Understanding the drivers of expert opinion when classifying species as extinct

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Data availability, time of last sighting, and population decline are critical attributes favored by assessors when inferring extinction.

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Abstract

The criteria as laid out by the International Union for the Conservation of Nature (IUCN) Red List are the gold standard by which the extinction risk of a species is assessed, and where appropriate biological extinctions are declared. However, unlike all other categories, the category of extinct lacks a quantitative framework for assigning this category. Given its subjective nature, here we explore attributes used by expert assessors working on a diversity of taxa when declaring a species as extinct. Using a choice experiment approach, we found that data availability, time from last sighting and population decline were critical attributes favored by assessors when inferring extinction. Although several of these attributes were significant in the decisions of assessors, this information provides a clear hierarchy of preference for certain attributes. This provides a basis for informing the development of specific criteria for more accurately assessing species extinctions.

Introduction

The world is in the midst of a mass extinction event caused by human actions such as climate change, habitat loss, and over-exploitation (Scheffers et al. 2011). Recent analyses suggest that the current extinction rate may be 1,000 times higher than that indicated by background extinction rates, and projected rates may be ten times greater still (Akçakaya et al. 2017; Butchart et al. 2005; Scheffers et al. 2011). However, determining whether a species still persists is not without its challenges and consequences. For example, a situation may arise where a species is declared extinct when it is still extant, resulting in the loss of directed conservation resources, which then leads to the species becoming extinct due to the lack of conservation effort, known as Romeo error (Collar 1998). Alternatively, a species declared extinct may be rediscovered, known as the Lazarus effect, potentially leading to a loss of trust in conservationists. Akçakaya et al. (2017) suggested that the conservation costs are higher for listing extant species as extinct, either due to a Romeo or Lazarus error. However, if we fail to list species as extinct, we are underestimating the current rates of biodiversity loss and risk misuse of limited conservation resources.

Whether a species is extinct is conceptually simple: either it is or it is not (i.e., when the population size (n) = 0). However, uncertainties often arise in determining when n = 0 due to data availability. As such extinction may be defined as when there is no reasonable doubt that the last individual has died (IUCN 2012).

The global gold standard for assessing extinction risk of a species is the International Union for the Conservation of Nature (IUCN) Red List criteria. The IUCN Red List categories include extinct, extinct in the wild, critically endangered, endangered, vulnerable, near threatened, least concern and data deficient. More recently, the category of critically endangered (possibly extinct) was added, which may be used when a species is in 'all probability already extinct' (Akçakaya et al. 2017). In such a case, there is a slight chance that the species may be extant and thus cannot be listed as extinct until adequate surveys have failed to find the species. These categories are designed to assess extinction risk, supported by quantified criteria applied to a set of variables such as population size and geographic distribution (Mace et al. 2008). For example, criterion A is based on population size reduction, B on geographical range, C on small population size and decline, and so on. Each criterion has an associated set of thresholds related to each extinction risk category. As such there are number of different ways a species could be listed as, for example, critically endangered. However, for a species to be listed as extinct, only a definition is officially provided, where there is no reasonable doubt that the last individual has died (IUCN 2012). While no explicit set of quantified variables with associated thresholds is given for the category of extinct, implicitly, only one variable and threshold exist, when the population size is equal to zero. As such, the amount of data required for this level of precision, compared to other categories is extremely high.

For many species, their persistence is uncertain due to a lack of data to infer whether n = 0. This may be due to a number of reasons, for example fieldwork within the species' range may be limited due to inaccessibility, safety or lack of adequate knowledge about the species distribution (Butchart et al. 2005). Conversely, the species may be challenging to detect because it is cryptic, nocturnal, or silent. These factors (or attributes) influence opinion regarding the continued persistence of a species, however, it is unclear the relative importance assessors place on these factors.

A number of modelling approaches have been proposed (Boakes et al. 2015), with much of the original model development focusing on the temporal distribution of sightings and their relationship to time since last sighting (Boakes et al. 2015). However, more recently, a modelling approach has been proposed that uses two models, one threat-focused and the other focused on records and surveys, and comparing this probability to thresholds determined based on a cost-benefit framework (Akçakaya et al. 2017; also see Thompson et al. 2017, Butchart et al. 2018).

Here we use choice experiments, a stated preference method developed in marketing, to explore attributes of importance when inferring extinction. This method is now widely use in environmental economics and more recently in conservation, such as for the selection of flagship species (Veríssimo et al. 2014), understanding stakeholders preference for forest attributes (Nordén et al. 2017), wild meat consumption (Shairp et al. 2016), and valuation of marine reserves (Rogers 2013). In this way we hope to provide an insight into the decision-making process of experts when assessing species extinction and help inform the development of solutions for inferring extinction, given the problems around data availability.

Methods

Ethics

This research received ethical approval from the Research and Ethics Committee of the School of Anthropology and Conservation, University of Kent.

Choice experiment design and pilot study

We initially used IBM Statistics 25 to design a pilot choice experiment so that main effects of attributes on preferences could be estimated from orthogonal independent attribute variables. We then used a shifted or cyclic design to pair these scenarios in which a constant was added to each attribute level of an orthogonal design to produce two more additional alternatives. We piloted the survey using surveygizmo.com in August 2014, with a sample of 27 staff and postgraduate students from the Durrell Institute of Conservation and Ecology, University of Kent. Based on the feedback received, we made substantial changes to the design (e.g., regarding the initial framing and the number of levels of different attributes), leading to a second pilot in November 2017 using Bristol Online Surveys (www.onlinesurveys.ac.uk). This survey sampled 32 conservation scientists from the personal networks of the authors. We made only minor changes in the visuals and framing of the choice experiment as a result.

We used results of this second pilot survey to produce the final Bayesian prior distributions needed for the choice experiment. We used Ngene 1.0.1 to produce a D-efficient Bayesian design for the main survey (Jaeger & Rose 2008). We chose this design type because it maximizes statistical efficiency in estimating preference parameters by minimizing D-error over the prior distribution of the parameters while accounting for uncertainty (Jaeger & Rose 2008). To allow for uncertainty, we used 500 Halton draws, and assumed all parameter priors have normal distributions. We then compared the mean Bayesian D-error of over 50,000 Bayesian designs, selecting the one with the lowest error at 0.555. This design had 12 choice situations, one of which is shown in Fig. 1. The design was attribute balanced, meaning each attribute level occurred equally often, which minimizes the variance in parameter estimates (Mangham et al. 2009).

The final survey included six attributes (Table 1), which were chosen to encompass the key aspects considered by IUCN Red List Assessors when assessing whether a particular species is likely to be extinct. These aspects are linked to the Red List's definition of "Extinct" which explicitly mentions, besides population decline, the need for exhaustive surveys, taking into account not only the existing suitable habitat, but also the life history and behavior of the species (IUCN 2012).

A 'neither' option was provided to reduce noise resulting from forced choices, and the experiment was unlabeled to ensure that respondents based their choice decisions on the attributes provided rather than any prior knowledge of specific species (Blamey et al. 2000; Kontoleon & Mitsuyasu 2006). In addition to the choice sets, we included questions about demographics (e.g., age, gender, nationality), prior IUCN Red Listing experience, IUCN specialist group membership and professional affiliation (i.e., academia, NGO and government) (Table 1).

Data collection

Our survey (using Bristol Online Surveys, www.onlinesurveys.ac.uk) was launched on the 26th of November 2018 and remained open for two weeks (Appendix S1). A link was sent via email by the IUCN Species Survival Commission (SSC) Chair's Office to all leaders of specialist groups and taskforces of the IUCN SSC, with a request to send it on to their members.

Analysis

We used NLogit 4.0 to construct a multinomial logit (MNL), random parameters logit (RPL) and latent class models (LCM) using NLOGIT (version 5.0, Econometric Software, Inc., New York, USA). The MNL provides the simplest but most econometric restrictive analysis of the discrete choice data. MNLs are often used to initially explore broad trends in preferences and model specifications such as the impacts of socio-economic variables on choice patterns (Hensher et al. 2005). However, this model type assumes that individuals with the same traits have the same preferences (Train 1998).

To allow for a more realistic understanding of preference patterns of our respondents we constructed both LCMs and RPLs, both of which have been widely used in the conservation literature to understand preferences (Hanley et al. 2018; Moro et al. 2013; Veríssimo et al. 2014). Exploring this heterogeneity is important due to the international nature of the IUCN SSC membership as well as the enormous diversity of taxa it encompasses, which may use the red listing process differently due to their different biological traits.

Regarding the RPL, we selected "Data availability" as a random parameter, considering that that was the only attribute where coefficients could logically take either sign depending on a respondent's attitudes towards uncertainty. To further explore the issue of uncertainty in determining trade-offs between attributes we explored several interactions between choice attributes and respondents' traits. We explored the interaction between "Red listing experience" and all choice attributes (Table 1) as we expected experience applying the criteria in a real-world context to influence trade-offs. We also considered interactions between "Data availability" and "Time from last sighting" with "Well known taxa" and "Academic affiliation" (Table 1). These two choice attributes were selected as they are the attributes that are more closely linked to human effort and thus have more potential for uncertainty. The choice of the two respondent variables is based on the expectation that how well known a taxa is would have impacts on the assessor tolerance of uncertainty and that academics would be less amenable to dealing with uncertainty than practitioners.

In terms of the LCMs, we kept a similar focus, selecting as respondent segmenting variables, "Red listing experience", "Academic affiliation" and "Well-known taxa". We used three statistical criteria (Table S2) to select the most parsimonious model (Scarpa & Thiene 2005; Veríssimo et al. 2014). As the three criteria considered were not in alignment in terms of which model to select, we chose the most parsimonious amongst the two models suggested, with six respondent segments (see Hinsley et al. 2015).

Results

A total of 674 respondents took part in the survey, of which 57 were discarded due to missing or invalid information. This resulted in 7,404 completed choice sets, from 617 respondents. Our respondent sample was 78% male, with a median age of 49 years, and with 69% having a PhD education. Regarding geographic representation, our sample included respondents from 69 countries, with 60% being European or North American, 14% Latin American, 14% Asian, 6% African and 6% from Oceania. In institutional terms, 49% of respondents were academics, while 23% were affiliated with NGOs and 16% with governments. In terms of taxonomic representation, mammals were the most represented taxa, being the focus of 35% of respondents. Other popular groups included birds with 14%, reptiles and plants with 12% each, while less popular taxa included amphibians (7%), invertebrates (7%), fish (6%) and fungi (1%). Lastly, most respondents (71%) had participated in the process of listing species in the IUCN Red List.

When respondents were treated as a homogenous group, as in the MNL, all attributes had a significant effect on choice (Table 2). Increased data availability was associated with a higher probability of actual extinction, as was longer time since last sighting, faster population decline, higher species detectability and lower habitat availability.

The RPL describes similar trends, although the inclusion of interaction and respondent traits allow for a more detailed understanding. For "Population decline" and "Habitat availability" the trends follow those shown in the MNL. For the interaction's terms reveal that those with Red Listing experience gave more importance to the attributes "Data availability", "Time from last sighting" and "Detectability" when considering a species extinction, while those respondents working with "Well-known taxa" gave more importance to the "Time from last sighting" variable. We also uncovered that respondents with no red listing experience and those that were working with more well-known taxa (i.e., mammals and birds) were overall less likely to consider species extinct.

Regarding the LCM, the most parsimonious model failed to show explanatory power when it came to respondent segmentation, with only one segment having a single statistically significant factor (see Table S2). This suggests that segmentation is done according to variables that are not part of the available dataset. Therefore, we have chosen to explore heterogeneity using the RPL model.

Discussion

We show that key factors for declaring extinction may include data availability, time from last sighting and population decline. This is important as it gives us a hierarchy of variables relied on by assessors of extinction. As such, this study is a starting point for understanding the factors that experts generally rely on to determine extinction.

All attributes in the choice sets returned significant estimates (Table 2). This is expected given that we selected attributes which are included within the definition for the extinct category of the IUCN Red List. It is therefore reassuring that when provided with the information, assessors make use of all the attributes in their assessment. However, the strength of preference and the direction of coefficients reveals more information on attributes positively or negatively favored by assessors. For example, habitat availability had a strong negative estimate (Table 2), academic as an attribute level was not significant, and red listing experience also had a negative effect. However, it is important to note that choice experiments represent a hypothetical situation and in the case of assessing extinction the reality of the experiment may vary depending on the taxa. For example, many taxa, such as plants (Margulies et al. 2019) and insects (Leather 2009), often suffer from a lack of data for many of the attributes in conservation assessments including assessments of extinction. It would therefore be interesting to conduct further choice experiments where data availability in the form of ‘no data’ is incorporated as an attribute level within each of the attributes, rather than as a single attribute. This is further illustrated by the fact that there was a significant positive interaction between time from last sighting and well-known taxa. With well-known taxa, that are likely to be well-studied, time from last sighting may be an appropriate proxy for other attributes in assessments of extinction. However, for those species that are poorly known, time from last sighting may have a greater level of uncertainty associated with it (Scheffers et al. 2011; Solow et al. 2012). Finally, it is interesting to note that there was a significant positive interaction between red listing experience and three of the attributes, time from last sighting, detectability and in particular data availability. This suggests that those with red listing experience acknowledge the uncertainty in extinction assessments and therefore put greater weight on the availability of data. This acknowledgement of uncertainty has also been accounted for in recent tools, such as using systematic methods to minimize geometric uncertainty when range size is disputable (Lee et al. 2019).

Future work could involve further nuance of the classification of taxa as 'well-known' and/or 'charismatic'. For example, birds and mammals may be well-known relative to some other taxa, however not all bird and mammals are 'well-known'. Likewise, while birds and mammals may be considered charismatic compared to other taxa, not all birds and mammals are considered charismatic. Thus, the description of a well-known taxa is confounded by what is charismatic within a group, between a group and within biodiversity as a whole (Courchamp et al. 2018). Further, the degree of charisma which a species holds may prevent the declaration of extinction, but may also attract the attention and funding needed to conduct the "exhaustive surveys" as required under the Red List for extinct. If more people are working on a species, then it may be too political or sensitive to describe a species as extinct, thus delaying the process of extinction declaration. This effect may be heightened given previous conservation failures such as that of the ivory-billed woodpecker supposed rediscovery, and the subsequent misdirection of valuable conservation funds (Scheffers et al. 2011; Solow et al. 2012). Finally, there are a number of examples of species deemed to be extinct (or likely extinct) that were rediscovered. Understanding attributes used in these cases may provide further insight into extinction declaration attribute preference and biases. Likewise, at the other and of the spectrum, understanding why certain species have only recently been discovered may provide additional insights.

Currently, when deciding whether to assign the Red List category of extinct, the sole criterion experts have to refer to is when the population size is equal zero, although this is not explicitly stated in the Red List criteria (IUCN 2012). However, as with other Red List criteria, guidance is provided (IUCN Standards and Petitions Committee 2022). As discussed in the introduction, multiple criteria, such as a reduction in population size or geographic distribution, exists for other Red List categories representing tangible measures to judge which category is most appropriate (Mace et al. 2008). Analogous categories could be created for the criteria of extinct, and the results presented here provide a starting point for a discussion as to what these criteria should look like. Since the declaration of extinction is greater implications than moving between any of the other Red List categories (Butchart et al. 2005), there is an urgent need for the existence of specific criteria for assigning the category of extinction.

Finally, the survey did not receive an equal number of responses across all taxa, and these were volunteer members of specialist groups, working within the official structures of the IUCN, which while a key group to understand given their role as part of the IUCN Red Listing process, commonly do not fully represent for example traditional and indigenous knowledge (Fernández-Llamazares & Cabeza 2018). Further, we chose to allow for flexibility in interpreting the attributes and levels to allow for the survey to work across diverse taxa. It was impossible to have standard values, for example, for what constitutes a long time since the last sighting for all taxa across fauna, flora, and funga. That said, we acknowledge this added uncertainty in some of these estimates.

Conclusion

Our study shows that there are differences when people are carrying out assessments as to whether a species is extinct. Certain groups rely more on or less heavily on certain criteria when conducting such assessments. By understanding which attributes assessors use in their decisions to declare a species as extinct, new guidance can focus on these attributes that assessors appear to be predisposed towards. These biases can be used to rank the most important variables for determining extinction in the future, and thus inform best practice guidelines for new IUCN criteria.

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Supporting Information

Appendix S1: Online choice experiment-based survey

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Table 1: Attributes and levels used in the choice experiment on likelihood of species extinction

Choice Attribute	**Levels**	**Description**
Time since last sighting	Recent; Medium; Long	How long it has been since the species was last sighted
Data availability	Poor; Good	How much information exists on the existence of the species considering the search effort
Population decline	No decline; Slow; Rapid	Whether the species population is in decline, and if so, the speed of this decline

Detectability	Cryptic; Non-cryptic	How easy it is to detect the species in the field
Habitat availability	Small area; Large area	How much available habitat currently exists for the species
Respondent traits	**Description**	
Well known taxa	Whether a species comes from a well-researched group, defined in this study as birds and mammals	
Red listing experience	Whether a respondent has previous experience applying the IUCN Red List criteria	
Academic affiliation	Whether a respondent had an academic affiliation	

Table 2: Main effects estimates of utility function for each attribute for Multinomial Logit (MNL; McFadden Pseudo $R^2 = 0.17$) and Random Parameters Logit (RPL; McFadden Pseudo $R^2 = 0.22$), with standard errors in parentheses; in the case of the RPL a number of interaction terms were included to explore the role of uncertainty.

Attribute levels	**MNL Mean effect estimates**	**RPL Mean effect estimates**	**RPL Standard deviation estimates**
Alternative Specific Constant	3.54** (0.08)	3.23** (0.17)	
Data availability	1.30** (0.04)	0.92** (0.15)	2.145** (0.08)
Time from last sighting	0.92** (0.03)	0.87** (0.06)	
Population decline	0.93** (0.03)	1.11** (0.06)	
Detectability	0.60** (0.04)	0.54** (0.07)	
Habitat availability	-0.81** (0.04)	-0.88** (0.08)	
Red listing experience		-0.65** (0.19)	
Well known taxa		-0.24* (0.10)	
Academic		-0.06 (0.10)	
Data availability × Academic		-0.05 (0.13)	

Data availability × Well known taxa	0.13 (0.13)
Data availability × Red listing experience	0.42** (0.15)
Time from last sighting × Academic	0.02 (0.05)
Time from last sighting × Well known taxa	0.11* (0.05)
Time from last sighting × Red listing experience	0.17* (0.07)
Population decline × Red listing experience	-0.08 (0.08)
Detectability × Red listing experience	0.18* (0.09)
Habitat availability × Red listing experience	-0.18 (0.10)

**, * = Significance at 1% and 5% level respectively

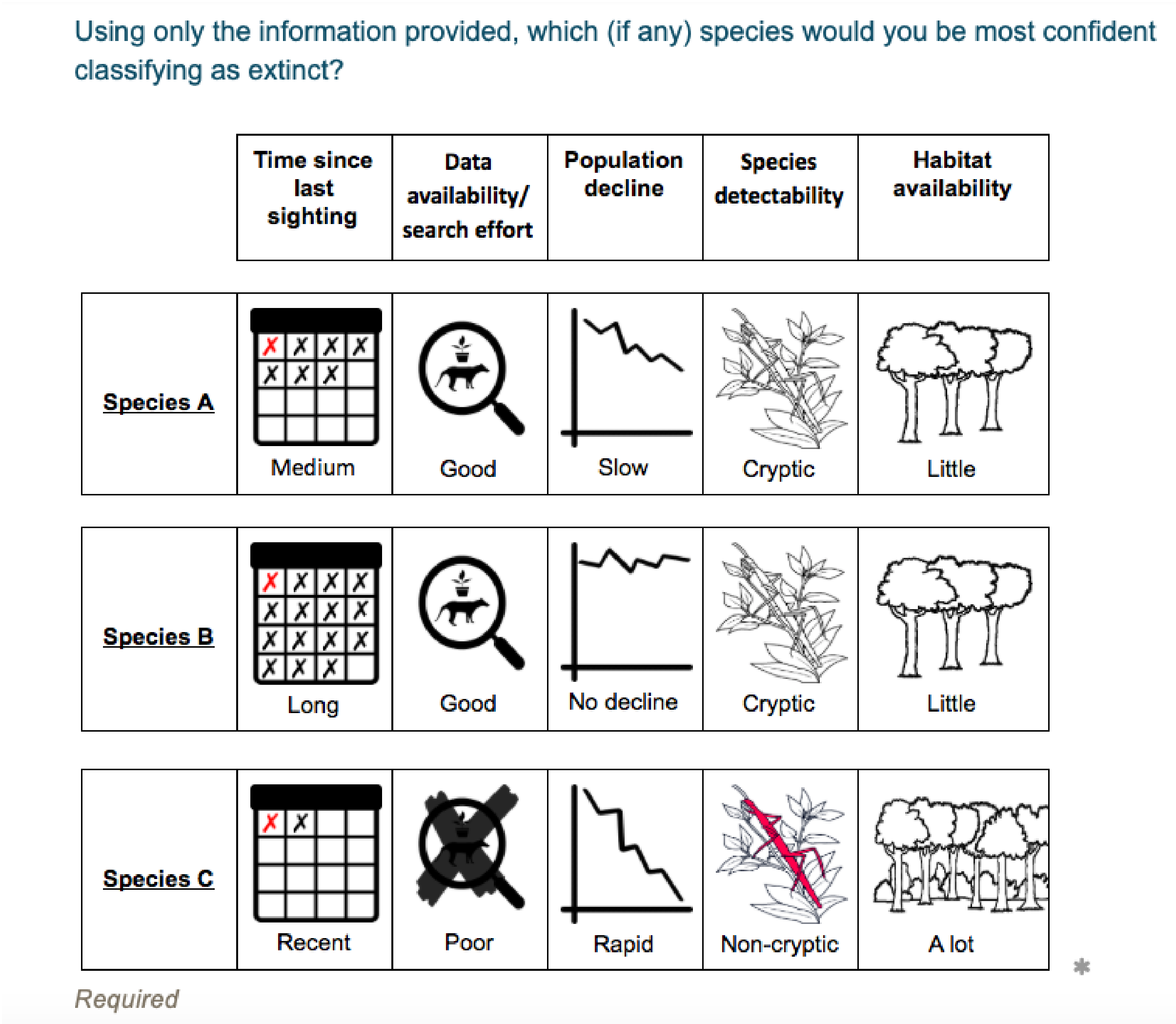

Figure 1. Example of a choice situation presented in the experiment, including the instruction given to respondents. Respondents were asked to select one answer from options: 'A', 'B', 'C' or 'None'.