has been verified for correct species identification. Thus, each occurrence record gets an attribute of whether or not it has been verified and confirmed or not. Therefore, for the lynx monitoring throughout the Alps in the SCALP framework, all data collected are assigned to one of three categories:

C1: Confirmed 'hard facts', verified and undisputable records of lynx presence such as (1) dead lynx; (2) captured lynx; (3) good quality and georeferenced lynx photos (e.g. from camera traps); and (4) samples (e.g. excrements, hair) attributed to lynx by means of a scientifically reliable analysis.

C2: Records confirmed by a lynx expert (e.g. trained member of the network) such as (1) killed livestock or (2) wild prey; and (3) lynx tracks or other assessable field signs.

C3: Unconfirmed category 2 observations (kills, tracks, other field signs too old or badly documented, where however the description conforms to a lynx sign) and all observations such as sightings and calls, which by their nature cannot be verified.

Along with C1 data, C2 form the core of the chance observations used for describing lynx distribution. Owing to a rather rigorous view about what constitutes a confirmed record of lynx presence, we assume that false-positive records are absent in C1 data, might rarely occur in C2 data and occur more frequently among the unverified records (C3). For lynx in the Alps, this categorization is done by the national body in charge of lynx monitoring, not by the individual network member.

Statistical methods

To describe the differences in the Alpine lynx distribution based on confirmed versus unconfirmed data, we fit a dynamic site-occupancy model (MacKenzie *et al.*, 2002, 2003, 2006; Royle & Kéry, 2007; Kéry & Schaub, 2011). This model jointly estimates the probability of occupancy and detection and therefore corrects the distribution estimate for detection probability, that is the probability to detect the presence of a species at a site where it occurs. We contrasted two periods to outline the effect of the categorization in time: 1995–1997 versus 2006–2008, with each year representing a sampling occasion. For this purpose, we covered the Alps with a grid of 2176 squares of 100 km^2 each. Our analysis makes two assumptions: (1) Lynx distribution remained unchanged within each of the two periods. This assumption may have been violated to some degree and as a consequence, our estimate of occupancy may refer to the area of use rather than of permanent presence of lynx (see MacKenzie *et al.*, 2006, for more on the distinction between permanent presence and occasional use). (2) Owing to the large number of persons and organizations that collaborate in the Alpine lynx monitoring, we assumed that there is a non-zero chance of detecting a lynx in every occupied 100 km^2 cell in each year (i.e. no cell was devoid of any monitoring efforts). Only if this assumption is met we can treat years without a lynx record as a zero rather than as a missing value in the detection history fed into the site-occupancy model. We strongly believe that this assumption holds for the vast majority of cells in our study area. Wherever it is invalid, our estimates of detection probability are underestimates and those of occupancy overestimated.

We modelled as data the number of years (out of the three) in which lynx records were obtained in a 100 km^2 cell. Hence, within a year we ignored more than one record per cell and simply distinguished between cells and years in which no lynx was recorded (yielding a '0') and those with at least one record (yielding a '1'). The dynamic site-occupancy model is a state-space model, that is it distinguishes a latent (only partly observed) ecological process, which produces a state of occurrence or non-occurrence, and a dependent observation process, which produces the actual detection/nondetection observations. The ecological process is defined by the occupancy probability (= occupancy) in the first year (ψ) and the dynamic parameters of survival (also called persistence), ϕ, and of colonization, γ, such that

$$z_{i1} \sim Bernoulli(\psi)$$

and

$$z_{i2} \mid z_{i1} \sim Bernoulli[z_{i1}\phi + (1 - z_{i1})\gamma]$$

Hence, the true state of occurrence of cell i in the first 3-year period (i.e. cell i is occupied, $zi_1 = 1$, or unoccupied, $zi_1 = 0$) is modelled as a coin flip with success parameter ψ. For the second 3-year period, the occurrence state is a function of the occurrence state of the cell in the previous period and the survival and colonization parameters.

The observation process is defined by the annual detection probability p_{it} for site i and 3-year period t, such that the observed data y_{it} (the number of years with a lynx detection in cell i and 3-year period t) is a binomial random variable: $y_{it} \sim Binomial(3, p_{it})$.

We fitted a separate model to the two sets of confirmed (C1 and C2) and unconfirmed (C3) data and assumed that the probabilities of first-year occupancy (ψ) and of survival (ϕ) and colonization (γ) were constant over the 2176 100 km^2 cells and that detection probability differed only by period, but not among cells nor among years within a period. This means that we averaged over any existing variability among cells and/or years within a 3-year period.

We fitted the model in the Bayesian framework of inference using Markov Chain Monte Carlo simulation techniques implemented in the WinBUGS software (Gilks, Thomas & Spiegelhalter, 1994; Lunn *et al.*, 2000), as did Royle & Kéry (2007) and Kéry & Schaub (2011). For all parameters, we specified conventional vague priors. Hence, all estimates will be dominated by the information in the data and resemble those obtained when using the maximum likelihood method (Kéry, 2010). For each analysis, we initialized three parallel Markov chains at random places and ran them for sufficiently long that visual inspection of the trace plots and the Brooks–Gelman–Rubin statistic suggested convergence to the target posterior distributions (Kéry, 2010; Kéry & Schaub, 2011).

The site-occupancy model yields a detection-corrected estimate of the species distribution based on the number of occupied 100 km^2 cells. As an alternative estimate of the extent of the lynx distribution, we buffered the location of each point with a 5-km radius, resulting in an area of approximately 80 km^2 for each record. This area corresponds roughly to an average female lynx home range size in the Alps (Breitenmoser-Würsten *et al.*, 2001). All maps were drawn in ArcGIS 9.3.1 (Environmental Systems Research Institute, Inc. Redlands, CA, USA).

Results

From 1995 to 2008 a total of 7465 records of lynx occurrence were collected throughout the Alps, of which 5% were categorized as C1, 56% as C2 and 39% as C3 data. There were remarkable differences between countries in these proportions: in Austria, 64% of the records were attributed to C3 and in Switzerland, only 29%. In Switzerland, a systematic monitoring scheme had been launched before 1995, and the

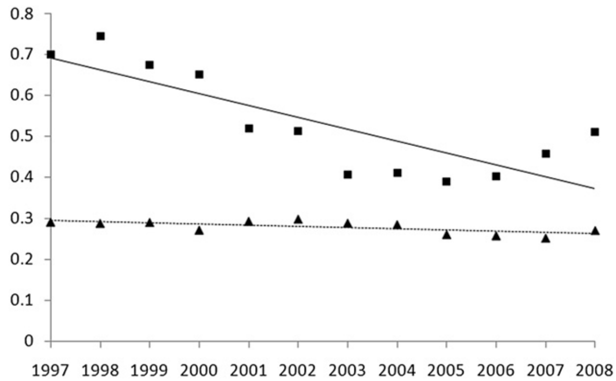

Figure 2 Proportion of unconfirmed data (C3) in the monitoring databases of Italy (black trendline and squares) and Switzerland (dashed trendline and triangles).

Table 1 Area occupied by lynx in the Alps when considering only hard fact data (C1), confirmed data (C2) and unconfirmed data (C3), and the ratio between them

	1995–1997	2006–2008
C1	1692 km^2	5238 km^2
C2	10 502 km^2	15 457 km^2
C3	18 148 km^2	23 809 km^2
Ratio	1:6:11	1:3:5

proportion of C3 records remained at a fairly constant, low level. In contrast, in Italy, the proportion of unconfirmed C3 records has been decreasing from a higher initial level (Fig. 2). This suggests that the proportion of confirmed (C1 and C2) data increases with the improvement of the monitoring scheme in accordance to our Hypothesis 4. Across the Alps, the proportion of unconfirmed versus confirmed data (C3 vs. C1 and C2) decreased from the 1995–1997 to the 2006–2008 period ($\chi^2 = 85$, degrees of freedom = 2, $P < 0.001$). The data was mainly upgraded through an increase of the proportion of hard fact data (C1).

The lynx distribution in the 1990s and in the 2000s inferred from the different classes of records differed greatly. From 1995 to 1997, 43% of the data collected were C3. Along with their 5-km buffer, they covered an area of 18 148 km^2 (Table 1). In contrast, 55% of the data that belonged to the C2 category covered 10 502 km^2 only (Table 1). Finally, when considering only C1 data, the perceived area of lynx occurrence shrank drastically to only 1692 km^2. The ratio of the perceived distribution areas as inferred from records of type C1:C2:C3 was 1:6:11. A decade later (2006–2008), plots of C3 data revealed a wider distribution covering 23 809 km^2 versus 15 457 km^2 for C2 data and 5238 km^2 for C1 data. Hence, the resulting ratio was now only 1:3:5. During 1995–1997, 71% of the area covered by C3 had not been validated with confirmed data. During 2006–2008, the area covered by C3 without confirmed records decreased from 71 to 59% (Fig. 3).

Both confirmed (C1 and C2) and soft (C3) data showed an increase in the area occupied over 10 years, but

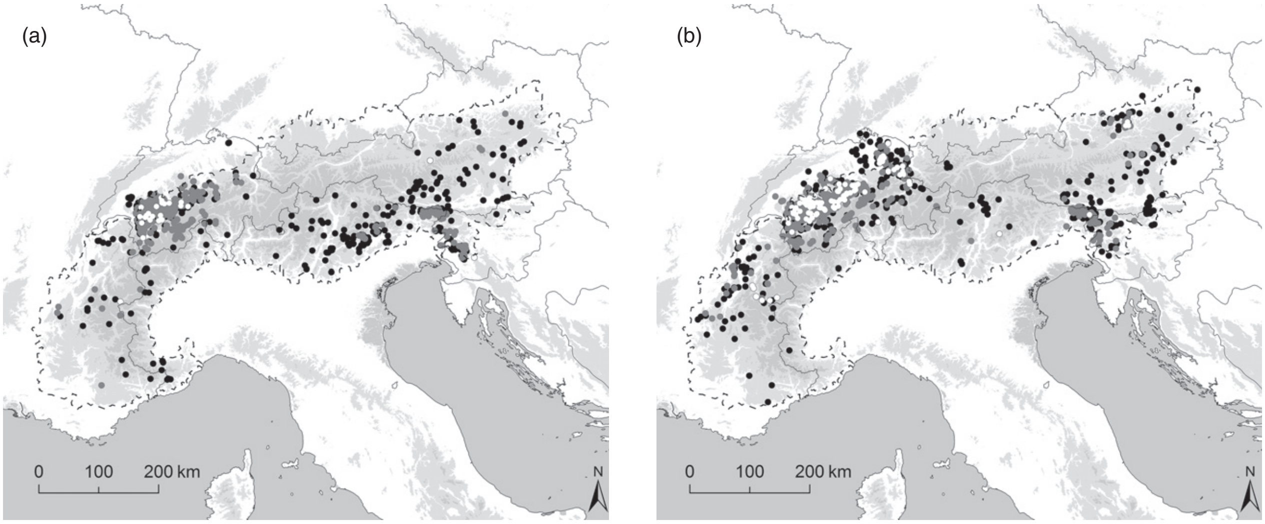

Figure 3 Distribution of lynx records in the Alps according to Status and Conservation of the Alpine Lynx Population categories: C1 hard fact data = white, C2 confirmed data = grey, C3 unverified data = black. Each dot represents a point observation buffered with a radius of 5 km (see methods for further details). (a) 1995–1997 and (b) 2006–2008.

Table 2 Observed number of occupied 100 km^2 cells and parameter estimates under the site-occupancy model (posterior means and standard deviations are shown)

	Confirmed data (C1/C2)		Unconfirmed data (C3)	
Metric of distribution	1995–1997	2006–2008	1995–1997	2006–2008
Number of occupied squares	108	170	236	284
Initial occupancy (ψ)	125.41 ± 6.31	186.67 ± 5.20	410.17 ± 33.87	445.99 ± 29.25
Ratio observed/estimated number of occupied squares	0.86	0.91	0.58	0.64
Probability of survival (φ_i)	0.74 ± 0.05		0.59 ± 0.06	
Probability of colonization (γ_i)	0.05 ± 0.01		0.12 ± 0.02	
Detection probability (p)	0.49 ± 0.04	0.56 ± 0.03	0.25 ± 0.02	0.29 ± 0.02

occupancy modelling revealed differences between confirmed and soft data (Table 2). With confirmed data, the ratio of observed and estimated number of occupied cells, survival probability (i.e. the probability that a cell occupied in period 1 is still occupied in period 2), and growth rate (i.e. the ratio of the occupancy probability in period 2 and 1) were estimated higher, while the probability of colonization (i.e. that an unoccupied square in period 1 will be occupied in period 2) was estimated lower (Table 2). Moreover, detection probability also increased, again suggesting an improvement of the monitoring over time.

Discussion

We introduce a simple method to assess the reliability of chance observations compiled for large-scale monitoring of lynx in the Alps by categorizing occurrence records. This method allowed us to distinguish between areas with confirmed lynx presence and areas where only unconfirmed data exist. Comparing such 'hard' (C1 and C2) and 'soft' data (C3) in space and time using site-occupancy modelling (MacKenzie *et al*., 2002, 2003; Tyre *et al*., 2003) revealed that cells with C1 and C2 observations had a higher probability of being detected and to persist, whereas cells with only C3 records had a lower probability of being detected and persistence, but a higher probability of colonization (Table 2). This may indicate a higher probability of false-positive records in the C3 data type. All Alpine countries had areas with only isolated C3 data, thus where the presence of lynx had not been confirmed. This may be due to the fact that (1) these areas were only briefly visited by transient individuals, or (2) these observations were mistaken, hence false-positive observations. Most often, these areas are situated at the edge of regions of expanding lynx occurrence, where it is difficult to distinguish between the two possibilities. C1 records – which are obviously relatively rare, compared with the other two categories – correspond well with the C2 observations, indicating that C3 information is indeed less reliable.

In either case, the uncritical or unfiltered integration of unconfirmed observations into a monitoring database may result in an overestimation of the (permanently) occupied area. False-positive observations are to be expected for elusive species with a high public awareness, a good example for this being charismatic and/or controversial predators such as the lynx. Furthermore, distributional changes may add to the potential of misinterpretation. In our situation with an expanding range, false-positive observations lead to an overly optimistic assessment of the recolonization. In situations with a diminishing range, false-positive observations may result in a dangerous underestimation of the population decline. This was for instance the case with the Critically Endangered Iberian lynx *Lynx pardinus* in Portugal, where, mainly based on direct sightings, the species was reported to exist in areas where no reliable evidence (our C1 and C2 observations) had been available for many years and intensive camera trapping failed to produce any lynx pictures (Sarmento *et al.*, 2009). As much as an involvement of the general public is desirable for the monitoring of a carnivore such as the lynx, it is to be expected that targeted public awareness campaigns provoke a considerable number of false-positive observations.

In the long term, the main solution to the problem of false-positive records in lynx monitoring in the Alps consists in the improvement of the monitoring scheme, by establishing a well-organized network of trained local assessors. Depending on the type of observation, the network member will verify the record either by photos or directly in the field. The verification requires well-trained assessors and a standardized monitoring scheme allowing integrating records from various regions into one data pool and a common interpretation and reporting. This will eventually lead to a reduction of C3 (with exception of the observations that cannot be verified) and an increase of C2 and C1 records. In the two observation periods in the Alps, the area covered only by C3 data decreased from 71 to 59%. Establishing such a network however takes time and needs a long term financial commitment. The SCALP project was launched in 1995, and 15 years later, the maintenance and expansion of the monitoring network is still a major task. For instance, in peripheral areas of lynx occurrence, the evaluation of chance observations is often not (yet) possible, and hence many reports will remain categorized as unconfirmed data (C3). These observations are nevertheless important, because they may indicate an interesting spatial development.

Given the serious consequences of inaccurate estimates of the status of rare species for conservation and management decisions, accounting for false-positive detections should be an important component of the design and analysis of monitoring programmes for rare species (Miller *et al.*, 2011). The contribution of this paper has been to suggest a categorization of the records of a rare and elusive species into different classes of reliability. Up to very recently, with current analysis methodology that accounts for false-negative errors only (i.e. classical dynamic site-occupancy models; MacKenzie *et al.*, 2003), the best advice would have been that least-reliable records be best discarded when evaluating the distribution of the species (Kéry, 2011). The reason for this is that false-positive errors are likely common in the latter and this will greatly inflate the perceived distribution range. Statistical models of species distributions for such contaminated data have been developed (e.g. Royle & Link, 2006), but they are unsatisfactory, because they cannot distinguish between among-site heterogeneity in detection probability and false-positive probability. As a consequence, these models have so far not been applied very often. However, the most recently developed site-occupancy models by Miller *et al.* (2011) can cope with uncertain detections, so there is no need any more to discard error-prone data (e.g. C3 in our case). These models distinguish between two or more classes of records, for one of which one must be able to exclude false-positives. These new models thus enable one to fully incorporate also uncertain records of our C3 type into distribution assessments, without the need to discard this soft, but abundant information source. Hence, in combination with such new modelling frameworks, our categorization is likely to pay even greater benefits in the future.

Categorizing field observations alone does not improve the quality of the data set, but it allows detecting methodological biases, possible shortcomings in the monitoring scheme, and areas requiring a more rigorous monitoring. Regions from where only unconfirmed data are reported should hence be marked specifically.

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