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Dealing with species misidentification to make the best of citizen science data: a case study with wolf distribution in France

M2 Internship report

Internship dates : 04/01/2017 – 24/05/2017
Laboratory : CEFE, Montpellier
Supervisor : Olivier Gimenez & Julie Louvrier
Nb of words : 4139

Previous Interships :
(keep only appropriate lines/ add lines if necessary)

	Year	Laboratory	Supervisor	Title or Subject
L3	2015	U.Edinburgh	Pr.John Grace	Urban flora of Scotland, a citizen science project
M1	2016	US Forest Service	Samuel A Cushman	Habitat suitability of Mexican Spotted Owl

Dealing with species misidentification to make the best of citizen science data: a case study with wolf distribution in France

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Summary: Citizen Science (CS) allows collecting data that can outperform in intensity and coverage those collected through scientific protocols only. Nevertheless, assessing the quality of data produced by volunteers remains the main challenge underlying any CS project. Because of their elusive behaviour and low densities, monitoring large carnivores can particularly benefit from CS. However, false positive detections due to species misidentifications may occur when informing the distribution of a species. Uncertain detections are commonly present in CS datasets but usually discarded to avoid incorrect results. We used dynamic occupancy model to account for species imperfect detection and we illustrated how to include uncertain data in order to deal with false positives when modelling species distribution. As a case study, we analysed opportunistic data collected on the grey wolf (*Canis lupus*) in France. We showed that uncertain data provide information on colonization at locations where no information is available otherwise. We also demonstrated that professional observers do not detect the wolf more often than amateurs but, when they do, they provide significantly more reliable detections. Overall, our approach allows making the best of CS data by incorporating uncertain data to infer species distribution.

Keywords: *Citizen Science, Dynamic Occupancy model, Grey wolves, Misidentifications, Species Distribution model.*

Introduction

Citizen science (CS) has become of significant importance over the last decade in ecology[1]. CS is usually defined as the practice of engaging the public in a project that produces reliable data and information usable by scientists and/or decision-makers[2]. Such data are now widespread in the fields of climate change, conservation biology and population ecology. One advantage of CS is that volunteers, in contrast with costly scientific monitoring programs, can prospect effectively large geographic scales[1,3]. Although several methods exist to improve data collection by volunteers (e.g. training or validation by experts)[1,3,4], questions are often raised about the quality of CS data. Even though datasets produced by CS can be of high quality[1,3,5], the same accuracy (i.e. degree to which observations are correct[3]) as in scientific protocols is difficult to reach. For example, species misidentification is a common shortcoming in CS datasets because it is often more difficult for a volunteer to identify a species with certainty than for a professional scientist[3]. Recent works have underlined the importance of accounting for misidentification in studies on species distribution[6,7]. Besides, even in the case of scientific surveys, it is not always possible to detect a species where it is present (i.e. imperfect detection)[6,7]. Being aware of these difficulties, a robust statistical framework is required to account for these uncertainties[1,3,4]. Here, we used the case study of the recolonization of grey wolves in France to showcase a recent statistical approach that allows inferring the distribution of a species while accounting for imperfect detection and misidentifications[6,8].

Grey wolves (*Canis lupus*) have been extirpated from France in the 30's[8,9]. They have persisted in Italy and came back to the Mercantour National Park in 1992[9]. From there, the population gradually expanded in size and space throughout the country. After colonizing most of the suitable habitat in the Alps, they reached the Massif Central, the Pyrenees Mountains and settled in the Vosges (north-east of France) in 2011[9,10,11]. They now occupy a range between 30,000 and 50,000km² across the country for approximatively 292 (204; 397) individuals[11,12]. Due to its impact on livestock and its protected status, the species is associated with conflicts involving political and economic stakeholders[13]. In this context, reliable information on wolf distribution is needed to inform management. However, the efficient monitoring of large carnivores is difficult, wolves being no exception[12,1413]. Elusive behaviors together with low densities make them hard to detect[9,10,12] and resemblance with dogs prone to misidentification. In France, wolf monitoring relies on a network of trained citizen scientists who collect signs of presence of the species. These data are categorized as certain (no misidentification) or uncertain after going through a validation procedure by experts. A previous study used the certain data to build a species distribution model and account for imperfect detection[11]. Here, we developed a dynamic occupancy model including uncertain signs of presence therefore using the whole dataset. We had three objectives. First, we assessed the impact of adding uncertain detections in terms of model prediction and compared our results to those obtained when using certain data only. Second, we explored the issue of CS data quality. To do so, we tested whether professional observers were better at detecting the species than amateurs. We also tested whether the presence of the species in the administrative department may affect the detection of the species elsewhere in the area. Third, we assessed what the drivers of colonization were, and if they were different from a previous analysis[11], depending on whether we included uncertain data or not.

Methods

Study area and data collection

We used detections of the grey wolf (*Canis* lupus) made by the Wolf-Lynx network of the French National Game and Wildlife Agency (Office National de la Chasse et de la Faune Sauvage, ONCFS) between 1994 and 2016 in France. This network is composed of both professional and non-professional observers. From a few hundred in 1994, the network has grown up to 3083 participants in 2016. Observers are from different socio-professional categories but all are trained during a 3-day course led by the ONCFS[13,15]. Training is known to improve observers accuracy[1,3]. Every wolf detection is coupled with a report that follows a standard procedure documenting, among others, GPS position and date[15]. Based on this report, wolf experts from the ONCFS assign the detection to one of the three categories: (i) 'wolf confirmed' (e.g. direct sighting with photo, fresh track, feces, etc.), (ii) 'wolf possible' (e.g. blurred photo, incomplete track, testimony, etc.), and (iii) 'wolf rejected' (e.g. inadequate data or obviously not a wolf) and thus excluded from this study[13,15].

Occupancy models

Occupancy models aim at predicting the distribution of a species from repeated observations[14,15]. One advantage of occupancy models is their ability to deal with species imperfect detection (i.e. false-negatives, we do not detect the species although it is present)[16]. Here, we used dynamic occupancy models[14,17,16] to study, besides occupancy, range dynamics through colonization and extinction. We defined sampling units (i.e. a site) as 10x10km cells[11]. An important assumption of occupancy models is that the ecological state of the site (i.e. occupied or non-occupied by the species) remains unchanged between surveys within a season. Thus, we restricted our dataset to detections made during winter (i.e. between the 1st of December and the 31st of March), which corresponds to the period between the two peaks of dispersal in spring and fall where individuals move relatively little[11,12].

We used a Hidden Markov model (HMM) formulation of occupancy models (Fig. 1)[16]. Each site can transit between two ecological states (i.e. "occupied" or "unoccupied") following a Markov process**.** Conditional on the ecological state, three possible observations can be made on a site: "certain detection" (from 'wolf confirmed' signal), "uncertain detection" (from 'wolf possible' signal), and "no detection" (when no detection or only 'wolf rejected' signals have been collected). This framework allows estimating three biological parameters while correcting for imperfect detection: (i) colonization probability (γ), probability that an empty site becomes occupied the next year, (ii) extinction probability (ε), probability that an occupied site becomes unoccupied the next year, and (iii) occupancy probability (φ), probability that the site is occupied. The three parameters estimated every year for every site. Regarding the observation process, although certain detections are necessarily linked to occupied sites, uncertain detections are possibly generated from one of the two states. An uncertain detection can occur on an occupied but also on an unoccupied site – i.e. a false positive due to misidentification. We resorted to three parameters to model the observation process: (i) P_{10}, probability of incorrectly detecting the species at an unoccupied site, (ii) P_{11}, probability of detecting the species at an occupied site, and (iii) δ, conditional on a detection made on an occupied site, the probability that the detection is certain[6]. We estimated the parameters in a Bayesian framework with Markov chain Monte Carlo simulations using JAGS[18]. For readability, we refer to the models as CU for 'Certain and Uncertain detections' and CO for the model with 'Certain detections' only.

Sampling effort and environmental covariates

Exhaustively monitoring elusive species such as wolves is almost impossible following standardized procedures because wide territories occupied by the species cannot simply be prospected[4,14,12]. At the country level, we only had opportunistic data, i.e. detections with no associated sampling effort. Assuming that detectability is the same over the whole study area would lead to bias (e.g. overestimating detectability when prospection is high). To address this issue, we accounted for the effect of the sampling effort on wolf detectability. We built a circular buffer around the home of every observer depending on his/her socio-professional category (a proxy for the prospection area), and calculated the number of observers per site[11]. This covariate was therefore season and site specific. We forced the detection on sites where the sampling effort was null to be 0. We also considered six environmental covariates possibly affecting the

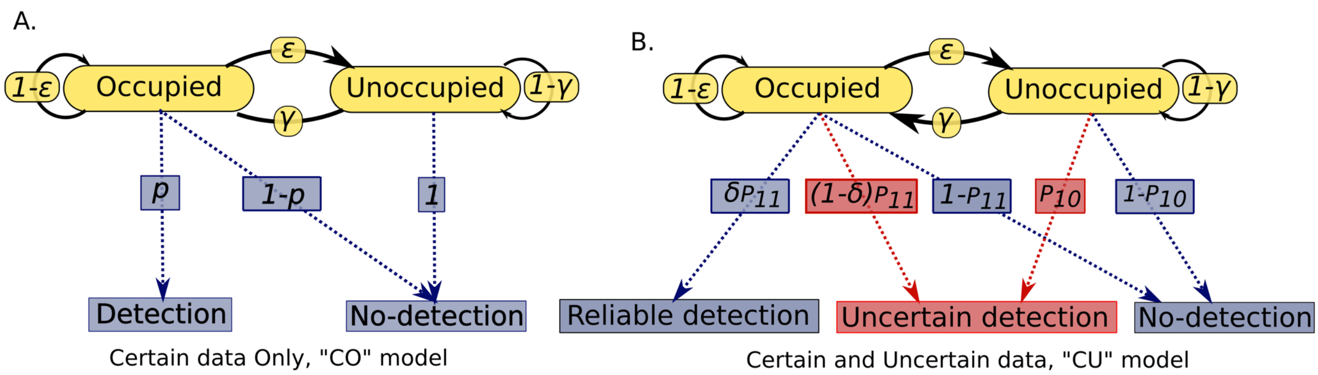

Figure 1: Hidden Markov model formulation of the dynamic occupancy models presented in this study. A. The model used in Louvrier et al. (2017)[11] using only data from certain detection of the species (CO model). B. The adaptation of model A, that includes data coming from uncertain detection (CU model), thus accounting for species misidentification. Red arrows and red squares represent the added elements of CU model compared to the CO model. The ecological (Markovian) process describing the dynamic of occupancy of a site is the yellow part; the site can be either 'occupied' or 'unoccupied' by the species and can transit between these two states following transitions probabilities. Parameters are the following ones: ε is the extinction probability that a site transits from 'occupied' to 'unoccupied' the next year; γ is the colonization probability that an 'unoccupied' site becomes 'occupied' the next year. In blue or red, the detection process involves three possible events when prospecting the site: 'reliable detection', 'uncertain detection', and 'no detection'. Three parameters permit to link the underlying ecological state of a site to the detection event: P_{10} is the probability of incorrectly detecting the species when the site is unoccupied (false positives); P_{11} is the probability of detecting the species when the site is occupied; δ is the probability that the observation is certain conditional on a detection made on an occupied site.

colonization parameter for each site (γ), namely the proportion of farmland cover, mean altitude, proportion of forest cover, proportion of altitude higher than 2500m, proportion of rock cover, distance to the closest barrier (e.g. highway, river, etc). We extracted these data from the CORINE Land Cover database (U.E – SOeS, Corine Land Cover, 2006[19]) and from the IGN BD_ALTIR database (250m resolution)[20]. We also used road density that we expected to affect positively detectability[11].

Because a site with occupied surrounding cells had greater chances of being itself occupied (i.e. established packs act as a source of dispersers[11,12]), we built two covariates to account for spatial autocorrelation between sites[11]. We expected presence of individuals at short-distance (i.e. number of occupied contiguous site) and long-distance (i.e. number of occupied site in a 150km radius area, value chosen based on observation of wolves dispersal in the western Alps[11,21]) to have a positive effect on the occupancy probability of a site.

Investigating citizen science

Besides accounting for misidentification and including uncertain detections, the originality of our work lies in that we considered two covariates based on the CS literature to explore and characterize the observation process. First, we assessed the effect of

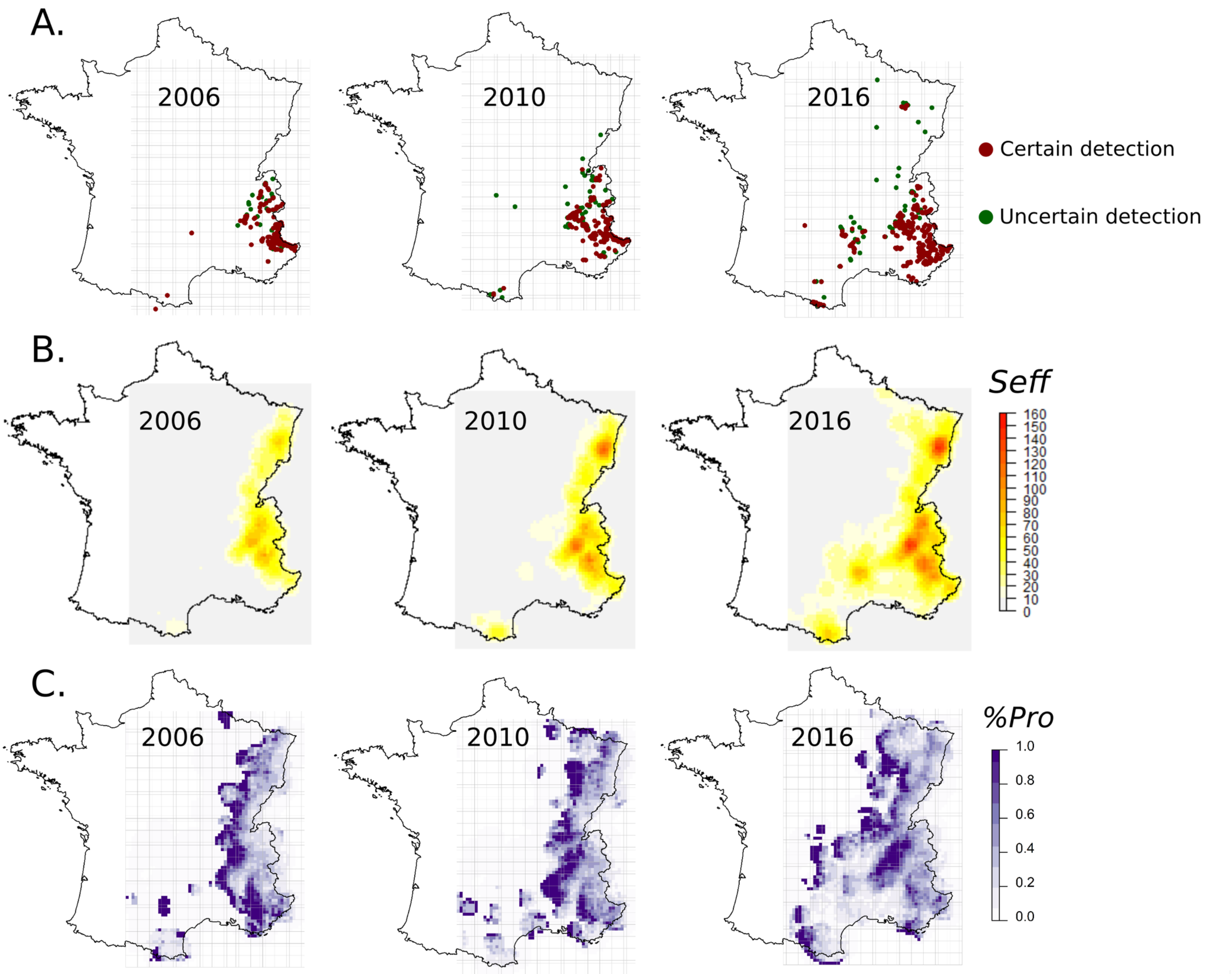

Figure 2: Characteristics of the observation network. A: Maps of the detections made respectively in 2006, 2010, and 2016 by the network. Red dots are certain detections while green ones are uncertain detections. Red dots are plotted above green dots because on sites where both detections occur, we kept the most certain one (i.e. red dots). B: Maps of the sampling effort (Seff) calculated respectively for 2006, 2010, and 2016. Sampling effort is the number of observers per site. C: Maps of the proportion of professional observers per site (%Pro) for years 2006, 2010, and 2016. respectively.

professional vs. amateur on the observation process. We built a covariate distinguishing professional observers (i.e. ONCFS, Forest National Office or National Parks, National Reserves, Regional Parks) from amateurs (i.e. other socio-professional categories). To do so, we considered the proportion of professional observers per site and we expect this covariate to affect both detectability (i.e. P_{10} and P_{11}) and reliability of the collected sign (i.e. δ). Second, we investigated whether the presence of a wolf in the administrative department influenced the detectability of the species elsewhere in the department (i.e. binary covariate that takes value 1 if wolf has officially been declared present and 0 otherwise). For example, can a detection of a wolf in the Aubrac forest in Lozère department increase the detection of the species in another area of the department? The scale was chosen to reflect wolf-related issue (i.e. depredation of livestock, hunting, network deployment, etc.) that are managed at the administrative department level.

Covariates selection

Our model included 36 different covariates possibly affecting the six parameters. First, we checked for correlation among these covariates with Pearson tests. Due to the prohibitive number of possible models (over 10^9) and the computational burden (a model took 15 days to fit with a single MCMC chain), we could not test for every combination of covariates. We therefore fit a global model including all relevant covariates and considered that a covariate had an effect if the 95% credible interval of its corresponding parameter did not include 0.

Map of differences

We calculated the occupancy probability for each site and considered the difference between CO and CU model estimates. A difference close to 1 suggested that adding uncertain data would lead us to conclude for the presence of wolf while using only certain data would not, and a difference close to -1 meant that CO model predicted wolf presence while CU did not.

Table 1: List of the covariates tested on the parameters of the dynamic occupancy model. CO model represents the model including "Certain detections Only", while CU model included "Certain and Uncertain detections". Regarding parameters: γ is the colonization probability, ε is the local extinction probability, P_{10} is the probability of incorrectly detecting the species, P_{11} is the probability of correctly detecting the species (certain or uncertain detection). Given that a detection was made on an occupied site, δ is the probability that the detection is certain, *p* is the detectability for the CO model. Parameters estimates are those from the CU model and are given under the form of posterior means, with standard deviations between parentheses.

Covariate	Parameters	Type	Effect on CO model	Effect on CU model	Numeric effect on CU model
Sampling effort (seff)	P_{10}, P_{11}, δ	Site & year dependent	Positive on *p*	Positive	P_{10} : 0.531 (0.059), P_{11} : 0.240 (0.026), δ: 0.777 (0.084)
Year effect	ε	Year dependent	No effect	No effect	NA
Month effect	P_{10}, P_{11}, δ	Site & year dependent	Positive on *p*	P_{10} and P_{11}: Positive, δ: No effect	P_{10}: 0.754 (0.287), P_{11}: 0.431 (0.065)
Short distance autocorrelation	γ	Site & year dependent	Positive	Positive effect	1.201 (0.041)
Long distance autocorrelation	γ	Site & year dependent	Positive	Negative	-1.466 (0.056)
Road density	P_{10}, P_{11}	Site dependent	Positive on *p*	P11: Negative, P10: No effect	-0.594 (0.045)
Proportion of farmland cover	γ	Site dependent	Positive	Positive	0.519 (0.121)
Proportion of high altitude (>2500m)	γ	Site dependent	Negative	Negative	-0.094 (0.050)
Proportion of rock cover	γ	Site dependent	No effect	No effect	NA
Distance to the closest barrier	γ	Site dependent	No effect	No effect	NA
Mean altitude	γ	Site dependent	Positive	Positive	0.946 (0.088)
Proportion of forest cover	γ	Site dependant	Positive	Positive	0.793 (0.086)
Sign of wolf in the department	P_{10}, P_{11}	Site & year dependent	NA	Positive	P_{10}: 2.053 (0.347) P_{11}: 0.575 (0.090)
Proportion of professional observers	P_{10}, P_{11}, δ	Site & year dependent	NA	δ: Positive, P_{10} and P_{11}: No effect	0.508 (0.114)

Results

Covariate selection and effect on parameters

We found no correlation among the candidate covariates. The covariates 'proportion of rock cover', 'distance to the closest barrier' had non-significant effect on colonization; similarly, 'year effect' had no effect on local extinction (Table 1). The other environmental covariates, short and long-distance autocorrelation had a significant effect (Table 1). Overall, we found similar patterns to a previous study using certain data only[11]. Regarding the observation process, the 'proportion of professional observers' had no effect on detectability (i.e. no effect on both P_{11} and P_{10}) while it positively affected δ (Table 1) and 'road density' did not impact the probability of producing false positives. However, increasing road density was associated with increasing detectability at occupied sites (Table 1). Presence of wolf in the administrative department had a positive impact on detectability. Sampling effort presented strong heterogeneity throughout our study area (i.e. 1 to 151 observers per site) and increasing sampling had a positive impact on P_{10}, P_{11} and δ (Table 1). P_{11} had stronger importance than P_{10} i.e. 0.17 (0.13; 0.24) vs 0.006 (0.003; 0.008), meaning that few errors outcome from adding uncertain data. δ had a mean value of 0.93 (0.86; 0.99).

Model differences

Predictions from both models were relatively similar. Among our 3547 sites, 95% of the sites x years occasions had a difference in predicted occupancy

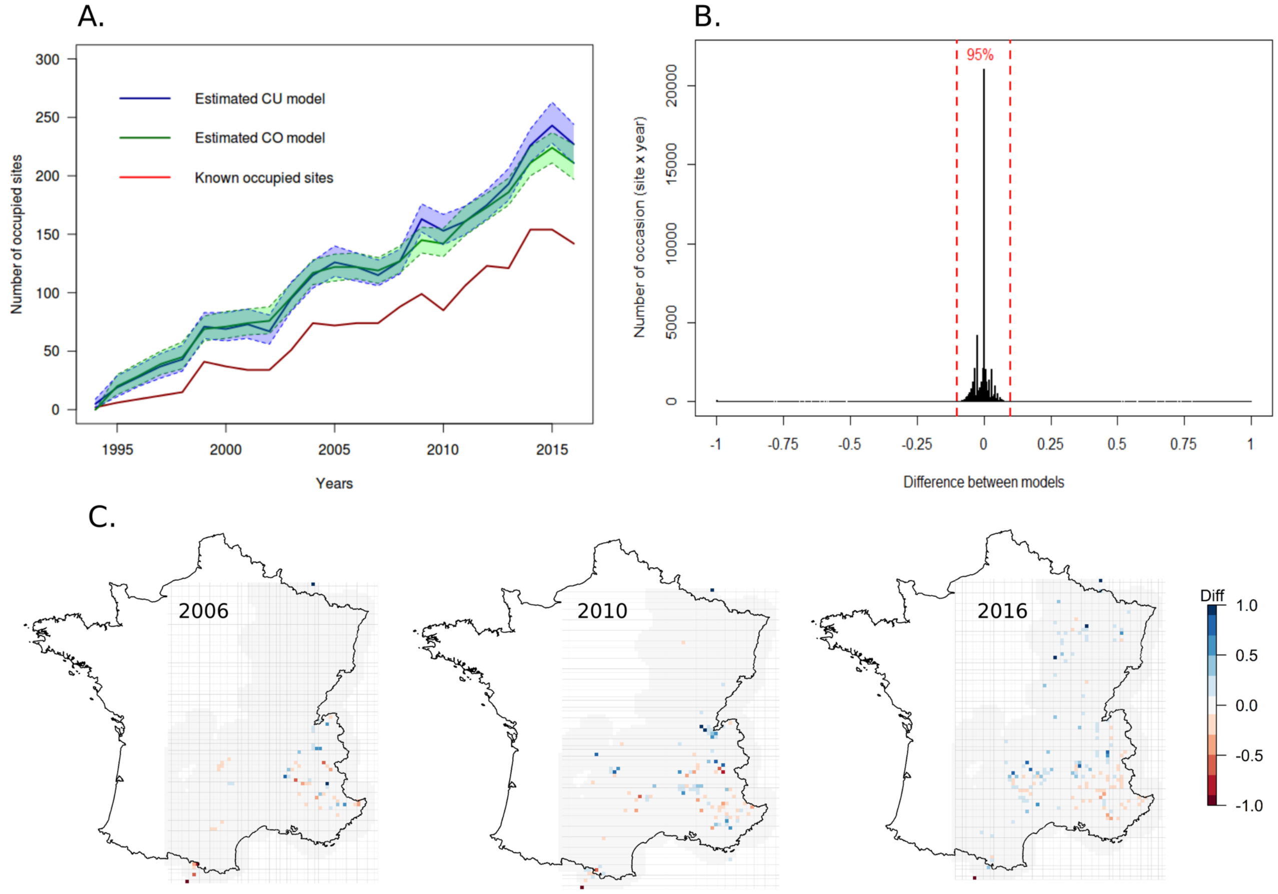

Figure 3: Differences in occupancy-related estimates between model including uncertain detections (CU) and model using certain detections only (CO). For each figure, was involved the difference between the latent states (1 occupied or 0 for non-occupied) estimated from model CU and model CO. A. Growth rate – the sum of the number of sites estimated as occupied by both CU and CO model for each year. Colored background represent the 95% confidence interval. The red line gives the number of sites where a certain detection was made. B. Distribution of the differences in occupancy – vertical red lines include 95% of the estimates, showing that models differ by less than 10%. C. Maps of occupancy differences between CU and CO models in 2006, 2010, and 2016 – Blue squares represent sites where CU model predicts wolf presence while CO does not. Red squares are the opposite.

probability smaller than 10% (Fig. 3A, 3B). Among occasions with differences in prediction over 10%, there were as many positive values as negative ones (Student test, p = 0.5459, NS). However, when looking at maps of model differences, there were geographical heterogeneities. CU model tended to predict more wolf presence in the colonization front (e.g. Jura, Vosges) than did the CO model, which predicted more presence in the core of wolf territory (e.g. Southern Alps, Fig. 3C).

Discussion

Making sense of citizen science data

For many large carnivore monitoring programs in Europe, data collected on species distribution often rely on opportunistic detections made by volunteers and professional observers. However, as in every CS program, the evaluation of the quality of collected data is a major concern[1,3,22]. Several studies have assessed whether professional observers displayed higher reliability than amateurs in data collection[3,4]. In most cases where it has been tested, the performance of volunteers was similar to that of professionnals[3,5]. Projects with validation showed that the accuracy of volunteers could present high scores of reliability[17,22,23] while volunteers' performance varied a lot depending on the species and the protocol. Because they distinguish ecological processed from their observation in the field, occupancy models formulated as HMMs allow testing specific hypotheses on CS. Our results showed that although professional observers did not help to obtain a higher detectability, they produced more certain data than amateur when they correctly detected the species (Fig. 4A). However, because amateurs were assigned to their hometown while professionals to their office, there was an important number of professional observers around the head office of the ONCFS in Grenoble (Fig. 2C). Moreover, when the network is deployed in a new administrative department, the first training session is mostly intended to professional officers first. This explains the important proportion of professional observers at the edge of the network. When looking

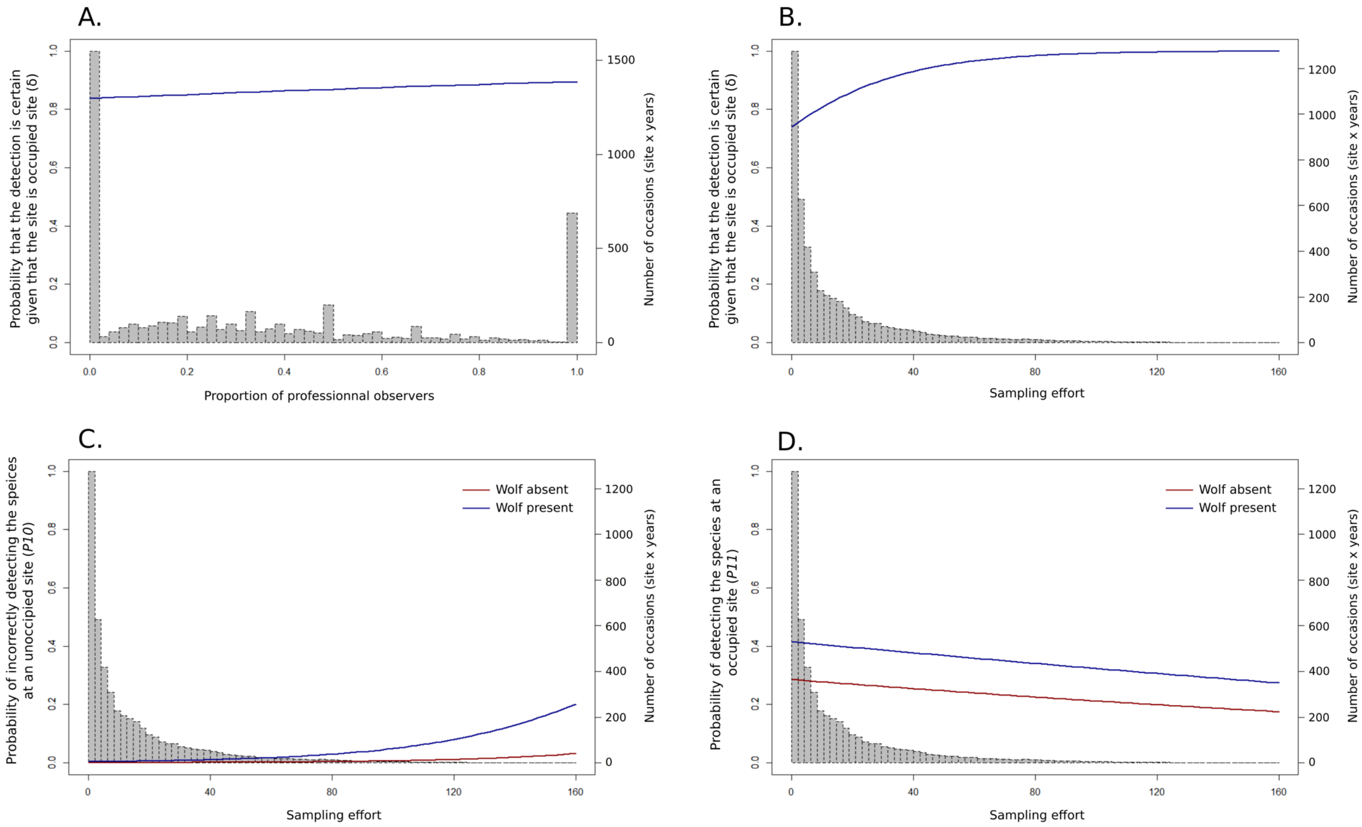

Figure 4: Effect of covariates on model parameters. A. Effect of the proportion of professional observers on δ, the probability of correctly detecting the species when the site is occupied. B. Effect of the sampling effort PO on δ. C. Effect of the sampling effort on P_{10} the probability incorrectly detecting the species at an unoccupied site. D. Effect of the sampling effort on P_{11} the probability of detecting the species at an occupied site. The relationship between a parameter and a covariate is obtained by fixing all the other covariates to their mean value. Histograms represent the distribution of the tested covariate across its range (right Y-axis).

at the distribution of detections, it appears that most uncertain data are located at the edge or outside of the known territories of the species. Therefore, uncertain signs of presence are more likely collected on sites with high proportion of professionals. As professionals produce more certain data when they detect the species, training them first is probably an efficient strategy.

Regarding our second hypothesis, we showed that being aware of wolf presence in the administrative department increased detectability (Fig. 4C, 4D). In particular, the probability of false positive increased, suggesting that the willingness of observers to detect a wolf might be a driving factor of detectability and hence lead to misidentifications. This change in observer attitude could originate from media coverage of wolf presence, as they relay information about wolf and hence may encourage amateurs to go out and track the wolf.

While increasing sampling effort increased δ, its effect on P_{10} and P_{11} need to be discussed. The positive effect on P_{10} was almost null in intensity (Fig. 4C), especially for the range of sampling effort that contained most of our dataset (95% of observations with less than 50 observers per site). The same argument is applicable for P_{11} (Fig. 4D), with the more observers there are on a site the less likely it is to detect the species. This counterintuitive effect might be explained by the effect of sites with high values of sampling effort. Very high sampling efforts are mostly located in urban areas (Fig. 2B) and hence on sites where wolf is unlikely to be present, which may drive negatively the relationship between P_{11} and the sampling effort.

Shall we include uncertain data?

Misidentification is a challenging issue when monitoring elusive species like large carnivores[6]. Although dynamic occupancy models have been shown to be of great reliability to infer range dynamics while accounting for false negatives, it is only recently that they have been extended to deal with false positives[6–8,24]. Usually, only certain signs of presence are used in standard occupancy models, therefore leading to wasting data, which might affect the motivation of the network observers[2,5]. Moreover, in the case of CS, an important question is the quality and the accuracy of the observation[3,22]. Usually such protocols lead to a classification of the observations into different class of certainty[15,25,26]. Thus, several outputs are possible: either to throw away uncertain data due to their important variability or either trying to use them, assess their accuracy and include them in statistical models. Besides, including uncertain data is sometimes the only way to bring information on locations where nothing else is available. For example, 15% of our dataset was composed of uncertain detections and such detections were often present at the edge of the wolf distribution (Fig. 2A) in areas where no certain data were recorded.

On average, there were only slight differences between predictions from CU and CO models (Fig. 3). However, we observed heterogeneities in the distribution of these differences, CU model predicting higher occupancy at the colonization front than the CO model. This is consistent with the higher presence of uncertain detections outside of the known range (Fig. 2A). Indeed, knowing that uncertain detections are often present at the colonization front (Fig. 2A), it is reasonable that CU model is more likely to detect wolves in such areas, especially as the probability of producing false-positive is low (0.006). According to the high value of δ and to the low value of P_{10}, one could treat uncertain data as if they were certain and use the CO model with this extended dataset. It remains to determine whether the differences between CU and this new model are significant to quantify the importance of accounting for false positives in our dataset.

Despite these results, we suggest bias may exist in assignation of sign as uncertain or certain. Due to the large amount of detections in areas of permanent wolf presence, uncertain signs are not collected by the observers (Duchamp, personal communication). Although standardized procedures exist, we hypothesize that wolf experts who classify the observation as certain or uncertain are more likely to assign an observation as certain if the wolf is already known to be present in the area. However, when signs of presence are recorded in new area of presence, further investigation is conducted by ONCFS involving all the wolf experts to counterbalance possible bias of assignation. Besides, wolf experts regularly proceed to blind assignation of signs to correct for heterogeneities between them.

Monitoring implications

This work underlined strengths of the wolf network that have never been investigated so far. The over-representation of professional at the edge of the network could be positive as they produce more reliable observations especially useful as red-flag in case of new colonization (Fig. 2C). The density of the network is another strong characteristic. It is particularly high on locations presumably hard to access with low population density. In such areas, involvement of volunteers is of great help to achieve a high detectability, which highlights the added value of considering the monitoring as a CS project. Clearly, observer effects due to differences in age[27], experience (this study), or time spent in the network[28] should be accounted for. To do so, a better follow-up of the observers is needed to, e.g., better quantify the sampling effort by recording the exit date of observers or address change. These are only suggestions and we acknowledge that an external evaluation conducted in 2012 by the IUCN about the monitoring of wolves in France reported its exceptionally high efficiency[10].

Being able to incorporate uncertain data could also have implications for conservation. CU model tended to predict wolves outside of its known range while CO model did not. The CU model predictions of wolf occupancy in such sites are based on available suitable habitat, distance to the closest patch and the uncertain signs collected while the CO model uses only habitat and distance to closest patch. Adding the uncertain data can therefore be a worthwhile indicator of a future colonization. Accumulation of uncertain signs precedes every colonization. As a perspective, one could analyze the correlation between CU model predictions (or differences between CU and CO) and the true signs of presence that would be collected a few years later on a colonized area. If there is a correlation between positive model differences and proximate wolf colonization, it would suggest that CU model can be used as predictor of future wolf colonization, which could be a significant tool to decision-makers.

Conclusion

Over the last decades, the number of CS projects has considerably increased[1,22]. CS allows collecting data on otherwise unachievable space scales, time periods, and intensity of prospection. To make sense of these data, we need statistical tools to assess and evaluate the uncertain data produced by volunteers. We demonstrated that dynamic occupancy models accouting for false positives are good candidates to do so.

Acknowledgements

First of all, I must warmly thank Julie Louvrier and Olivier Gimenez for their support during this internship and for involving me in my first published article[11]. I am grateful to the *Biostatistic and Population Biology* team at CEFE. I am also thankful to Christophe Duchamp from the ONCFS for the week I spent in Gap during which I learnt about the biological and political issues related to wolves in France. I would also like to thank Baptiste Rochedy Maltèse for taking me to the field for tracking wolves. Thanks to Dr. Aurélien Besnard for evaluating this work.

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