



# Volunteer-based surveys offer enhanced opportunities for biodiversity monitoring across broad spatial extent



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## ABSTRACT

The growing public interest in biodiversity projects provides great opportunities to monitor biodiversity across broad geographic areas at low cost. Such volunteer-based surveys should however need careful consideration during statistical analysis since the presence of residual spatial autocorrelation and over-heterogeneity can lead to misguided inference. The recent development of new statistical tools allows accounting for these problems in all steps of the statistical analysis. Especially, the spatial leave-one-out method allows accounting for spatial autocorrelation in the variable selection step while the R-INLA tool box provides a useful way to estimate complex spatial hierarchical models in a minimum computation time. We applied such tools on a dataset collected by volunteers between 2000 and 2013 giving the relative abundance of 12 raptors breeding in France. We then estimated their spatial distribution, population sizes and trends with a particular emphasis in quantifying the uncertainty of our estimations. Our results suggest that broad-scale volunteer-based surveys offer enhanced opportunities for monitoring widespread species but may fail in giving accurate information for less common species, especially when sampling is too scattered. Providing uncertainty of estimations helps in identifying species and areas from which estimations are the more reliable and thus gives more powerful information for conservation practitioners.

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## 1. Introduction

The '2010 biodiversity target' aiming at a significant reduction in the rate of biodiversity loss by 2010 has not been achieved (Butchart et al., 2010; Convention on Biological Diversity Secretariat, 2010). This objective has thus been renewed by 2020, with 20 important biodiversity targets being proposed to reach this task (Mace et al., 2010; Perrings et al., 2010, 2011; Rands et al., 2010). Evaluating whether these targets are fulfilled relies on the existence of valid indicators reflecting, as accurately as possible, the exact global biodiversity condition (Butchart et al., 2010; Jones et al., 2011). While existing indicators were shown to be efficient, they still should be improved by 'collecting data in a way that reduce existing bias' (Jones et al., 2011). A critical way to improve the reliability of global biodiversity indicators is to collect data at broader spatial extent, which is the actual scale for both population functioning and policy decision making (Jones, 2011; Jones et al., 2011; Pereira and Cooper, 2006). However broad-scale species monitoring is very costly, while funds to manage biodiversity are very limited, highlighting the need to maximize the cost-effectiveness of monitoring programs.

A promising solution to reduce the cost in collecting biodiversity data arose recently with the growing public interest in biodiversity

projects (Silvertown, 2009). The participation of hundreds if not thousands of volunteers in such projects has rapidly grown over the past decade (see Dickinson et al., 2010). Concomitant with the citizen science wave, new communication tools such as internet and the free availability of remote sensing databases (Kerr and Ostrovsky, 2003) have marked the emergence of new quantitative approaches able to address questions on the species distribution across very broad geographic areas (Dickinson et al., 2010). However, broad-scale data involving volunteers also raised new concerns in regard to the statistical analyses to be used since such data may have potentially higher heterogeneity than expected by conventional models (e.g., overdispersion, see Hinde and Demétrio, 1998) and in addition will present strong spatial autocorrelation (Beale et al., 2010; Dickinson et al., 2010; Hothorn et al., 2011). These two issues may lead to overconfident statistical inference if not properly treated. In this paper, we argue that combining broad-scale volunteer-based survey and appropriate statistical analyses can be highly valuable to estimate species population parameters, such as distribution, abundance and trends, at spatial scales that have not been addressed so far.

As a case study we analysed a national volunteer-based survey on the abundance of 12 raptors breeding in France (about 550,000 km<sup>2</sup>) between 2000 and 2013. We additionally used free remote sensing climatic and habitat (land cover) datasets to link observed abundance with environmental variables suspected to directly or indirectly influence their abundance (see Le Rest et al., 2013). A particular emphasis

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concerns the statistical analyses, since they should account for both overdispersion and spatial autocorrelation at each step of the modelling framework, i.e., from variable selection to model predictions. The spatial-leave-one-out (SLOO, Le Rest et al., 2014) is used for variable selection, which allows choosing relevant variables while avoiding undesirable effect of spatial autocorrelation. Variables selected were then used in a spatially explicit model with a negative binomial distribution, i.e., a model accounting for both spatial autocorrelation and overdispersion. The spatial random effect will correct for the parameter estimation and improve spatial predictions by interpolating at unsampled locations.

## 2. Materials and methods

### 2.1. Study species

Raptors are predators belonging principally to families Accipitridae and Falconidae. Raptors have long been used as biological indicators in terrestrial ecosystems (see Newton, 1979; Sergio et al., 2005, 2006, 2008). There are 24 breeding species of diurnal raptors in France (Thiollay and Bretagnolle, 2004), several of them being present in tiny numbers either because their breeding habitat is restricted, or because their breeding distribution is very limited. We focus here on the 12 most abundant species of France, which are (in decreasing order of abundance) the Common Buzzard *Buteo buteo*, the Common Kestrel *Falco tinnunculus*, the Eurasian Sparrowhawk *Accipiter nisus*, the Black Kite *Milvus migrans*, the European Honey Buzzard *Pernis apivorus*, the Hen Harrier *Circus cyaneus*, the Eurasian Hobby *Falco subbuteo*, the Northern Goshawk *Accipiter gentilis*, the Montagu's Harrier *Circus pygargus*, the Short-Toed Snake Eagle *Circaetus gallicus*, the Red Kite *Milvus milvus* and the Marsh Harrier *Circus aeruginosus*.

### 2.2. Survey and datasets

The dataset comes from a national survey aiming at monitoring diurnal raptors breeding in the whole country of France. Field surveys were carried out by volunteer ornithologists under the supervision of the National NGO, *Ligue pour la Protection des Oiseaux* (LPO). The field protocol consists in counting the total number of breeding pairs of each raptor species on 25 km<sup>2</sup> quadrats (5 × 5 km; see Thiollay and Bretagnolle, 2004 for details) during the whole breeding season. The survey began in 2000 by 3 years of intensive field work (1260 quadrats were surveyed between 2000 and 2002) with the aim to obtain an accurate starting point about the distribution and population size of raptors in France. From then a reduced yearly monitoring program was set up to estimate trends, based on a much lighter sampling effort (about 65 quadrats per year but with high variations depending on the number of volunteers motivated). Fig. 1 shows the quadrats sampled over the entire period.

Each quadrat was described using climatic (Hijmans et al., 2005, Bioclim, [www.worldclim.org/bioclim](http://www.worldclim.org/bioclim)) and land cover (CLC: Corine Land Cover, [www.eea.europa.eu](http://www.eea.europa.eu)) remote sensing datasets. The climatic dataset consisted in 19 variables measured between 1960 and 1990, providing robust measures of climate at a resolution of approximately 1 km. This data allowed accounting for broad-scale variations of climate over our study area (e.g., hot versus cold, wet versus dry areas), but the true effect of climate on raptors could not be assessed properly due to the time difference between the climate data and the survey. Not surprisingly, high correlations occurred between climatic variables. A principal component analysis (PCA) was performed on this dataset and principal components were used as climatic variables (see also Le Rest et al., 2013). The label "ClimDim.x" was used to nominate the xst principal component from the climate dataset. The land cover dataset had 44 variables depicting land use in 2000 on a 100 × 100 m cell resolution. From these 44 classes, 10 habitat hyper-classes were built from a functional (ecological) point of view for raptors (see Appendix A). The

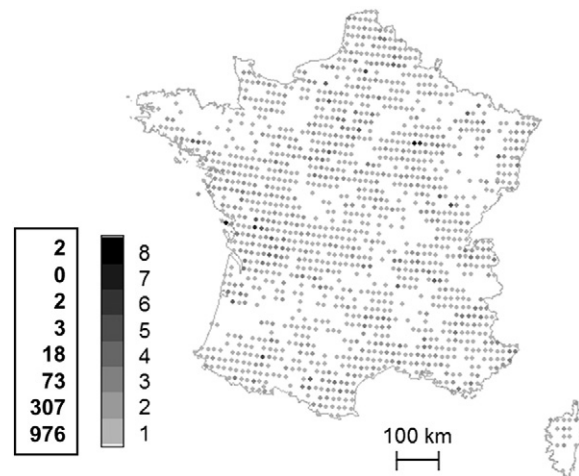


Fig. 1. Location of the 1924 quadrats surveyed between 2000 and 2013, the grey scale indicates the number of time each quadrat has been surveyed during this period, from 1 in light grey to 8 in black. The left frame indicates the total number of quadrat respectively involved.

percentage of coverage per 25-km<sup>2</sup> quadrat was calculated for each of these habitat hyper-classes.

### 2.3. Statistical modelling

Some calculated habitat variables showed highly skewed distributions, which could impact the parameter estimation. A log-transformation was thus done on these variables. A variable selection step was then performed in order to identify the variables improving significantly the prediction power. The spatial-leave-one-out method (SLOO, Le Rest et al., 2014) was chosen in order to deal with spatial autocorrelation. SLOO consists in performing leave-one-out cross-validation while spatially autocorrelated observations between the validation and the training sets are removed (see also Le Rest et al., 2013). Linear terms were first selected through a step by step process and then interactions as well as quadratic terms were involved. For this step, only the first 4 years of data (2000–2003, 1265 quadrats) were used, which reduced the impact of habitat changes between 2000 and 2013 in the selection of variables. The variable selection process stopped when the gain of SLOO log-Likelihood was less than one (which is equivalent to choose a delta – AIC of 2) in order to avoid the selection of variables not improving significantly the prediction power. The Short-Toed Snake Eagle had a too huge range of residual spatial autocorrelation, which prevented using SLOO in a usual way (range over ¼ of the studied area; see Le Rest et al., 2014). For this species we thus tested four threshold distances (100, 150, 200 and 250 km) and only kept the jointly selected variables, alleviating the effect of the threshold considered.

Selected variables were then used in a hierarchical model with a distance-based spatially structured random effect (a spatial explicit hierarchical model, see Beale et al., 2010; Saas and Gosselin, 2014). A negative binomial distribution was assumed to account for the over-heterogeneity present in the data (i.e., overdispersion, see Greene, 2008; Hinde and Demétrio, 1998). At this second step all data were used (2000–2013) and a linear temporal effect (the year) was added to the model in order to estimate the population trends. For the Red Kite, one variable selected resulted in non-convergence of the model when used in a spatial explicit framework. For this species, we have thus restricted the variable selection step by removing this variable from the candidate ones.

Spatial explicit models were computed by using R-INLA, which allowed fast Bayesian inference using the integrated nested Laplace approximation (INLA, Rue et al., 2009). R-INLA proposes an easy way to

compute continuous spatial processes by using the stochastic partial differential equation (SPDE) method with a Matérn covariance matrix (Lindgren et al., 2011). There is recent and flourishing number of papers and tutorials about this method, making possible the estimation of complex spatial models possible in a minimum computation time (Beguin et al., 2012; Cameletti et al., 2013; Lindgren, 2013; Lindgren and Rue, 2015). Using R-INLA with SPDE required constructing a constrained refined Delaunay triangulation. Since our data locations were rather regularly spaced, we defined the triangulation based on our data locations without refinements. For more details on this step, see the SPDE tutorial (Krainski and Lindgren, unpublished).

For each raptor species, we estimated the spatial distribution, the relative population size and the linear population trend between 2000 and 2013. The spatial distribution was obtained by predicting the relative number of pairs for the year 2000 over a grid of France (22,363 quadrats of 25 km<sup>2</sup>). R-INLA allowed predicting both the posterior mean and its standard deviation (i.e., the standard error), which allowed displaying both maps easily (see Krainski and Lindgren, unpublished; Lindgren and Rue, 2015). The relative population size was estimated by sampling 1000 times from the approximated posterior distribution of the model and summing the predicted values for the whole study area. This process allowed giving a 95% confidence interval (2.5% and 97.5% quantiles). Linear trends resulted from the linear temporal effect (year) estimation and were expressed in average population growth rate per year.

### 3. Results

#### 3.1. Spatial distribution

The predicted abundance maps (see *abundance* in Fig. 2) should not be interpreted without their associate prediction errors (see *se* in Fig. 2). The latter map actually reflects the precision of the predictions and is thus as important as the predicted abundance (Rocchini et al., 2011). Prediction error maps showed that the precision of the predictions was rather heterogeneous in space. Errors were higher in high abundance areas but this was expected from the type of data used since mean and variance are linked in count data analysis. Moreover, the triangulation used led to a slight increase of the predictions errors (outside the triangulation nodes) but this effect was marginal and could only be detected when the standard errors were very low in comparison to the predicted abundance. More importantly, higher prediction errors occurred in areas having less sampled habitats, e.g., water bodies, wetlands, and/or less sampled geographic space, e.g., study area bounds, islands. For instance, predicted map for the Marsh Harrier (not shown here), a species which mainly breeds in wetlands, showed very high

standard errors in some areas, which outlined unreliable predictions in these areas. A possible visualisation would be to combine the abundance and the standard error maps in order to give more reliable information, e.g., abundance maps hiding areas having too high prediction errors, thus acknowledging for the fact that the exact abundance cannot be known anywhere from our data.

#### 3.2. Population size

Population sizes produced in Table 1 were not corrected for the detection bias but could give an idea of the real population sizes for the well detected species, e.g., Common Buzzard, Common Kestrel, Kites and harriers. Relative population sizes were fairly precisely estimated, though some species in low numbers presented less precise estimation. For example, the Marsh Harrier had an upper bound of the 95% confidence interval being about twice the lower bound.

#### 3.3. Trends

Five raptor species showed positive trend between 2000 and 2013 (at the 0.05 level, see Fig. 3), the Common Buzzard, the Black Kite, the Eurasian Hobby, the Short-Toed Snake Eagle and, although less precision, the Red Kite. Seven species showed non-significant linear trends, indicating either stable population size or undetected trends. The Common Kestrel showed a near significant decline and the three harrier's species showed non-significant decline. Apparently therefore, raptors breeding in agricultural landscapes were declining whereas raptors breeding in natural areas (e.g., forests) were stable or increasing. Some species showed rather large confidence intervals preventing any decision in regard to their apparent trends, unless trends were very strong. Species concerned were those occupying restricted ranges in France.

### 4. Discussion

The major problem to address when using volunteer-based surveys is to account for the high heterogeneity amongst observer performances (Dickinson et al., 2010). To overcome this issue, usually great care is imposed on field protocols. The best solution would be to quantify the observer detection effect, and then use it in the statistical analyses (see Royle, 2004; Royle and Nichols, 2003). But at broad-scale, such information is often missing, either because protocols correcting for observer detection are not yet developed when the survey begins (e.g., in cases of long term monitoring) or because it involves too much constraint for volunteers, at the risk of diminishing the number of volunteers motivated in participating to the survey. The

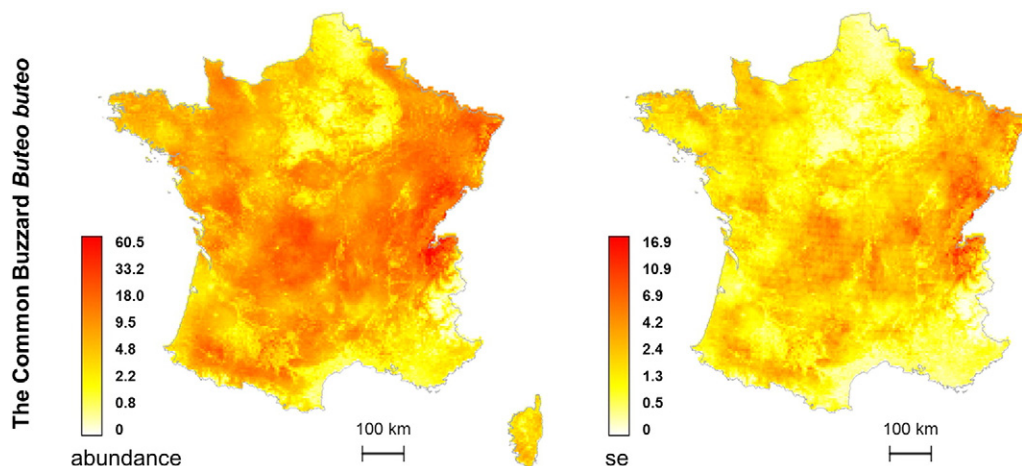


Fig. 2. Example of the predicted relative number of pairs (*abundance*, left: number of pairs/100 km<sup>2</sup>) and prediction errors (*standard errors/se*, right) for the Common Buzzard.

**Table 1**  
Relative number of pairs for 12 raptor species breeding in France (set for the year 2000). The 2.5%, 50% and 97.5% quantiles are given.

Species	2.5%	50%	97.5%
<i>Buteo buteo</i>	160,038	166,765	174,526
<i>Falco tinnunculus</i>	103,626	107,702	112,170
<i>Accipiter nisus</i>	44,243	46,761	49,369
<i>Milvus migrans</i>	25,099	28,003	31,660
<i>Pernis apivorus</i>	19,606	21,207	23,162
<i>Circus cyaneus</i>	14,228	15,490	16,945
<i>Falco subbuteo</i>	11,064	12,062	13,214
<i>Accipiter gentilis</i>	8415	9391	10,477
<i>Circus pygargus</i>	5880	6863	8287
<i>Circaetus gallicus</i>	4005	4747	5541
<i>Milvus milvus</i>	3554	4349	5287
<i>Circus aeruginosus</i>	3229	4275	6452

heterogeneity involved by heterogeneous detection capacities actually leads to two main problems. First, it leads to bias in abundance estimates (the mean) with more likely an underestimation of the true number due to failure in detecting some individuals (Anderson, 2001, 2003). Second, it leads to an inflated variance with the counts varying much more than under homogeneous detection probability. Statistical models accounting for overdispersion, such as the negative binomial distribution used here, allow correcting for the inflated variance (see Hinde and Demétrio, 1998; Richards, 2008) but do not correct for the bias problem. Our data thus did not allow addressing the estimation of true abundance but rather a relative abundance, i.e., the abundance that is detected on average by observers. Even if relative abundance may sometimes be convenient for population monitoring (Engeman, 2003), it may not be suited however for monitoring rare species because the true density or population size becomes the measure of interest, as reflecting the risk of extinction (Courchamp et al., 1999).

The design of our survey, with few quadrats surveyed for long term monitoring (less than 100 quadrats per year) limited the probability of detecting population changes in the case of least common species. Indeed, our results showed that species occupying a restricted range in France (e.g., Marsh Harrier) had the highest uncertainty in population sizes and trend estimations. Conversely, widespread species provided more confident estimated population parameters. Common species play a major role in ecosystem functioning and being able to provide information about their distribution, population sizes and trends can be

highly valuable (Gaston, 2010; Gaston and Fuller, 2008). Such a strategy may increase the efficiency of future conservation actions since it is much easier to conserve population having high densities (Courchamp et al., 1999). True abundance remained however difficult to assess without detection correction, but this may not be much critical for common species since they are far away from the extinction.

In the absence of detection measure, one could be sceptical in regard to the validity of the estimated distributions and population trends. Models used here assumed that the over-heterogeneity (and thus, detection bias) is random in space and time, i.e., constant overdispersion. Yet, we cannot rule out that volunteers may increase their performances through time by improving field-experience over years, resulting in wrong positive trends. The sampling scheme used here was built in order to avoid this learning effect, i.e., quadrats were chosen randomly each year (see also Jiguet, 2009) and were usually surveyed by several observers. If a learning effect is expected, it is possible to account for it *a posteriori*, e.g., by using an additional measure in the model indicating the number of time the quadrat was surveyed or a measure of the overall time passed in.

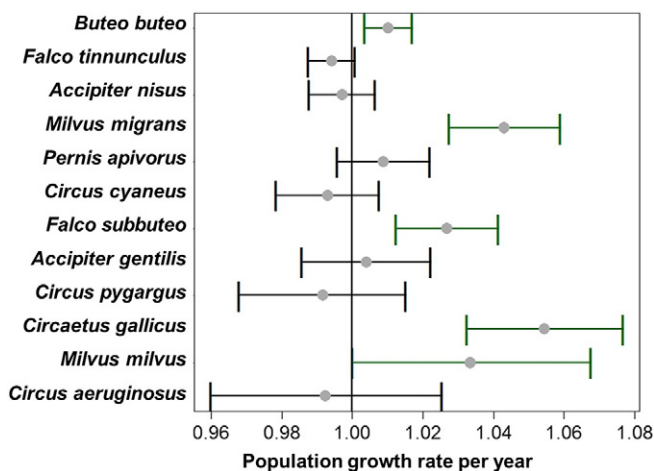
Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.ecoinf.2015.08.007>.

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**Fig. 3.** Population trends between 2000 and 2013 for 12 raptor species breeding in France. Trends are presented as average population growth rate per year, e.g., 1.05 means that the population size is multiplied by 1.05 each year (i.e., +5% per year), thus increasing. Significant trends (positive in green) have their 95% confidence interval excluding 1.

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