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Reconciling expert judgement and habitat suitability models as tools for guiding sampling of threatened species

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Summary

1. Up-to-date knowledge on species distribution is needed for efficient biodiversity conservation and management decision-making. Implementing efficient sampling strategies to identify previously unknown locations of species of conservation-concern is therefore a key challenge. Both structured expert judgement and habitat suitability models may help target sampling towards areas where chances to find the species are highest. However, practitioners often object to the use of models and believe they do not result in better decisions than the subjective opinion of experts, thus potentially constraining an optimal use of available methods and information.

2. To illustrate the potential of habitat suitability models for guiding sampling strategies, we evaluated and compared the ability of experts and models to identify important areas for the conservation of a bird species (*Lanius collurio*) in Luxembourg. We conducted extensive fieldwork to find as many unknown bird territories as possible according to three independent sampling strategies: (i) a sampling strategy based on structured expert judgement, (ii) a sampling strategy based on the predictions of a habitat suitability model and (iii) a general-purpose stratified random sampling strategy used as a baseline reference.

3. Both the expert-based and the model-based sampling strategies substantially outperformed the general-purpose sampling strategy in identifying new species records. In addition, the model-based sampling strategy performed significantly better than the expert-based sampling strategy.

4. *Synthesis and applications*. This study explicitly shows that habitat suitability models can efficiently guide field data collection towards suitable areas for species of conservation-concern. Results may facilitate the involvement of practitioners in the development of habitat suitability models with the objective of maximizing the robustness of modelling applications in conservation practice and management decision-making.

Key-words: birds, conservation decision-making, expert elicitation, expert knowledge, *Lanius collurio*, prospective sampling, species distribution models

Introduction

Accurate knowledge on species occurrence is a prerequisite for appropriate biodiversity conservation decision-making, such as reserve selection (e.g. Cabeza & Moilanen 2001), management of biological invasions (e.g. Gormley *et al.* 2011) or identification of key habitats for threatened species (e.g. Brotons, Mañosa & Estrada 2004). Such information often consists of opportunistically collected data available as museum records or from web-based

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biodiversity data-gathering portals (Sardà-Palomera *et al.* 2012). Field data are also increasingly collected during structured field sampling, such as biodiversity mapping (e.g. atlas projects) or monitoring programmes (e.g. Robertson, Cumming & Erasmus 2010). For rare species or species of conservation-concern, information is often lacking or incomplete; finding new presence areas is critical because increased knowledge on their distribution may provide key guidance on their conservation and management (Guisan *et al.* 2006). However, the collection of additional field data can be costly in terms of manpower, time and budget. It is therefore highly important to define the most efficient sampling strategies to minimize costs and maximize gains in knowledge (Aizpurua *et al.* 2015). The distribution of species of conservation-concern may be geographically limited due to their restricted habitat requirements or population sizes. Hence, identifying new presence areas for those species might be challenging and sometimes inefficient using general-purpose sampling designs (Le Lay *et al.* 2010).

To find new presence areas for species of conservation-concern, information on their habitat requirements is needed (e.g. Anadón *et al.* 2009). One option to obtain such information is the application of methods that aim to elicit information from experts (Franklin 2009). Experts have achieved high knowledge on a particular topic through their life experience (Kuhnert, Martin & Griffiths 2010; Burgman *et al.* 2011) and are classically defined by their qualifications, track record and professional standing (Burgman *et al.* 2011). One advantage of expert elicitation is the possibility of obtaining high-quality and structured information on species distributions with a relatively low cost (Murray *et al.* 2009; Cerqueira *et al.* 2013). This may prove useful when available information on species distribution is insufficient to implement more quantitative methods (Doswald, Zimmermann & Breitenmoser 2007; Cerqueira *et al.* 2013; Turvey *et al.* 2015). For instance, reliable information on local distribution and abundance of the spur-thighed tortoise *Testudo graeca* L. was easily obtained by interviewing local shepherds about the number of encounters with the species (Anadón *et al.* 2009). Eliciting expert information involves dealing with multiple expert judgements, with different sources of biases in the elicited information and with uncertainty around expert estimates (Martin *et al.* 2012; McBride *et al.* 2012). For example, expertise may be restricted to the region of interest of the experts (Murray *et al.* 2009). Hence, a careful pre-elicitation analysis of expert availability and the preparation of a structured elicitation design are needed to account for such potential biases and to obtain the highest quality of information (Martin *et al.* 2012; McBride *et al.* 2012). Sampling design based on structured expert judgement may then prove to be cost-efficient for identifying important presence areas for the conservation of threatened species (Murray *et al.* 2009; Cerqueira *et al.* 2013).

Habitat suitability modelling is a more recent tool that uses existing data and may assist in identifying sites where additional sampling is to be conducted. Here, a statistical link is established between the locations where the target species has been observed and a series of variables describing the environmental conditions in those sites (Guisan & Zimmermann 2000; Franklin 2009; Elith *et al.* 2011). Such predictive models may be used to inform on potentially suitable habitats in areas where the species presence is unknown, which may constitute an efficient data-driven approach to guide further sampling (Guisan *et al.* 2006; Crall *et al.* 2013). Models also suffer from important limitations including geographical biases, data availability and uncertainties in their predictions (Barry & Elith 2006). A variety of statistical methods exist to evaluate their ability to predict species distributions accurately (e.g. Vaughan & Ormerod 2005).

Although predictive models have the potential to play a key role in supporting conservation and management decision-making, practitioners are often not easily inclined to rely on their outcomes for on-the-ground interventions (Jeltsch *et al.* 2013). Addison *et al.* (2013) provided evidence of common objections to the use of models in environmental decision-making and reported that practitioners often believe that models do not result in better decisions than those supported by the subjective opinion of experts. Alternatively, managers may object to the use of such approaches as they consider that models fail to capture the different factors influencing conservation and management options (Hajkowicz 2007), or provide outcomes that are uncertain and poorly communicated (Borowski & Hare 2007). An additional objection relates to the need for a considerable level of conceptual and technical expertise or to the amount of resources and time needed to implement such procedures and to obtain enough input data (Borowski & Hare 2007).

A stronger linkage between modelling science and conservation practice has been recently advocated to help modellers improve the effectiveness, relevance and usefulness of their work in supporting conservation and management decision-making (Guisan *et al.* 2013). In the last few decades, effort has been invested on integrating structured expert judgement into modelling approaches to improve model predictions (Krueger *et al.* 2012). Such expert-informed modelling can contribute to bridging the gap between modellers and practitioners. Structured expert judgement may be incorporated in predictive models at different stages of the modelling procedure (Pearce *et al.* 2001), for example for the preparation of input data, the selection of relevant variables or the refinement of model predictions.

An alternative option to illustrate the potential of predictive models is to compare the ability of such quantitative approaches with that of an approach based on expert elicitation to guide on conservation decisions (Drolet *et al.* 2015). Rather than integrating structured expert judgement into the modelling procedure, we compared the capability of models and experts to optimize the detection of previously unknown presence areas for a bird species of conservation-concern. First, we designed three separate sampling strategies: a sampling strategy based on structured expert judgement without the aid of modelling approaches; a sampling strategy based on the predictions of a habitat suitability model independent of expert judgement; and a general-purpose strategy based on a stratified random sampling design. Secondly, we conducted ground validation according to the different sampling strategies to evaluate and compare their effectiveness to update our knowledge on the distribution of the target species (Williams *et al.* 2009; Rebelo & Jones 2010). We hypothesized that predictive models are useful to guide sampling if a model-based sampling strategy performs better than a general-purpose strategy (Le Lay *et al.* 2010) and as good as an expert-based sampling strategy (Drolet *et al.* 2015). To the best of our knowledge, using structured expert judgement to illustrate the effectiveness of habitat suitability models to achieve a management and conservation objective in an explicit and straightforward way, as we propose here, has not been reported to date. We believe this may contribute to encouraging the use of models among practitioners as an accepted tool to support biodiversity conservation and management decision-making.

Materials and methods

STUDY AREA AND SPECIES

The study was conducted in Luxembourg (2586 km^2, Fig. 1a). *Lanius collurio* L., a passerine bird categorized as nearly threatened in this country (Lorgé & Melchior 2010), was chosen as a model species of conservation-concern. This bird breeds in semi-open areas under a management regime of extensive farming with scattered and thorny hedges and bushes for nesting (Titeux *et al.* 2007). Individuals arrive to the breeding sites from late April to late May and the breeding period extends until late July. Their sit-and-wait hunting strategy and their territory-defence behaviour make *L. collurio* easily detectable (Titeux *et al.* 2007).

SAMPLING *STRATEGIES*

A total of 737 known *L. collurio* territories recorded during the period 2000–2009 (Table S1, Supporting information) were made available from the national data set managed by the bird conservation association in Luxembourg (BirdLife Luxembourg, Kockelscheuer, Luxembourg). These known territories were used as a common source of basic information to design the expert-based and model-based sampling strategies as described below (Fig. 1b). Data included presence-only records with varying spatial precision, but only the records with a precision ranging from 10 to 100 m were retained for subsequent analyses.

Expert-based sampling strategy

We interviewed nationally recognized bird experts who agreed to participate in this study. Judgement was elicited from seven experts to obtain a reliable selection of sampling sites and to decrease the possible geographical biases (McBride, Fidler & Burgman 2012). These experts were considered to have the best knowledge on *L. collurio* in Luxembourg (see Appendix S1). Elicitation sessions were conducted individually and independently to enhance the diversity of knowledge elicited and to avoid experts being unduly influenced by group pressures (Martin *et al.* 2012). Experts were provided with the locations of the known *L. collurio* territories to produce their guidance on the sampling areas. Using the 1-km resolution grid system in Luxembourg, each expert was asked to select 30 squares with the potential to find as many new shrike territories as possible during ground validation. Experts were informed that a new territory would be considered as such during ground validation if previously known territories were absent within a 200-m distance. Once provided with such information, they were left to select 1-km resolution squares with or without previously known territories. Each expert was asked to allocate the 30 selected squares to three classes: 10 squares classified as high priority, 10 squares as medium priority and 10 squares as low priority for further sampling. To aggregate the elicited expert judgements, we used a simple mathematical equal-weighted opinion pooling (Martin *et al.* 2012) that did not involve any interaction among experts and where they were viewed as equivalent (Clemen & Winkler 1999). A simple spatial overlay rule in a GIS environment (e.g. Sugurmaran & Degroote 2010) allowed us to identify those squares selected by at least two experts. We considered them for sampling as they reflected among-expert agreement on potentially suitable squares. Then, we randomly sampled additional squares among the remaining ones classified as high priority by the experts so as to obtain an expert-based set of 30 sampling squares for ground validation (Fig. 1d).

Model-based sampling strategy

Habitat suitability models were developed using a maximum entropy procedure (Maxent) (Phillips, Anderson & Schapire 2006). Maxent is a machine-learning and user-friendly technique based on the principle of maximum entropy that is recommended when using presence-only species data (Phillips, Anderson & Schapire 2006; Franklin 2009; Elith *et al.* 2011). Maxent was used to build a habitat suitability map for *L. collurio* based on the link between the known territories of the species and the environmental conditions in those sites (Elith *et al.* 2011). Shrike records were allocated to 100-m resolution grid cells nested in the same 1-km resolution grid system as the one used during expert elicitation. We selected 10 environmental variables considered to characterize the most important habitat conditions for *L. collurio* (Titeux *et al.* 2007) (Table 1). All environmental data, available at various resolutions, were resampled to correspond to the 100-m resolution grid with the species presence data, and values were derived for each cell. The quadratic terms of the continuous environmental variables were included in addition to the linear functions. We used a five-fold cross-validation approach to define the training and test data sets to fit the models and to statistically evaluate their performance using the area under the receiver operating characteristics (ROC) curve (AUC). AUC values reflected the ability of the model to discriminate between shrike presence records and randomly selected grid cells (Phillips & Dudík 2008).

The modelling outputs at 100-m resolution were aggregated at the scale of the 1-km resolution squares, by adding up the habitat suitability values predicted in the 100-m grid cells enclosed within each square. Aggregated habitat suitability values were then used

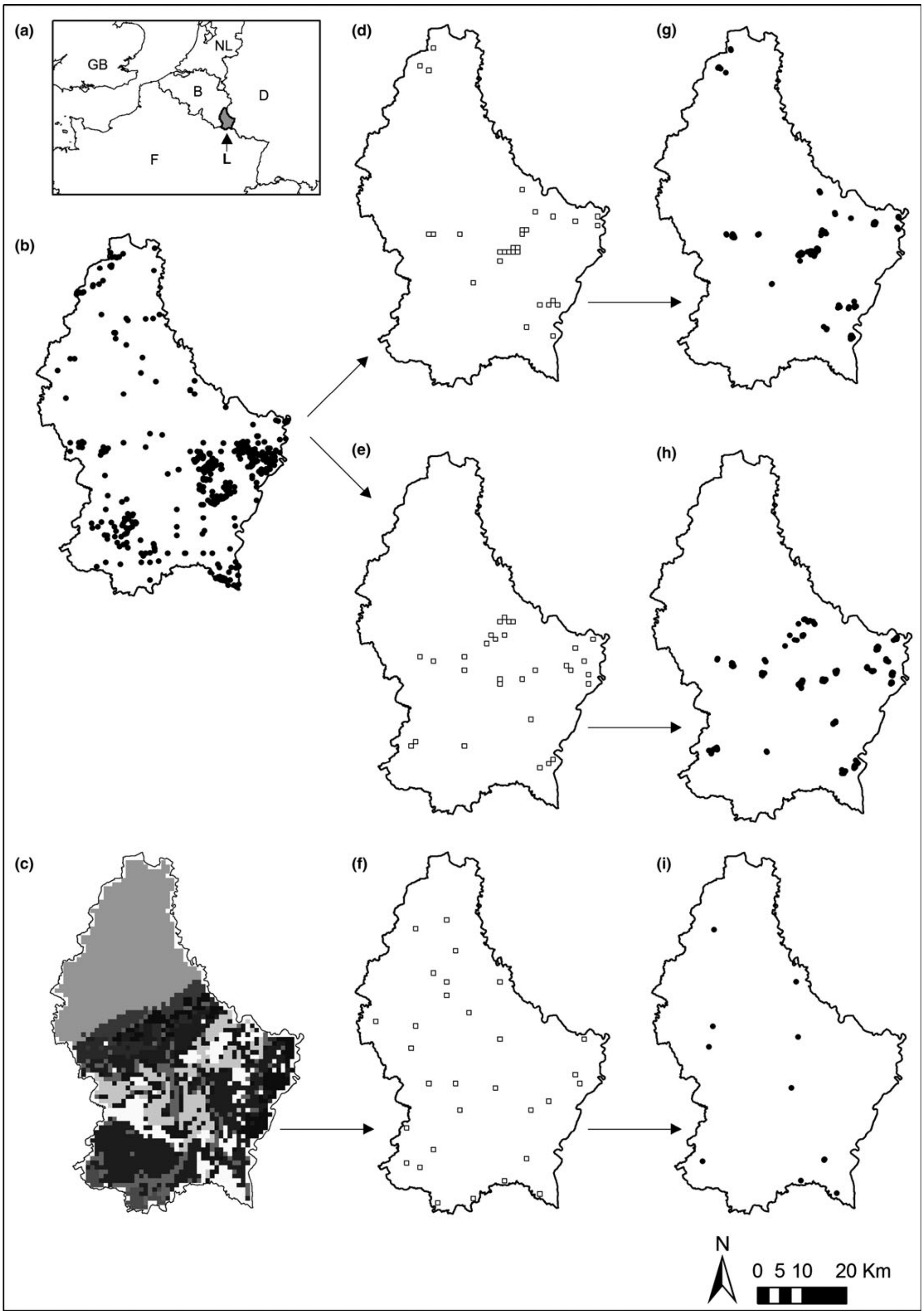

Fig. 1. Overview of the different sampling strategies used to identify new territories of *Lanius collurio* in Luxembourg. (a) Luxembourg in north-west Europe. (b) Known *L. collurio* territories in Luxembourg (2000–2009). (c) Environmentally homogeneous strata in Luxembourg (Titeux *et al.* 2009). Sampling squares selected using (d) expert-based, (e) model-based and (f) stratified random sampling strategies. Location of the new *Lanius collurio* territories found according to (g) expert-based, (h) model-based and (i) stratified random sampling strategies.

to rank the squares in decreasing order of suitability for *L. collurio* across Luxembourg. Squares with five or more known shrike territories were eliminated as we considered that the chances of finding additional territories beyond a 200-m distance around the previously known ones were low. From the remaining squares, we selected the top-ranked, most suitable ones (Williams *et al.* 2009) to create the model-based set of 30 sampling squares for ground validation (Fig. 1e).

Table 1. Environmental variables used in a habitat suitability model to identify suitable areas for the red-backed shrikes *Lanius collurio* in Luxembourg

Variable	Source	Year	Units
Predominant soil type	Soil map of Luxembourg	1970	–
Mean percentage slope	Digital elevation model	2001	%
Topographic moisture index*	Digital elevation model	2001	–
Annual crops	Land cover map of Luxembourg	2007	m^2
Meadows and pastures	Land cover map of Luxembourg	2007	m^2
Urbanized areas	Land cover map of Luxembourg	2007	m^2
Distance to closest urbanized area	Land cover map of Luxembourg	2007	m
Forests	Land cover map of Luxembourg	2007	m^2
Distance to closest forest	Land cover map of Luxembourg	2007	m
Hedges	Topographic map of Luxembourg	1998	m

Digital elevation model: '*Modèle numérique de terrain du Luxembourg*'.
Land cover map of Luxembourg: '*Occupation biophysique du sol*'.
Topographic map of Luxembourg: '*Base de données topo-cartographique du Luxembourg*'.
*Topographic moisture index was calculated following Beven & Kirkby (1979).
Soil map of Luxembourg: adapted from '*Carte pédologique du Luxembourg*'.

Stratified random sampling strategy

We also selected a set of sampling squares according to a stratified random sampling strategy recently implemented in the common bird monitoring programme in Luxembourg (Titeux *et al.* 2009). Based on a series of environmental variables known to influence biodiversity (see Table S2), the whole set of 1-km resolution squares in Luxembourg was divided into 10 environmental strata (Fig. 1c). In order to cover the main environmental conditions in the country, a stratified random sampling procedure was applied to select a number of squares within each stratum in proportion to their spatial extent. For the common bird monitoring programme, a set of 30 squares was randomly generated and is used for yearly sampling of breeding birds. This set was used here as a baseline reference to reflect a general-purpose sampling strategy (Fig. 1f).

GROUND VALIDATION

Fieldwork was conducted to detect and count *L. collurio* territories in the 1-km resolution squares selected according to each sampling strategy. In the squares selected based on the expert- and model-based sampling strategies, transects with a length of 2·5 km were delineated in potentially suitable open land for shrikes. For the squares selected according to the stratified random sampling strategy, 2·5-km-long transects were randomly delineated across all habitat types in the squares, as they constituted the sampling units reflecting a general-purpose sampling strategy. All transects were sampled on foot at a walking speed. Shrike territories were searched with the aid of binoculars and based on auditory cues, and they were georeferenced with the highest possible spatial accuracy.

To maximize the probability of finding shrike territories during the breeding season, the selected squares were surveyed once in June and once in July during two consecutive years (2010 and 2011). The squares were sampled by different observers ($n = 7$) within the same dates and using the same field procedure. After the two breeding seasons, field data were integrated with previously known territories to identify the new *L. collurio* territories found in each 1-km square.

DATA ANALYSIS

The number of new territories found during ground validation was used as a measure of efficiency of the three sampling strategies. This measure was compared among sampling strategies to evaluate whether the model-based sampling strategy performed better than by chance (stratified random sampling strategy) and whether it was as useful as experts (expert-based sampling strategy).

A likelihood ratio test (LRT) within a generalized linear modelling (GLM) framework with a Poisson distribution was used to compare the efficiency of the three sampling strategies. Year of sampling and observer identity were included as factors in the GLM to account for their effect on the response variable. Interaction terms were not considered, as there was no biologically relevant reason to do so. A post hoc analysis with multiple comparisons and Bonferroni correction were used to compare the efficiency of the different sampling strategies with each other.

We also tested whether the elicitation of structured expert judgement led to the identification of new *L. collurio* territories closer to the network of established protected areas than methods that explicitly ignored such features. The distance between each new territory and the closest protected area designated under the European Union Directive on the Conservation of Wild Birds (Directive 2009/147/EC) was calculated. Distances were square-root-transformed and compared among sampling strategies within a linear modelling (LM) framework with a normal distribution. Year of sampling was included as a factor in the analysis. We also performed a post hoc analysis to test whether there were differences in the mean distance to protected areas between each of the sampling strategies.

Results

A total of 87 1-km resolution squares were sampled during ground validation to evaluate the efficiency of the different sampling strategies to identify new shrike territories. Among the squares selected by the experts, 27 squares were identified by at least two of them and three additional ones were randomly chosen among the rest of the squares classified as high priority by the experts. None of the squares selected based on the general-purpose stratified random sampling strategy were selected according to the expert- or model-based strategies. Only three squares overlapped between expert- and model-based sampling strategies, indicating a high level of discrepancy between the areas identified as with the highest probability of finding new *L. collurio* territories by the experts and the models.

The average AUC value obtained from the five-fold cross-validation in the modelling procedure was $0{\cdot}85 \pm 0{\cdot}021$. This means that there is an 85% probability that a grid cell occupied by the shrike receives a habitat suitability value higher than that of a randomly selected grid cell. Based on this statistical evaluation, model outcomes can be considered as potentially useful (Phillips & Dudík 2008).

A total of 95 new shrike territories were found during ground validation in 2010–2011 when using habitat suitability models, while only 11 new territories were discovered in the squares selected based on the stratified random sampling strategy (Table 2). The average number of territories per km^2 found according to the model-based strategy was 2·73 in 2010 and 2·66 in 2011 (range: 0–7), while 0·23 new territories per km^2 were found in 2010 and 0·2 in 2011 (range: 0–2) based on the stratified random sampling strategy (Figs 1 and 2). The species was not detected in only three squares selected based on the model-based sampling strategy (in both 2010 and 2011), and this was the case in 24 (in 2010) and 25 (in 2011) squares selected with the stratified random sampling strategy. According to the expert-based sampling strategy, 72 new territories were found during ground validation in 2010–2011 (Table 2), with an average number of territories per km^2 of 2·03 in 2010 and 1·73 in 2011 (range: 0–8) (Figs 1 and 2). *Lanius collurio* was not detected in six (in 2010) and eight (in 2011) squares selected according to the expert-based sampling strategy.

The GLM analysis indicated that sampling strategy was the only significant ($P < 0{\cdot}05$) factor explaining the variation in the number of new *L. collurio* territories within the sampling squares (Table 3). The post hoc multiple comparisons showed that a significantly higher number of new shrike territories were found when using the sampling strategies targeting on the shrike (Table 4): there was a

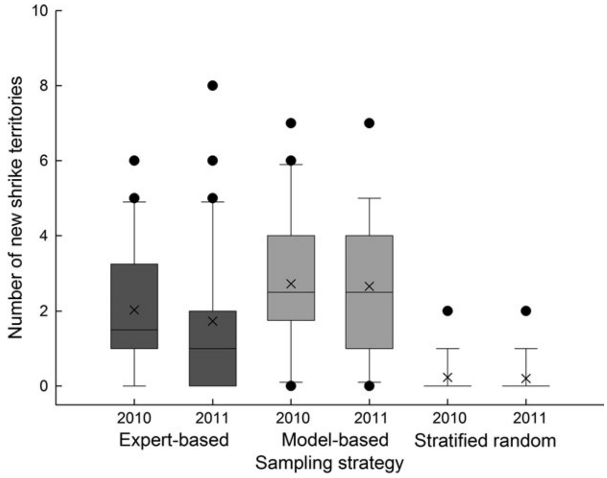

Fig. 2. Box-and-whisker plots (⊥ and ⊤: 5th and 95th percentiles, ●: outlying values, x: mean value, –: median value) for the number of new *Lanius collurio* territories found per km^2 during 2010 and 2011 according to the expert-based (dark grey), the model-based (light grey) and the stratified random (white) sampling strategies.

7·5-fold and a 5·3-fold increase in the number of new territories found per km^2 when using the model-based and expert-based sampling strategies, respectively, compared to the stratified random sampling strategy. The model-based sampling strategy performed also significantly better than the expert-based sampling strategy in guiding sampling towards areas with a higher number of unknown territories (Table 4): there was a 1·4-fold increase in the number of new territories per km^2 when using the model-based sampling strategy compared to the expert-based sampling strategy.

New *L. collurio* territories found according to the expert-based sampling strategy were on average closer to protected areas for birds than those found using model-based or stratified random sampling strategies ($F_{2,284} = 5{\cdot}29$, $P = 0{\cdot}005$). The post hoc multiple comparisons showed that new territories found using the expert-based sampling strategy were significantly closer to protected areas than those found according to the model-based sampling strategy ($t = -2{\cdot}96$, $P = 0{\cdot}008$). The results of the post-hoc comparisons with the stratified random sampling strategy are uncertain due to the low number of new territories found during ground validation when using this sampling strategy.

Table 2. Total number of new *Lanius collurio* territories found during 2010 and 2011 according to the expert-based, model-based and stratified random sampling strategies

Sampling strategy	2010	2011	Total in 2010–2011*
Expert-based	61	52	72
Model-based	82	80	95
Stratified random	7	6	11

*Some shrike territories were observed during both years (2010 and 2011).

Table 3. Results of the generalized linear model (GLM) and likelihood ratio tests (LRT) used to determine which factors explained the number of new *Lanius collurio* territories observed during ground validation

Factor dropped	d.f.	Deviance	LRT	P (>Chi)
(full model)		215		
Sampling strategy	2	241·33	26·337	1·91E-06
Year	1	218·83	3·837	0·051
Observer	6	225·83	10·834	0·093

Table 4. Results of the post hoc multiple pairwise comparisons with Bonferroni correction used to compare the efficiency of the different sampling strategies to find new *Lanius collurio* territories during ground validation

Sampling strategy	Estimate*	SE	*z* Value	*P* (>|z|)
Model-based – Stratified random	2·022	0·516	3·921	<0·001
Expert-based – Stratified random	1·666	0·524	3·177	0·003
Model-based – Expert-based	0·356	0·124	2·861	0·009

*Estimates are provided using a log scale and have to be inverse transformed using exp() to compare the relative efficiency of different sampling strategies on a linear scale.

Discussion

Decision-making for biodiversity conservation and management often involves dealing with alternative options when ecological knowledge is incomplete and outcomes are uncertain (Regan *et al.* 2005). In day-to-day practice, practitioners work with short timelines and limited resources (Cook, Hockings & Carter 2010). Hence, they frequently use expert opinion to support conservation and management decision-making (Fazey *et al.* 2006; Addison *et al.* 2013). The subjective opinion of experts may induce opaque or ill-informed management decisions due to psychological and/or motivational biases (Burgman *et al.* 2011). It is expected that the use of quantitative data and scientific tools by managers and practitioners to support their decisions will improve the overall efficiency of conservation and management interventions (Sutherland *et al.* 2004; Drolet *et al.* 2015).

Among other available scientific tools that use quantitative data, habitat suitability models have been proposed to play a key role in supporting conservation decision-making (e.g. Guisan & Thuiller 2005). With the limited funds available for biodiversity conservation and management, the implementation of predictive modelling approaches is often considered costly and resource intensive (e.g. hardware, technical requirements, need for in-house expertise) in comparison with the experience and knowledge of practitioners (Borowski & Hare 2007). However, one of the main advantages of such approaches is that, once they are operational, they can be applied routinely to a large number of species and outcomes may be repeatedly updated in a cost-efficient way as new data are collected (Guisan *et al.* 2006). Yet, despite the demonstrated performance and benefits of predictive models, practitioners may remain sceptical about their usefulness and sometimes object to their use for conservation practice, as they often believe models do not outperform expert opinion or consider models to be wrong, inaccurate or inappropriate (Addison *et al.* 2013; Jeltsch *et al.* 2013). As a consequence, model outcomes are rarely translated into actions and decisions that actually contribute to biodiversity conservation and management (Guisan *et al.* 2013). Among the few examples of the successful application of models in a management decision-making framework, Brotons, Mañosa & Estrada (2004) used habitat suitability models to identify critical habitats for endangered bird species and this information was used in a legal decree to guide land-use decisions in a farmland area affected by a large-scale irrigation plan.

As other authors have stressed, we also believe that there is a need for a stronger linkage between practitioners and modellers to improve the relevance of models as tools to support conservation and management decision-making. Involving experts in the modelling procedure might be one way to reinforce the link between the two communities. Such integration within an expert-informed modelling framework is expected to reduce the reluctance that some practitioners may show for model-based approaches and to increase their relevance and field of application (Krueger *et al.* 2012). Another way to contribute to convincing practitioners of the usefulness of habitat suitability models is by confronting the efficiency of such tools with that of structured expert judgement to guide conservation decision-making. McConnachie & Cowling (2013) even go a step ahead and examine the ability of practitioners to learn and update their beliefs after being provided with the outcomes from model-based approaches.

Here, we used a structured ground validation procedure to evaluate and compare the ability of experts and models to achieve a clearly defined conservation objective, that is optimizing the detection of new presence areas and improving the current knowledge on the distribution of a bird species of conservation-concern. A stratified random sampling strategy was first used as a baseline reference to evaluate the outcomes of the other sampling strategies targeting on the focal species. As expected, these sampling strategies performed much better than the stratified random sampling strategy. Guisan *et al.* (2006) and Le Lay *et al.* (2010) also showed that model-based sampling strategies considerably increase the discovery rates of new populations of rare plant species compared to random sampling designs. Stratified random sampling approaches are general-purpose designs classically implemented in biodiversity mapping or monitoring projects. However, they remain poorly suited to detect rare or threatened species, either because of the low probability of finding the species by chance across the study area or because the species may be restricted to particular habitat types that have been overlooked in the stratification approach (Le Lay *et al.* 2010).

In contrast with most studies that assessed the efficiency of model-based sampling strategies by comparing it to the results obtained according to a random sampling procedure (Guisan *et al.* 2006; Le Lay *et al.* 2010), we also directly challenged the performance of a model-based sampling strategy with the outcomes of a structured expert-based approach using the same baseline presence data (Clevenger *et al.* 2002; Drolet *et al.* 2015). We implemented extensive fieldwork, and we showed that the model-based sampling strategy significantly outperformed the expert-based strategy, increasing the number of new shrike territories found per km^2 in Luxembourg by a factor 1·4. If we are to advocate on the usefulness of model-based approaches to address a management objective, providing such evidence that models may guide the prospective sampling of species of conservation-concern as good as, and even better than structured expert judgement, is really needed for two reasons. First, objection to the use of models often comes from the fact that decision-makers consider that model outcomes do not result in better predictions than those provided by the subjective opinion of experts (Addison *et al.* 2013). Secondly, modelling outcomes alone might be insufficient for practitioners to change their beliefs (McConnachie & Cowling 2013).

As we used a single-species approach due to the extensive fieldwork needed during ground validation (see also Guisan *et al.* 2006), we acknowledge the limitations associated with the overall conclusions that may be derived from this study. Structured expert judgement may prove to perform better than models in the case of rare or elusive species due to insufficient or low-quality data to build reliable models (Doswald, Zimmermann & Breitenmoser 2007; Turvey *et al.* 2015). Hence, it is now warranted to make such comparisons using a number of species across a range of scales because it is still open for discussion whether the observed pattern is actually representative of a larger sample of species, experts and regions. It would also be needed to examine alternative procedures to deal with the multiple judgements of several experts in the identification of the priority squares for further sampling as this might influence the performance of the expert-based sampling strategy. We regard the results of the present study as an incentive to test further the usefulness of habitat suitability models through a direct comparison with structured expert judgement. We anticipate that the outcomes of such an extensive comparison will help to reduce the scepticism and prejudice against information derived from modelling procedures and will contribute to convincing practitioners of the usefulness of such tools to improve on the management of species of conservation-concern.

Interestingly, the new territories found according to the expert-based sampling strategy in our study were on average closer to protected areas designated for bird conservation than those found using the model-based sampling strategy. These results indicate that eliciting expert judgement may guide sampling strategy towards protected but potentially less suitable areas for the target species, whereas models ignore information on protected areas and have the potential to identify unprotected but highly suitable areas. This probably reflects some geographical, psychological or motivational biases in expert judgement (Burgman *et al.* 2011). Although sophisticated elicitation procedures are available to mitigate such biases and could be further implemented in this context, they remain among the most important limitations of structured expert judgement. Cowling *et al.* (2003) also showed some differences between expert-based and systematic approaches when identifying important conservation areas for biodiversity and highlighted the importance of considering these two approaches as complementary instead of mutually exclusive. Based on our results, we also suggest that expert-based methods may be best suited to guide possible extensions or enlargements of already existing protected areas, while predictive models may contribute to guiding the creation of additional protected areas when data, time and resources are available. Thus, even though the modelling process and expert judgement elicitation were carried out independently in our study for comparison purposes, our results suggest the importance of moving forward with integrated model- and expert-based approaches for conservation and management decision-making, rather than emphasizing the dichotomy between both (Guisan *et al.* 2013; Drolet *et al.* 2015). More generally, we encourage managers and modellers to work hand in hand to help bridge the research–implementation gap between conservation science and real-world action (Knight *et al.* 2008; Sutherland & Freckleton 2012).

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Data accessibility

All data are available in the Supporting Information.

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Supporting Information

Additional Supporting Information may be found in the online version of this article.

Table S1. Red-backed shrike territories recorded during the period 2000–2009 in Luxembourg.

Table S2. Environmental variables used in the stratified random sampling strategy.

Appendix S1. Expert selection and qualifications.