Recent tools for population abundance estimation adjustment and their use in long-term French red-legged partridge survey

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Abstract – The consistency of population estimates is crucial for long term surveys, especially for conservation and management purposes, and particularly for game species as the red-legged partridge *Alectoris rufa*. Most monitoring programs simply assume that count indexes are proportionally related to abundance. However, this assumption cannot be made when detection varies spatially and temporally, as it is mostly the case. Advances of statistical tools allow now detection modeling using spatially and temporally repeated count data and lead to less-biased estimates than raw counts, and sometimes to less effort in the field. In the future, they might become highly relevant for monitoring programs; however field biologists might have to be trained or assisted for data modeling. We illustrate the case of the French survey of red-legged partridge populations (*Alectoris rufa*), the method being also used for the survey of a northern Italian population.

Key-words: *Alectoris rufa*, CMR, count method, detectability, bird survey, N-mixture model, population estimates.

The need for adjusted surveys

Consistent estimates in bird surveys are crucial for many purposes and a multitude of techniques is available (Bibby *et al*. 1992). Surveys must be employed, when we need a reliable estimate or an index (estimate unadjusted for detection issues) of the population size of a particular species in a given area (Sutherland *et al*. 2004).

Surveys are undertaken to elucidate avian-habitat relationship, to estimate spatial distribution or to evaluate the impact of anthropogenic development on nature conservation value (Blondel *et al*. 1981). Furthermore, in exploited (e.g. hunted) species, a consistent prediction of population trends may help to maintain the population sustainably and to set management priorities (Julliard *et al*. 2004, Johnson 2008).

A complete count of bird numbers or "true census" in an area is hardly ever possible for a multitude of reasons (Sutherland *et al*. 2004), therefore "incomplete counts" are mostly used. Either, they are based on indexes or on reliable abundance estimates.

Generally, when using indexes, we assume that counts are strictly proportional to true abundance. To estimate a number, N, of individuals present in an area from a raw data sample count, C, of that area, the expected value of the count is given by

$$E(C) = Np$$

where p is the "detection probability" (Nichols *et al*. 2000) or "index ratio" (Bart & Earnst 2002). The use of C (raw count data) to estimate the change in N over time (i.e. trend), requires the already above mentioned "proportionality assumption" (Thompson 2002), i.e. that there is no trend in p (McCallum 2005). In most cases, this exact proportionality between indexes (i.e. unadjusted counts) and true abundance cannot be assumed (Pollock *et al*. 2002, Williams *et al*. 2002, Kery & Schmidt 2008). Statistically, two crucial issues regarding the use of an abundance index are i) sampling and ii) observability/detectability, which account two kinds of errors, namely sampling and observation errors (Aubry *et al*. 2012). Precision of abundance index and underestimation e.g. of obervation errors are treated elsewhere (Aubry *et al*. 2012).

Here we focus on one of the most complex problems for a survey program based on reliable abundance estimates: the variability of detection due to different factors intervening during the count surveys. Sources of varia-

tion can be intrinsic to the life history traits of a bird (e.g. season and daytime activity, territoriality), or related to the biotic environment, e.g. vegetation density among and within the sites, the varying population density, or perception of observer, e.g. the experience (Pollock *et al*. 2002, Alldredge *et al*. 2007a, Aubry *et al*. 2012). Even with the highest standardization of a field protocol, these variations cannot be completely excluded without testing for them.

Therefore, the relation among the abundance estimate and population size remains often unknown, ignoring the magnitude of the underlying bias. To obtain such reliability and among space and time comparability of abundance estimates we have to adapt surveys, not yielding only indexes, but real abundance (and in the step further: density). This need for valid abundance estimates has spawned a number of models for estimating *p*, which is a detection probability (Burnham 1981, Nichols *et al*. 2000). Detection probability estimates are then used to account for animals present but not detected on surveys (Thompson 2002).

Although accuracy and precision of most techniques currently used to count birds has been questioned because of their failure to provide estimates of detection probability p (Nichols *et al*. 2000, Rosenstock *et al*. 2002), surprisingly 95% of surveys still deal with naïve data counts (McCallum 2005). This might partly be related to the novelty of methods (but some methodology exists since the 80's), the unfamiliarity of modeling for field workers, and the difficulty of obtaining sufficient data on possible variation sources.

Two groups of count methods (i.e. field protocols related to specific statistical tools) for detectability estimation can be coarsely distinguished, both applied in a growing number of surveys of national interest. First, a group we call here for simplicity the "point count methods" (Presence – absence, Capture-mark-recapture, Removal, Double count), and second, the distance sampling (Borralho *et al*. 1996, Buckland *et al*. 2001, Williams *et al*. 2002). Main differences between the two include the assumptions for detection in the field (see paragraph i), e.g. the assumption of the method is that all animals present at distance = 0 are detected (Buckland *et al*. 2001), which is not given e.g. during visual counts in closed vegetation areas.

Distinct from other vertebrates, birds are mostly surveyed without capturing or marking individuals. A number of passive sampling techniques, e.g., spot-mapping, line transects, and point counts, are commonly used for estimating numbers of birds. A taxonomy of sampling and analytical methods is given by Thompson (Thompson 2002). Several methods are mainly adapted to bird surveys at a

larger scale (Sutherland *et al*. 2004), such as models adapted to repeated point counts, allowing estimation of detection probability and therefore adjustment of abundance estimates later onwards (Buckland *et al*. 2008). Somewhat more complex than working with raw counts, the data treatment of these results allows us to obtain mean abundance with confidence intervals and to follow changes in bird populations at a larger scale and time period. Population management policies can then be based on these trends.

Thus, globally, statistical tools for adjusted survey counts strongly progressed in recent times, supporting the field protocols, which are constraint by field conditions and species biological traits (Besnard 2009). In the framework of regional and national surveys and networks in monitoring programs multi-species or mono-species surveys are multiplying recently (Escandell 2005, van Strien *et al*. 2010).

The approach chosen in the *Alectoris rufa* survey in southern France is now also applied on survey data of partnership in Northern Italy and forthcoming in north-eastern Spain.

This paper had two purposes: i) to give a general overview on recent tools for abundance estimate adjustment via detectability by assisting field biologists and managers in understanding the concepts underlying detection probability and ii) to use the example of the existing French red-legged partridge survey network (since 1992) to depict an a-posteriori integration of estimate adjustment.

I. Recent tools for abundance estimate adjustment via detectability

It is now acknowledged that the relation of abundance index and real abundance in surveys, especially for birds, is rarely linear and might be divided into in four general categories (Besnard 2009). The survey type **a** shows the very rare model case, where the index is proportional to the real bird number, and a quasi exhaustive sampling was done (Fig.1).

In type **b**, the relation is linear, but index increases slower than abundance, detection probability is thus not 1 but constant, independent from bird density. In the present case the detection probability is 0.5 (50%). In the type **c**, the index is proportional to true abundance of birds up to a certain bird density, and then it shows a saturation effect, for example, because at high density it can be difficult for observers to distinguish all individuals or birds modulate their song interval to be heard. This is a classic case for territorial male birds and index would not be reliable. In the
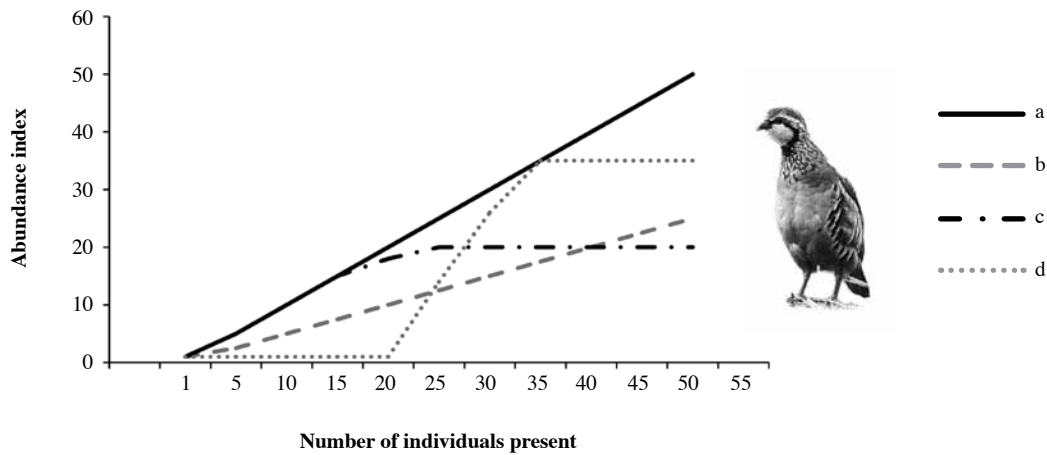
Figure 1. Real number of birds present in function of abundance index; the four most common categories (a-d) for this relation (see text) are shown.

type **d** the index does not increase until a certain threshold value, then increases rapidly and saturates at a new threshold. Such a case corresponds to e.g. male singers, without song activity until a certain bird density where they stimulate each other, and saturating afterwards as in type **c**. As cases **c** and **d** are frequent in bird field surveys, simple indexes have to be tested or treated with caution when used for conservation and management purposes.

Hence, to be able to make inferences from raw count data (C) of abundance estimates without worrying for untested assumptions, it is necessary to introduce statistical tools for the estimation of abundance (N). The generalized estimate is $N = C/p$ (Nichols *et al.* 2000), where the common value of the parameter p is the probability of detecting a typical individual.

The greatest difficulty consists in determining p. Distance sampling models, now frequently used in bird surveys, will establish the detection probability as a function of the distance from the observer, making necessary that detection is 1 at a distance of 0 m (Buckland *et al.* 2001). This assumption is not always fulfilled, e.g. for visual red-legged partridge detection in closed vegetation habitats (Borralho *et al.* 1996). Plots are chosen and may be sampled from fixed points or a transect line (Ramsey & Scott. 1979, Rosenstock *et al.* 2002).

In the group that we call here "point-count models" the detection probability p includes the probability that the bird sings or produces some other detectable cue (ps) and the probability that it is detected, given that it sings (pd/s) (Farnsworth *et al.* 2002), also called the availability of the bird (McCallum 2005). In comparison, distance sampling considers that all animals present perform detectable acts during the survey period, thus in fact considering

only pd/s, not p. Therefore, for surveys based on discrete cues, such as aural signals, e.g. bird song, this subdivision makes sense. As low availability might be a problem for non-detection, observers have to take it into account, either by choosing optimal availability conditions (e.g. day-time with highest activity, season etc.) or by triggering cue appearance, e.g. by playback use. We obtain p through the following:

$$p = ps\,(1-(1-p1d)\,s)$$

where p1d is the probability of detecting an average cue, and s is the number of cues, i.e., songs or other detectable acts that the bird actually produces during the count period.

Several of the above mentioned methods are "rapid surveys" (e.g. presence-absence), owing the advantage to be less time consuming in the field than marking programs.

II) Adjusted abundance estimates in survey of *Alectoris rufa*

We take here intentionally the example of a farmland and game species with a large distribution and existing data-sets, in our opinion illustrating well the possibility of a posteriori data treatment and the interest for acquisition of long-term data. The species declined for the past 30 years across European countries (Birdlife International 2004). The French population was estimated to be 300,000 pairs in 1998 (Reitz 2003), with an annual hunting bag of 1.5 Mio individuals, including those released (Ponce-Boutin *et al.* 2009). In Europe, the species declined about 25%

over the last 20 years (Aebischer & Potts 1994). Regular inquiries on hunting bags do not provide a reliable long-term assessment of population trends, even if a comparison between 1995 and 2000 gives some indices (Ponce-Boutin *et al*. 2009).

As reported above, there is a need to include the idea of count adjustment via detection in surveys aiming at long term and larger scale monitoring. It seems crucial to obtain such viable long-term trends for a game species as the red-legged partridge, as populations are suffering from i) habitat loss or deterioration in southern France (main distribution area outside Spain) in particular due to agriculture abandonment, ii) release of reared birds, impacting negatively on wild bird populations when used to artificially increase hunting bags (Ponce-Boutin *et al*. 2006).

The red-legged partridge survey has been implemented since 1992 in the Mediterranean part of France. Since 2010, the survey protocol is also applied in Northern Italy by Tizzani *et al*. (Tizzani 2011) and hopefully in 2013 on some territories of Northern Spain. The applied field technique consists in a three times repeated aural point count transect reinforced by playback (see http://www. oncfs.gouv.fr/IMG/protocole_denomb/protocole_denombrement_perdrix_rouge_2012.pdf for detailed protocol), comparable to common point counts 1970 (Ferry & Frochot 1970).

We obtained over 16.000 resulting data from 47 sites on naïve counts of partridges (*Alectoris rufa*). These raw data can not be compared directly with estimates of other raw data results of other field techniques, regularly employed for partridge counts (e.g. quadratic sampling, kilometric index). To counteract this lack, from 2009 onwards, a slight reorganization of field protocols (division of the initial aural count period into small time intervals) and the application of recent statistical tools such as CMR and later a special class of occupancy models, so called N-mixture models, were used to improve and adjust the estimates (Jakob *et al*. 2010).

At the beginning of the study, the main problem of existing spring counts in red-legged partridges beared the bias of variability in abundance estimation and unknown detection (Pépin & Fouquet 1992). Frequent sources of variation were differences in vegetation cover, variable song activity during daytime (Fig. 2), differences in observer experience, management and bird densities. Furthermore other count methods, such as kilometric index and quadrat sampling were applied sometimes, and conversion among results from different methods can not be done, so there was no generalized information on a local or regional scale.

The aim was to find a survey method adapted for a broad number of cases (i.e. date, open habitat or matoral, different experience of field workers), to counterbalance availability of a low-responsive species via playback broadcast, to minimize field effort vs precision optimization and to test for linearity of abundance estimates pro-
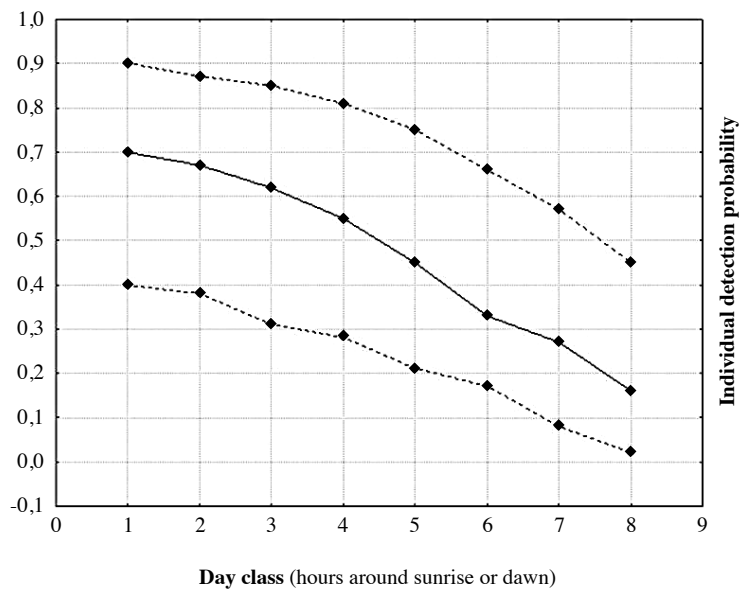
Figure 2. Results from French red-legged partridge survey. The decreased detection probality (up to 0.8, i.e. 80%) during daytime classes (1 to 5). Best detection found for 1 = 1h before sunrise, 2 = sunrise; 3 = 1h after sunrise. Axes: Individual detection probability (y - axis) in function of time classe (X - axis). Mean value (full line), and confidence intervals (dotted line).

vided by the different methods, i.e. comparable with other methods (e.g. other galliforms [Bernard-Laurent & Laurent 1984]). Thus, we aimed to produce comparable abundances in time and space through estimated detectability.

First, we used CMR model on a small data set in order to test playback effect on availability of a low-responsive species and to increase detectability (Alldredge *et al*. 2007b). Indeed, Dawson *et al*.'s results (Dawson *et al*. 1995) suggest that the lower values of p are more sensitive to sampling variation. The results showed that the supplementary use of playback during point count surveys counterbalances low availability and the detection increases significantly during sessions with playback, improving abundance estimates (Jakob *et al*. 2010).

In a second step the whole 19 years dataset was modelled by N-mixture model (Royle 2004) to cope with variable sampling situations (i.e. covariates such as habitat closure), to obtain confidence intervals for estimates (Fig. 3), and to compare via a second model not detailed here results among survey methods, including the Square Sampling (considered as an exhaustive census method), the Kilometric Abundance Index by car (Ricci 1989) and the Blank Beat (Ponce-Boutin *et al*. 2001).

The results are encouraging (Jakob *et al*. 2013), as we obtained moderate confidence intervals of abundance estimates for each site and year. Comparison of methods was possible via a linear relationship among density estimations of the different methods.

Figure 2 shows the example of the relationship between daytime and detection probability and more precisely the availability of the red-legged partridges to detection decreasing during morning hours. Such an effect (as well as those of season vegetation closure) can be taken in account either by the field protocol (e.g. avoiding the hours with less detection) or being afterwards included as covariate in the applied model.

Up to now, in the framework of the French red-legged partridge survey network, we can offer to participating field biologists and site managers a rapid and cost efficient field method, supported by a statistical tool and able to generate viable estimates for the spring counts, which are also comparable among methods and sites (about 50 sites). An outlook for the future will be to test its general validity for generating large scale and long term data, including numerous sites in other parts of the species distribution area and maybe testing linearity with further count results (Borralho *et al*. 1996). The conversion into density values for local management purposes is also tested and will outcome soon (e.g., Villain 2012).

In summary, there is a promising new approach for generalized data in bird monitoring, in terms of viable estimates for large-scale population abundance and population density trends (BirdLife International 2004, van Strien *et al*. 2010).
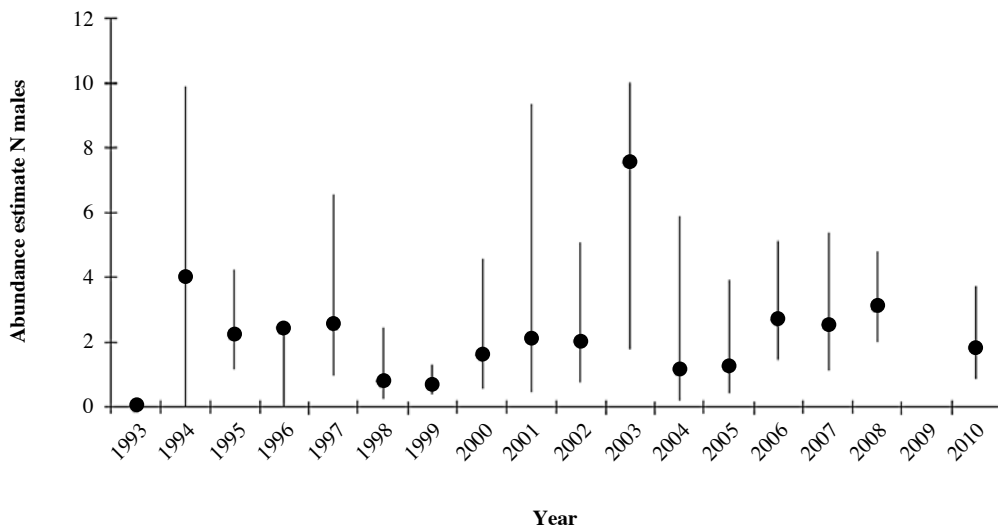
Figure 3. Example of abundance estimates for one site based on results of 18-years count data treated by probability of detection tool (N-mixture model). The estimate of mean male number per point and year with SE is given.

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