

Bridging the research-implementation gap in IUCN Red List assessments

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Bridging the research-implementation gap in IUCN Red List assessments

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Bridging the research-implementation gap in IUCN Red List assessments

Abstract

The IUCN Red List of Threatened Species is central in biodiversity conservation, but insufficient resources hamper its long-term growth, updating and consistency. Models or automated calculations can alleviate those challenges by providing standardised estimates required for assessments, or prioritising species for (re-)assessments. However, while numerous scientific papers have proposed such methods, few have been integrated into assessment practice, highlighting a critical research-implementation gap. We believe this gap can be bridged by fostering communication and collaboration between academic researchers and Red List practitioners, and by developing and maintaining user-friendly platforms to automate application of the methods. We propose that developing methods better encompassing Red List criteria, systems and drivers is the next priority to support the Red List.

Keywords

Extinction risk; species conservation; biodiversity; remote-sensing; automated assessment; user-friendly platforms

18 Glossary

19 **Assessor:** An appointed expert, often a volunteer, who applies the IUCN Red List categories
20 and criteria following associated guidelines, using all relevant data to assess the taxon
21 appropriately, and ensures that the assessment has the required supporting information.

22 **Red List categories:** Ordinal set of extinction risk classes used by the IUCN Red List,
23 including two non-threatened categories [Least Concern (LC) and Near Threatened (NT)],
24 three threatened categories [Vulnerable (VU), Endangered (EN), Critically Endangered (CR)],
25 and two extinct categories [Extinct in the Wild (EW), Extinct (EX)]. When data are insufficient
26 to assign a species to one of these categories, it is classified as Data Deficient (DD). Species
27 that have not been assessed yet are classified as Not Evaluated (NE). A subset of Critically
28 Endangered species are tagged as Possibly Extinct [CR(PE)] or Possibly Extinct in the Wild
29 [CR(PEW)].

30 **Red List criteria:** Set of five criteria, and nested subcriteria, associated with quantitative
31 thresholds used to assign Red List categories. These criteria relate to A: population size
32 reduction in the past (A1 and A2), future (A3), or both (A4); B: small geographic range, either
33 in the form of Extent of Occurrence (B1) or Area of Occupancy (B2), combined with severe
34 fragmentation, and / or continuing decline in population, distribution or habitat quality, and /
35 or extreme fluctuations; C: small population size and decline; D: very small or restricted
36 population; E: quantitative analysis.

37 **Red List guidelines:** Public document produced by the IUCN Red List Standards and Petitions
38 Committee detailing how to apply the IUCN Red List criteria to assign categories.

39 **Red List parameters:** Estimates which are compared with the quantitative thresholds listed in
40 the Red List criteria to classify species into Red List categories. For instance, an ongoing
41 reduction in population size of $\geq 30\%$ over the last 10 years (or three generations, whichever
42 is the longer) qualifies a species as Vulnerable (VU) under criterion A2. In this example, the
43 reduction in species' population is the parameter compared with the 30% threshold to apply
44 the criterion.

45 **Red List Unit:** Technical unit working for the IUCN Global Species Program.

46 **Major challenges for the IUCN Red List**

47 The IUCN (International Union for Conservation of Nature) Red List of Threatened Species
48 (hereafter “Red List”) provides assessments of extinction risk for > 130,000 species of animals,
49 fungi and plants [1]. These assessments are pivotal to inform conservation action, target
50 resources and monitor global biodiversity trends and conservation effectiveness [2–7]. The Red
51 List also informs international policies and reports (e.g., CBD, IPBES, CITES) by providing
52 information and underpinning analyses on species’ status and trends, distributions, threats and
53 conservation actions. The Red List uses a set of standard quantitative **criteria** (see Glossary)
54 relating to species’ population size, trend, and distribution that are applied by **assessors** to
55 assign species to a **category** of extinction risk [8,9].

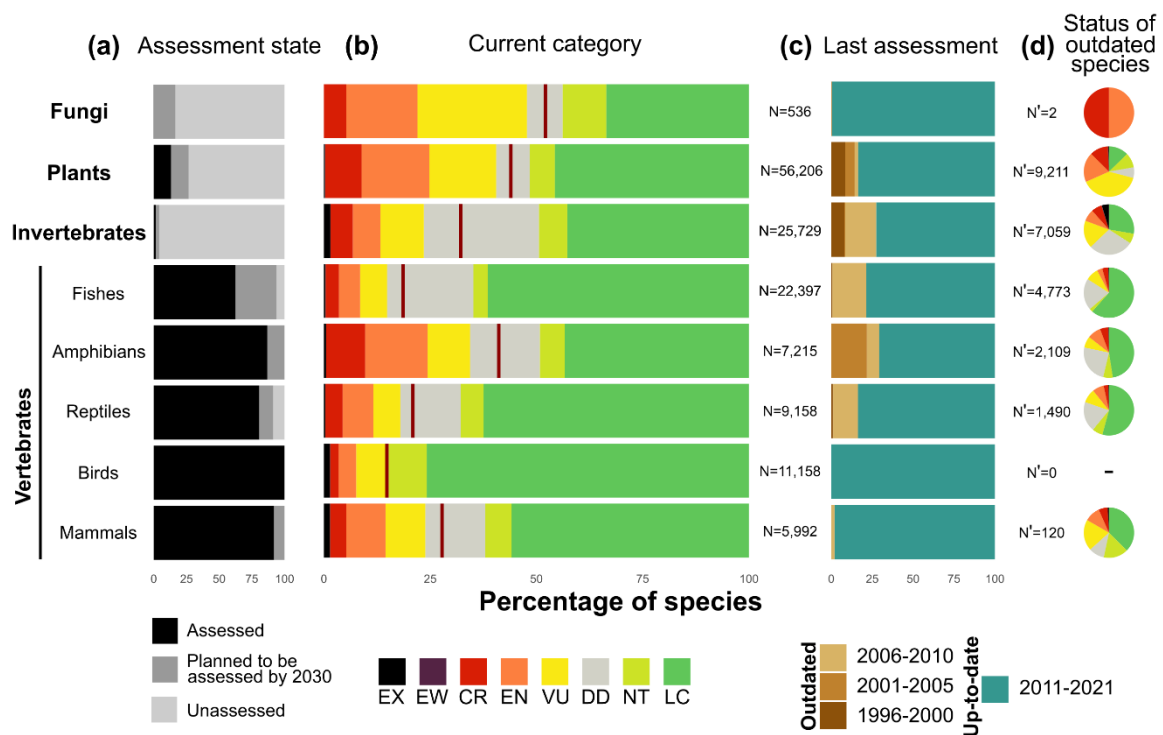
56 Despite its influence, the Red List operates with a largely insufficient budget and staff [10,11],
57 resulting in four major challenges that jeopardize its breadth and currency in the long term.
58 First, assessments are concentrated on vertebrate species [12–14], with few for invertebrates
59 and plants relative to the number of described species and very few for fungi (Fig. 1A). This
60 taxonomic imbalance is being slowly reduced by the ongoing expansion of the Red List in
61 accordance with an agreed strategic plan (Fig. 1A; [15]). Second, 14% of assessed species
62 (N=19,394) are classified as Data Deficient due to insufficient information available to apply
63 Red List criteria (Fig. 1B), which introduces uncertainty in estimated proportions of threatened
64 species and may preclude some species from receiving appropriate conservation efforts [16–
65 18]. Third, while species should be reassessed at least every 10 years [19], 18% of assessments
66 (N=24,764) are currently outdated (Fig. 1C). About 2,100 species were last assessed 25 years
67 ago, of which more than half are listed as threatened (Fig. 1D). Fourth, Red List assessments
68 are conducted inconsistently across and within taxonomic groups [12,13,20], partly because of
69 heterogeneity in available data among species, but also because of variation in the assessment
70 process and criteria application. The **Red List guidelines**, which aim at reducing the latter by
71 providing detailed information on how to apply the criteria [19], have expanded and evolved
72 to further clarify the calculation of **parameters** and the resulting assignment of categories (see
73 examples in Table 1), but substantial discrepancies among taxa or regions remain.

74 In the last decade, many studies have proposed methods to capitalise on the increasing
75 availability of ecological data and remote-sensing products to address the above-mentioned
76 challenges, by enabling faster, more rigorous and more consistent assessments (e.g., [21,22]).
77 In particular, relevant data, tools and models have been proposed to standardise the estimation
78 of Red List parameters (e.g., Extent of Occurrence or population trends) or predict species’
79 Red List categories. However, while many methods have been published, very few have been
80 implemented in practice [23].

81 Here, we systematically reviewed recently published methods that aim either at identifying
82 correlates of extinction risk, or at predicting species’ extinction risk categories for groups of

83 species using modelling or automated calculation (considering papers published between 2001
 84 and June 2021; see Supplementary Information). We then evaluated their utility from a
 85 practical perspective and discussed the main barriers to their uptake in Red Listing. Finally, we
 86 suggested how to bridge this important research-implementation gap, and highlighted potential
 87 future research directions.

88



89

90 **Figure 1. Information on Red List assessments per taxonomic group.** (a): Proportion of described species that are
 91 currently assessed (as in <https://www.iucnredlist.org/resources/summary-statistics>), planned to be assessed by 2030
 92 (calculated from [15]), or unassessed. (b): Proportion of assessed species in each Red List category (coloured bars) and
 93 proportion of these that are threatened (red line), assuming Data Deficient species are threatened in the same proportion
 94 as data-sufficient species. (c): Proportion of assessed species with an outdated assessment (year of last assessment
 95 coloured in 5-year classes up to 2010; more detail in Fig. S1). (d): Distribution of current Red List categories of outdated
 96 assessments (colours as in B). N refers to the number of assessed species per group, N' refers to the number of species
 97 with outdated assessments. Data were extracted from the version 2021.2 from the Red List, using the *rredlist* package
 98 [24].

99 **Table 1.** Examples of changes made in the Red List guidelines over the last two decades to strengthen consistency and
 100 rigour of Red List assessments, with year of inclusion in the Red List guidelines (multiple years indicate stepwise
 101 implementation) and references related to the issue (the reference may precede change in guidelines (e.g., if it suggested
 102 and provided rationale for such change), or follow it (e.g., if it tested or explained such change). Red List criteria and
 103 categories are detailed in the Glossary.

Red List criterion	Change made in guidelines	Year	Related references
A - E	Using fuzzy arithmetic to propagate data uncertainties and identify the range of plausible Red List categories	2001	[25]

A, C1	Extracting species generation length from databases of calculated and predicted generation lengths for entire taxonomic groups (mammals and birds)	2003, 2011	[26,27]
B2	Measuring Area of Occupancy (AOO) at the reference scale of 2x2 km	2003	[28]
B1	Measuring the Extent of Occurrence (EOO) as the area of the minimum convex polygon	2006	[29]
A3	Using ecological niche models and climate projections outputs to infer future reductions resulting from climate change	2010	[30,31]
A2	Calculating 3-generation reduction of species with large fluctuations using statistical models fitted to longer time series	2011	[32,33]
B	Calculating upper bounds of AOO and EOO based on habitat maps and Area of Habitat	2014	[34]
Red List category			
DD	Differentiating (and flagging) three types of Data Deficient	2008	[16]
EX, CR(PE)	Defining (and flagging) species likely but not yet confirmed to be extinct as "Critically Endangered (Possibly Extinct)" CR(PE).	2008	[35]
EX, CR(PE)	Inferring that a species is extinct based on threats and time series of records and surveys	2019	[36,37]

104 **Published methods to predict Red List categories**

105 **Four main objectives of published studies**

106 Of the 98 studies identified in our review, 46% aimed at predicting Red List categories, and we
107 identified three related objectives depending on the species group targeted (Fig. 2). The first
108 objective aimed at prioritising or informing first assessments by assigning plausible Red List
109 categories to unassessed species (e.g., [38]; 13% of studies). The second aimed at resolving
110 Data Deficient species' status (e.g., [18]; 11% of studies), by providing information that may
111 enable assigning data sufficient categories to species with no taxonomy uncertainty [16,17].
112 The third aimed at prioritising or informing reassessments, by highlighting species likely to be
113 misclassified (e.g., [22]; 22% of studies), sometimes also including Data Deficient species'.

114 Additionally, 54% of studies aimed at understanding correlates of extinction risk using Red
115 List categories as a proxy for risk (Fig. 2). These studies showed, for instance, that mammals
116 with high weaning age, small geographic range size, and high human population density within
117 their geographic range were particularly likely to be categorised as threatened [39]. We define
118 this objective as fundamental, in the sense that it does not aim to assist Red List assessments
119 directly, but rather contributes to understanding vulnerability to extinction, which in turn may
120 guide the development of predictive approaches.

121

122 **Two main approaches to predict Red List categories**

123 To meet the objectives mentioned above, studies have relied on two main approaches (Fig. 2):
124 (1) the modelling or automated calculation of Red List parameters, then used to apply Red List
125 criteria (*criteria-explicit*) or (2) using correlates of extinction risk to predict Red List categories
126 with no explicit use of criteria (*category-predictive*).

127 *Criteria-explicit* approach

128 *Criteria-explicit* methods mirror the process of assessments by applying Red List criteria based
129 on Red List parameters that have been automatically calculated from data such as species
130 occurrences, species habitat requirements, and remote-sensing products (N=25; Fig. 2). For
131 example, species occurrence data can be used to estimate Extent of Occurrence and Area of
132 Occupancy (e.g., [40]), and several platforms and R packages have been developed to calculate
133 these parameters automatically (e.g., *GeoCAT* and *rCAT* [41]; *red* [42]; *ConR* [43]; *redlistr*
134 [44]; *rapidLC* [45]). These methods are particularly useful if species' geographic distributions
135 have not been mapped although substantial occurrence data exist, and are thus more often used
136 for plant and invertebrate groups. Similarly, abundance data can allow estimating population
137 trends [46], although extensive temporal data are required.

138 Other studies use habitat and geographic data, often derived from remote-sensing products, to
139 estimate Red List parameters (Fig. 2). For example, combining current land cover and digital
140 elevation maps with data on species' habitat preferences and elevational limits allows mapping
141 an estimate of the Area of Habitat of species. This in turn can be used to calculate upper bounds
142 of the Extent of Occurrence and Area of Occupancy [34], and inform application of criteria B
143 and D2 [47,48]. Similarly, land cover time series can be used to estimate past or future trends
144 in suitable habitat within species range, which enables inferring population trends and apply
145 criteria A, B and C (e.g., [49–51]). Most studies focus on only one or two Red List criteria
146 rather than the full spectrum (Fig. 2), although two studies applied each of criteria A to D; one
147 focused on past data [22] and the other on future projections [49].

148 It may perhaps be surprising that criterion E – related to quantitative estimates of extinction
149 probability – is rarely considered in these studies. This criterion is also rarely used in
150 assessments (currently only used for four species, always in combination with another criterion
151 [1]). This scarce use of Criterion E results from the large amount of information required (e.g.,
152 demographic data or patterns of occupancy used to perform Population Viability Analyses;
153 [19]), which is not available for a vast majority of species. This may also explain the lack of
154 relevant multi-species studies targeting Criterion E. We found one single study attempting to
155 apply criterion E on a large set of species [53], with extinction probability estimated from very
156 limited information (generation length and past transition between categories), thus being
157 unreliable at the species level.

158

159 *Category-predictive* approach

160 *Category-predictive* methods rely on comparative extinction risk analyses using statistical
161 models that link Red List categories with other species-level information (see below; N=73
162 studies; Fig. 2). These statistical relationships are then used to identify the main drivers of risk
163 (e.g., [53,54]) and/or to predict Red List categories of unassessed species (e.g., [55]), Data

164 Deficient species (e.g., [18]), or species with outdated assessments (e.g., [56]). In addition to
165 species-level predictions, these approaches have estimated and mapped proportions of
166 threatened species for incompletely assessed taxa or regions [40,55].

167 Many species-level predictors have been used [57], the most common being biological traits
168 (e.g., body mass, weaning age; 86% of studies), and range characteristics (often range size,
169 sometimes insularity or spatial configuration; 67%; Fig. 2). Many studies also included
170 predictors representing levels of human pressure within species' ranges (e.g., human footprint
171 index, river fragmentation; 40%), which are important correlates of extinction risk [54,58].
172 Other predictors include conservation actions in place (e.g., proportion of species' range
173 overlapping with protected areas; 4%), which may be important covariates of extinction risk
174 [59–61]. Importantly, we found only nine studies using the threats listed in species Red List
175 assessments as predictors (e.g., [53,62]), although these can modulate trait-extinction risk
176 relationships (e.g., human consumption more strongly threatens large frogs whereas pet trade
177 threatens small frogs; [63]).

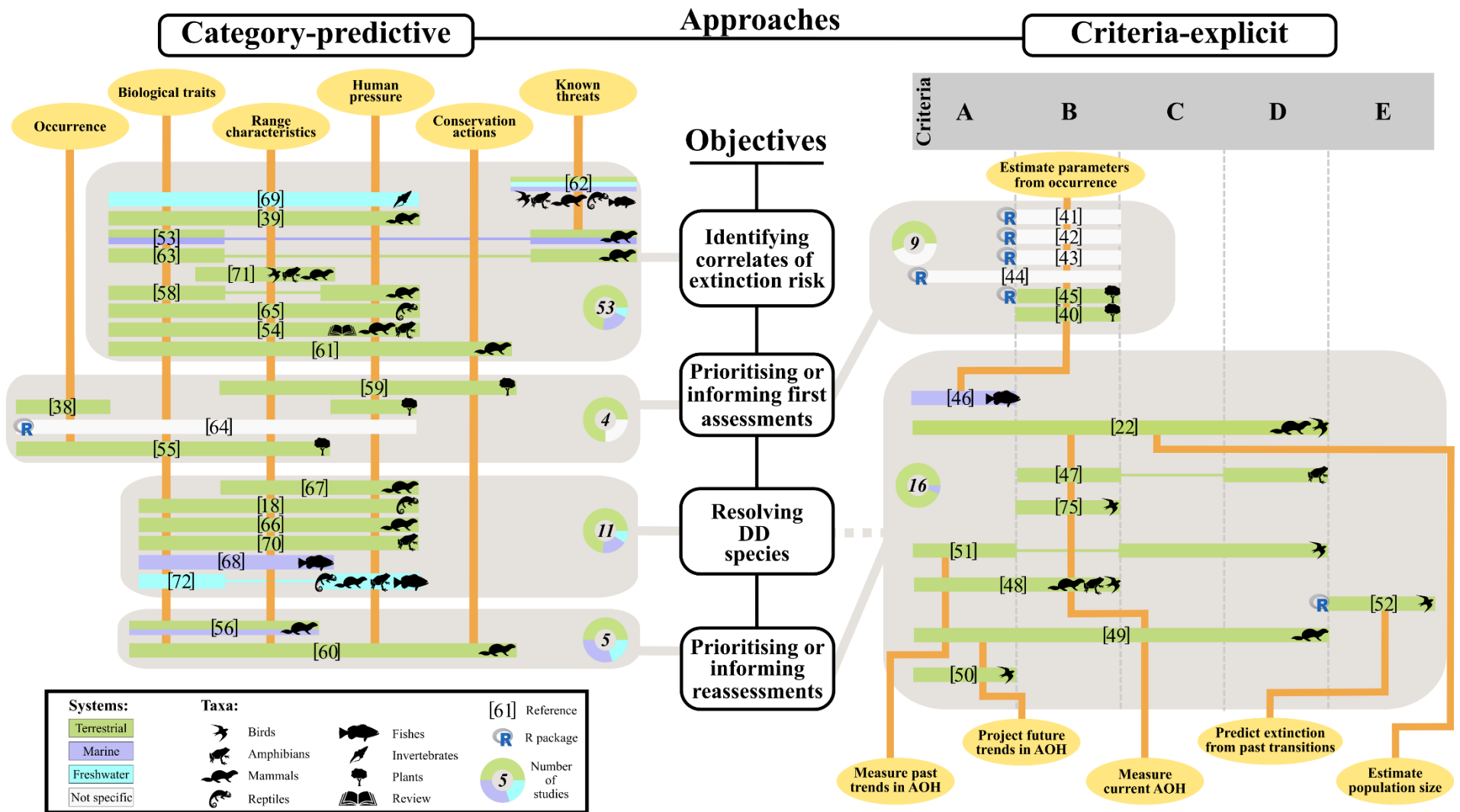
178 Two main types of models are used in this *category-predictive* approach: machine learning
179 (e.g., Random Forest [55] or Neural Networks [64]) and statistical linear models (e.g.,
180 Generalised Linear Models [65]). Studies comparing their performance in predicting extinction
181 risk are yet too scarce to provide clear guidance on which modelling method is best [66]. An
182 important consideration when building these models is in how to define the extinction risk
183 response variable. Risk can be binary (threatened *vs* non-threatened; 43% of studies; e.g., [67]),
184 include individual Red List categories (15%, e.g., [68]) or transforming them in a discrete
185 quantitative variable (39%, e.g., [69] where LC=1, NT=2, etc), or be described as the change
186 in categories between two assessments (3%, e.g., [58]). The preferred option depends on the
187 envisioned applications of the predicted Red List categories. For instance, binary threat
188 predictions are often more accurate [70] and can be sufficiently detailed for a first sorting of
189 species likely to be threatened [45], whereas category-specific models may be needed to inform
190 and prioritise reassessments. When category-specific predictions are needed, using a discrete
191 quantitative variable requires making assumptions about the distance between categories that
192 are generally untested. This could be resolved by using Cumulative Link Mixed Models, which
193 deal with multinomial ordered variables [68,71].

194 Many studies investigating range size as a correlate of extinction risk have excluded
195 assessments made under criterion B as they could introduce circularity (e.g., because range size
196 is highly correlated with Extent of Occurrence used in criterion B1; see [57,71]). This exclusion
197 is necessary when the objective is fundamental (i.e., to understand if range size correlates with
198 extinction risk), but not necessarily required when the objective is predicting species Red List
199 category.

200

201 System and taxonomic biases

202 Our review revealed biases in extinction risk research across taxa and systems, with 73% of
203 studies focusing only on terrestrial species, vs 11% on marine and 3% on strictly freshwater
204 species (rare examples include [69,72]); 13% cover several systems. Additionally, only one
205 *criteria-explicit* study focused specifically on marine species and none on freshwater species
206 (Fig. 2), possibly because it is less straightforward to derive binary maps of suitable habitat
207 from remote-sensing products for these systems compared to the terrestrial system. Marine and
208 freshwater species, however, are facing particular threats and thus need specific data and
209 methods (e.g., to estimate impacts of dam-induced fragmentation on Area of Habitat; [69]).
210 Studies were also strongly biased towards tetrapod species (74% of studies), while they would
211 be particularly valuable for groups that are less known, such as fishes, invertebrates, plants and
212 fungi.



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Figure 2: Graphical summary of studies reviewed, presenting the two approaches and the four objectives of studies developing modelling or automated calculation methods to predict Red List categories. All studies cited in the main text are reported in the figure in brackets (full references in Fig. S2); the total number of studies found in the systematic review per approach and objective is given in the doughnut plots. Colours denote the system investigated, with freshwater designating only fully aquatic freshwater species and “not specific” for R packages that can be applied to any system. Yellow ellipses present the main types of variables used in the *category-predictive* approach and the main methods used in the *criteria-explicit* approach (AOH: Area of Habitat). Thin horizontal lines are used to illustrate studies belonging to several adjacent columns (e.g., including criteria B and D, but not C for [47]). Red List criteria are detailed in the Glossary. DD: Data Deficient. Grey boxes encompass studies that share the same objective and approach. The dotted grey line indicates that only some studies in the grey box share the objective.

220 **From research to implementation**

221 The limited uptake of methods developed to support Red List assessments is striking. Perhaps
222 the most widely used tools are platforms and packages that facilitate the use of criterion B from
223 occurrence data, such as *GeoCAT* [41], which have been cited in 8,921 assessments as of early
224 June 2021, or *red* [42]. Additionally, some studies have been conducted in collaboration with
225 groups undertaking Red List assessments, or have been communicated directly to assessors
226 [22,48,50,51], and have thus informed actual assessments. So far, however, most studies
227 remain research exercises.

228

229 **Overcoming barriers**

230 The important research-implementation gap can be broadly attributed to a lack of
231 communication between extinction risk researchers and Red List practitioners [23]. From the
232 research side, implementation is hindered by misunderstandings or misapplications of Red List
233 criteria in the proposed methods, mismatches between researchers' interests and assessors'
234 needs, or because developed methods do not provide the outputs needed by assessors [73] (Box
235 1). This may be partly due to researchers being unclear about the most appropriate entry points
236 in the Red List system to discuss and propose change. On the Red List side, assessors may not
237 be able to use potentially relevant tools if these require detailed input data, substantial time, or
238 advanced technical skills and capacity to apply (Box 1). Additionally, some tools have been
239 implemented and used by assessors but, because of a lack of funding, are not being maintained
240 (e.g., the Freshwater Mapping Application, used in many assessments, had no funding to
241 support development and maintenance at the time of writing).

242

243 **Box 1: Main barriers to the implementation of recent methods to predict Red List** 244 **categories**

245 ● **Misunderstanding of Red List criteria:** in many publications, the Red List guidelines are
246 ignored or misinterpreted [31,74], rendering outputs unhelpful for Red List assessments. For
247 instance, considerable confusion has arisen over the interpretation of the slightly ambiguous
248 language around the Extent of Occurrence metric (e.g., [75]), despite attempts to clarify how
249 this should be calculated [29,34,76].

250 ● **Divergent interests:** there may be differences between what is needed by Red List assessors
251 and what is appealing to researchers. While assessors need tools that give them easy access to
252 basic information (e.g., deforestation rates within species ranges) or readily applicable
253 estimates of Red List parameters, researchers may be more interested in developing
254 sophisticated modelling methods, to increase the novelty of potential publications).

255 ● Misaligned output: methods may sometimes output parameters in formats that are not directly
256 usable in Red List assessments. For instance, a model predicting species' Red List categories
257 cannot be used by assessors if it fails to output the specific parameters that assessors must
258 provide to justify categories (e.g., typical of the *category-predictive* approach).

259 ● Lack of data: methods that require extensive species-specific data (e.g., occurrences across
260 range [41], life-history traits across taxa [66]) cannot be applied to all taxa.

261 ● Insufficient skills, capacity, or time: Red List assessors vary in their ability to use
262 technological tools (e.g., GIS, R scripts) and may lack the necessary background, skills and
263 time to learn how to use newly developed methods if they are not easy to apply (e.g., [22]). For
264 example, the success of *GeoCAT* [41] is likely due to its user-friendly interface. Specific
265 training on how to use newly developed tools (e.g., courses, tutorials, fora), is very rarely
266 offered.

267 ● Disconnect with the Red List database: all Red List assessments are conducted in the IUCN's
268 online database (the Species Information Service, SIS). Uptake of new methods and approaches
269 would be greatly increased if outputs, such as Red List parameters, could readily be integrated
270 into SIS (e.g., through the existing SIS Connect tool).

271

272 These barriers could be mitigated in various ways. First, the best means of resolving poor
273 communication between researchers and practitioners is by involving Red List stakeholders
274 early in the development of new approaches and methods to ensure effective orientation of
275 research efforts and avoid misunderstanding or misapplication of the Red List categories and
276 criteria, or of assessors' needs and constraints [77]. This could include members of Red List
277 Authorities, the Red List Committee and its working groups, IUCN Red List Unit or IUCN
278 Standards and Petitions Committee (noting that part of these members are also recognised
279 experts in extinction risk research), or sending a request to the generic IUCN Red List email
280 address when researchers cannot identify the correct entry point. Particular attention must be
281 given to the ultimate outputs to ensure they are useful in practice. On this point, *criteria-explicit*
282 methods which, by definition, estimate Red List parameters that can be directly used by
283 assessors to apply Red List criteria, seem more useful than *category-predictive* methods.
284 However, the latter could prove useful to designate priorities for species (re-)assessment (see
285 Future research directions).

286 Second, because of the heterogeneity in assessors' backgrounds, uptake of any new method
287 requires easy use. This can be achieved by releasing methods through user-friendly online
288 platforms, such as Shiny Apps (e.g., [45]), and ensuring their long-term maintenance and
289 update with new data and methods. At the same time, any information provided should come
290 with high transparency (so that assessors can understand basic assumptions and limitations of

291 underlying methods), with explicit uncertainty bounds, and be open-source. In addition,
292 platforms could benefit from allowing assessors to adjust some methodological choices (e.g.,
293 selecting variables to include in a given model) based on their expertise. However, this may
294 come at the expense of consistency and may increase the risk of cherry-picking (e.g., assessors
295 may be tempted to adjust methods to meet the output they expected).

296 Finally, these platforms should be promoted to assessors, provided with adequate guidance and
297 training (e.g., through webinars, workshops, documentation, video tutorials), and connected
298 with IUCN database (the Species Information Service, SIS). From a longer-term perspective,
299 it is also important to enable assessors to provide feedback on these platforms to inform future
300 development, and to track their use (e.g., through citations in assessments).

301

302 **Future research directions**

303 In addition to making developed methods accessible to assessors, further research is needed to
304 create methods that (1) better support the assignment of Red List categories and (2) help
305 prioritise assessments and data collection. Before implementation, all methods have to be
306 rigorously validated to measure their performance (Box 2).

307

308 **Supporting assignment of Red List categories**

309 **Considering the diversity of threats:** With most published methods targeting terrestrial
310 habitat loss (especially in the *criteria-explicit* approach; Fig. 2), it is important to develop
311 methods that focus on the impact of other threats on species extinction risk (e.g., harvesting,
312 pollution, diseases, invasive species), including those specific to freshwater and marine species
313 (e.g., dams, water pollution, overfishing). In particular, while climate change is threatening
314 >10,000 species [1] and can significantly increase extinction risk [78], estimating its impact
315 consistently across species is complex [19,79]. We need tools providing assessors with species'
316 exposure to past and future climate change (e.g., change in climatic envelope, sea-level rise,
317 frequency of extreme climatic events, ocean acidification), and the ability to integrate this
318 knowledge with information on species' sensitivity to climate change [80–82] in accordance
319 with Red List guidelines [19,79].

320 **Facilitating the application of criterion E:** A wider use of criterion E would have two main
321 advantages: direct incorporation of quantitative analyses in Red List assessments, and explicit
322 consideration of longer time frames than all other criteria (up to 100 years in the future,
323 regardless of generation length). Methods may build on allometry-driven parameters (e.g.,
324 [83]) and population density estimates [84] to inform extinction risk simulations on entire
325 groups of species. Extinction probability could also be estimated by modelling the probability

326 that a species' Area of Habitat disappears in the future, according to climate and land-use
327 change projections [19].

328 **Predicting the probability of meeting thresholds:** In analogy with the *category-predictive*
329 approach (i.e., linking extinction risk of multiple species to species-specific data such as
330 biological traits or human pressure in the range), models could be developed to predict the
331 probability of meeting the threshold for a given criterion (e.g., the probability that past
332 population decline is $\geq 30\%$ over 10 years), instead of the categories themselves. Such models
333 would thus benefit from the power of multi-species comparisons inherent in *category-*
334 *predictive* methods, but provide an output more likely to be useful to assessors.

335 **Accounting for biotic dependencies:** Informing assessors on biotic dependencies between
336 species (e.g., parasite-host, plant-pollinator, or plant-phytophagous relationships) can lead to
337 better integration of associated co-extinction risk in assessments [12], which could affect
338 several thousands of species [85–87]. For instance, the population trend of Barrett's Plant-louse
339 *Trioza barrettiae* – an endemic bug from Australia – was estimated based on the population
340 trend of its Critically Endangered and sole known host plant Brown's Banksia *Banksia brownii*,
341 and the louse was consequently categorised as Critically Endangered [1].

342 **Predicting down-listing:** While previously mentioned methods can also identify species
343 warranting down-listing to lower categories of threat, specific research efforts should focus on
344 predicting positive population trends (considering for instance conservation actions
345 undertaken) or range expansions. Such methods may later support assessments of the IUCN
346 Green Status of Species [88,89].

347

348 [Prioritising assessments or data collection](#)

349 **Prioritising first assessments:** Both *category-predictive* and *criteria-explicit* approaches can
350 help prioritise assessments to optimise allocation of limited resources [11]. Specifically, for
351 assessors or teams undertaking first-time assessments for large groups of species, these
352 approaches can be used to help provide an initial indication of whether species are likely to be
353 threatened (e.g., [55,59]) or Least Concern (and hence could be fast-tracked [45]).

354 **Prioritising reassessments:** Given that reassessments rates are currently insufficient to
355 provide updates every 10 years for most groups (Fig. 1C), the identification of species most
356 likely to have changed their category is also relevant [22,60]. Additionally, a period of 10 years
357 between assessments may be too long to detect rapid changes in some species' status (e.g., the
358 Mount Gorongosa Pygmy Chameleon, *Rhampholeon gorongosae*, Least Concern in 2014 was
359 Endangered five years later following rapid habitat loss; [1]). Identifying which species are
360 most likely to have changed in status since the previous assessment could inform targeted
361 reassessments and thus help to keep the Red List up-to-date. Similarly, it would be useful to

362 develop tools that flag Data Deficient species for which recent increases in data availability
363 may allow application of Red List criteria (e.g., through accumulation of new information on
364 citizen science platforms).

365 **Prioritising data collection:** Methods that predict species or areas for which data collection
366 would make the biggest difference for Red List assessments can deliver useful information to
367 guide data collection. For instance, Data Deficient species that are predicted as threatened by
368 *category-predictive* methods may be prioritised for data collection [66]. Further, predicting
369 where data collection may be the most valuable for conservation (e.g., species that could
370 become data sufficient with few additional data, or regions where collecting contextual
371 information would benefit many species) can also be useful to guide fieldwork efforts
372 [16,90,91]. Synergies with the IUCN Species Monitoring Specialist Group, which aims to
373 produce prioritized lists of existing species data gaps, would be beneficial.

374

375

376

Box 2: Best practices to validate methods predicting Red List categories

377

Model validation is necessary to assess the ability of models to correctly predict species' Red
378 List categories.

379

- In the *criteria-explicit* approach, validation simply requires comparison of predicted
380 categories with the actual categories from published assessments.

381

- In the *category-predictive* approach, three main validation methods can be undertaken:

382

- Temporal block validation is the most recommended method, if applicable (i.e.,
383 species have been assessed at least twice), where models are trained on Red List categories
384 from past assessments and validated against current assessments. This is relevant only if
385 changes in categories are “genuine” (i.e., not due to improved knowledge or other non-genuine
386 reasons, this is specified in Red List data).

387

- Phylogenetical or spatial block validation, is the most recommended method when
388 temporal block validation is not applicable, where each independent taxon or region is
389 separately set aside (i.e., not used in model training) and used for validation (e.g., [65]).

390

- Other split sample validation methods randomly split the dataset into training and
391 testing sets (e.g., [67]). This is the least recommended, as accuracy can be overestimated due
392 to the autocorrelation in training and testing samples [92].

393

- For both approaches, we advise systematically reporting confusion matrices and measures of
394 accuracy (i.e., proportion of species correctly categorised), sensitivity (proportion of threatened
395 species correctly categorised) and specificity (proportion of non-threatened species correctly
396 categorised), as they provide key and complementary information [93]. Models with high
397 sensitivity are particularly useful to identify species likely to be threatened, while models with

398 high specificity can rule out species unlikely to be threatened. A model with intermediate
399 specificity and sensitivity is less informative. Additionally, exploring how geographically /
400 taxonomically consistent is model performance may provide important insights on model
401 limitations.

402 ● For both approaches, we advise sub-setting the species used for validation, keeping only the
403 most accurate assessments, to avoid underestimating the accuracy of the developed methods.

404 We suggest selecting species:

405 - With up-to-date assessments

406 - Threatened by processes accounted for in the modelling (e.g., species threatened by
407 habitat loss when validating methods based on Area of Habitat).

408 - With high certainty in Red List category, although in practice it may be difficult to
409 identify such assessments.

410

411 **Concluding Remarks**

412 The multiple approaches reviewed in this paper include some with significant potential to assist
413 Red List assessments. Improved communication between researchers and the Red List
414 community is required to develop the tools and outputs most relevant for assessors. Uptake
415 also requires additional research to tackle key remaining methodological challenges (see
416 Outstanding Questions) and deliver practical tools. We believe that further development of
417 such tools, and ensuring their long-term availability to assessors, could constitute an important
418 milestone for the future of the Red List.

419 Importantly, the proposed methods will neither substitute nor reduce the role of assessors, but
420 rather support them with appropriate and readily usable outputs and techniques. In doing so,
421 these methods may help fast-track or prioritise assessments. However, it is important to note
422 that they will not address the urgent need to increase Red List resources for targeted fieldwork,
423 workshops, tool development, fora and remunerated assessors.

424 Increasing resources and embracing new data and methods will enable the Red List to become
425 more taxonomically and geographically representative, data sufficient, up-to-date and
426 consistent, and thus remain the standard and authoritative source of information on species'
427 extinction risk [11]. This is crucial to ensure that the Red List can best guide future conservation
428 actions [2,3], and support accurate monitoring of the effectiveness of global conservation
429 efforts under the post-2020 global biodiversity framework [6,94].

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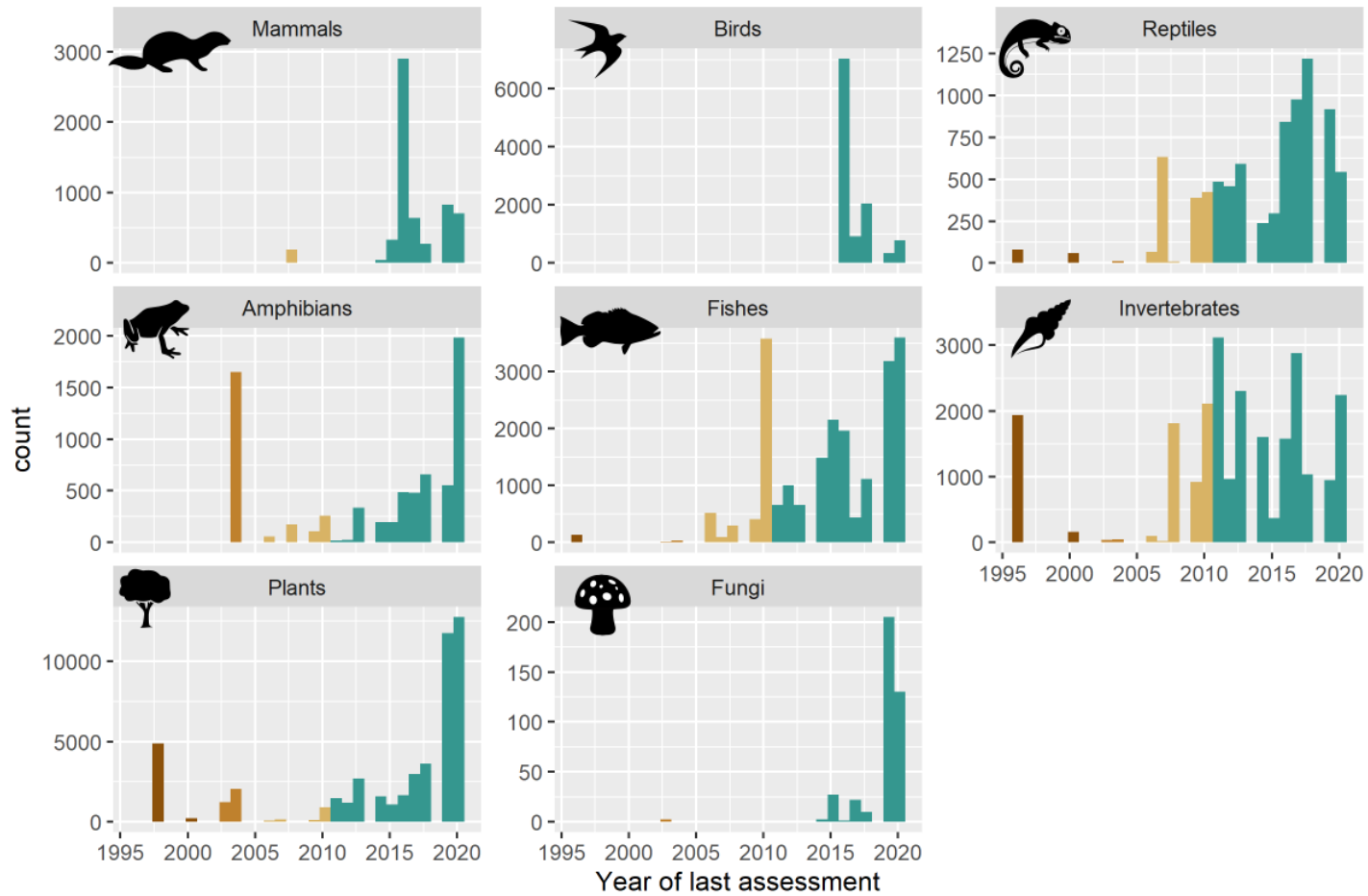
Supplemental information

Bridging the research-implementation gap in IUCN Red List assessments

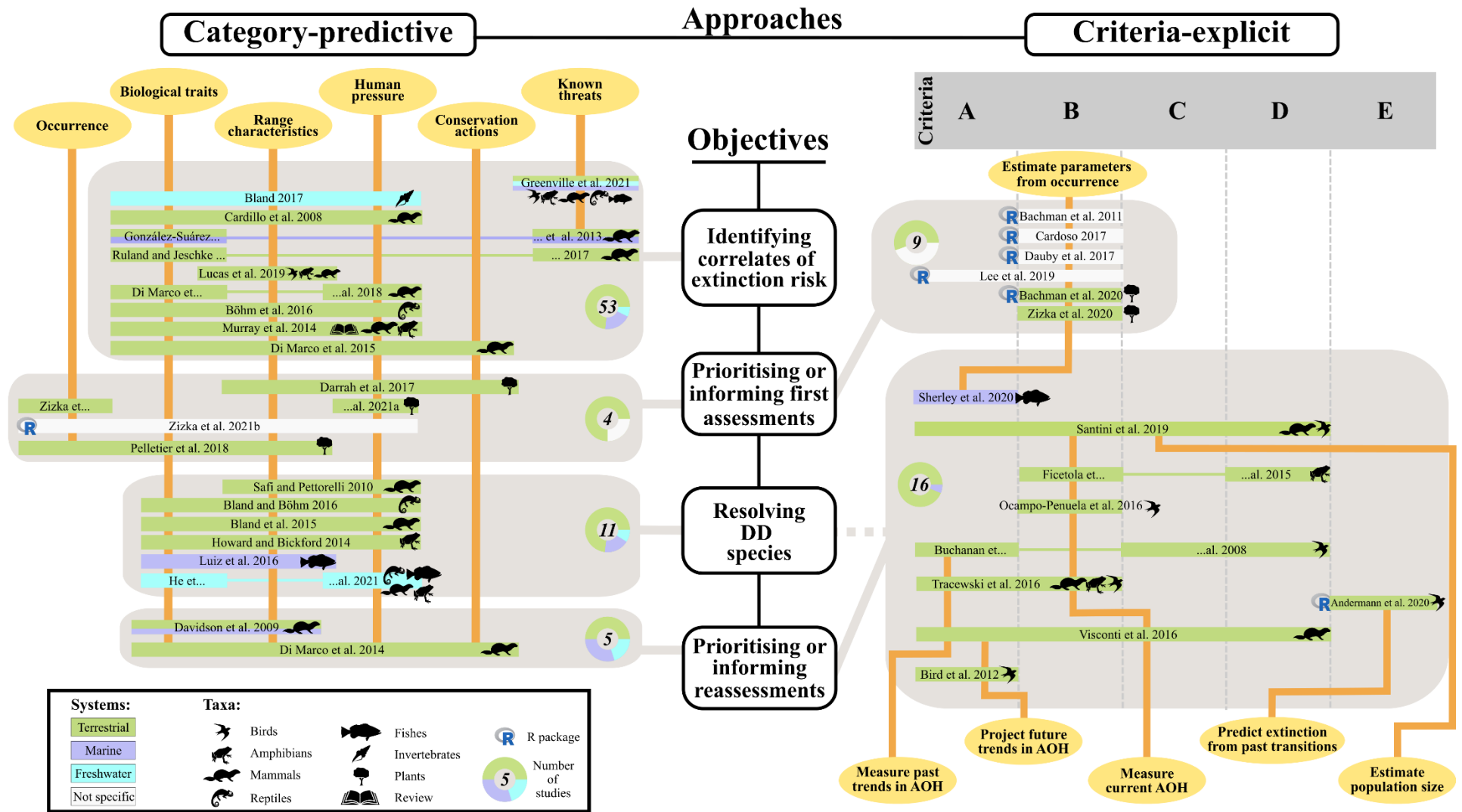
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Supplementary Figures



Supplementary Figure 1: Histogram of date of last assessment per taxa (detail of Fig. 1C). Colours as in Fig. 1C.



Supplementary Figure 2: Copy of Fig.2 with full references

Systematic review

Methods

We systematically searched for scientific articles that developed models or automated calculation methods aiming at predicting global Red List categories for groups of species. We did not consider studies focusing on National or Regional Red Lists, as they are based on other criteria.

We also included studies aiming at identifying correlates of extinction risk (i.e., using models to link Red List categories with species-level predictors), because they can inform method development of applied studies.

We ran a search in the Web of Science (complete collection) on the 2nd of June 2021, searching for the following keywords in the articles “Topic” (i.e. title, abstract, keywords): *extinction AND ("IUCN" OR "International Union for Conservation of Nature" OR "Red List*") AND (model* OR "remote sensing" OR "analys*" OR "predict*" OR "data-driven")*. We only considered publication published later than 2001.

We screened titles and abstracts of the 1132 hits and extracted 78 relevant studies. In addition, we included 20 studies that were not detected by the systematic search but that we were aware of (e.g., cited in the studies found in the systematic search, recent preprints...). Pooled together, we thus found 98 studies.

Final set of articles

When a paper achieved several of the objectives, we classified the paper in the category of their main objective and specified the other objectives achieved.

Category-predictive – Identifying correlates of categories

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Category-predictive – Prioritising or informing first assessments

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Category-predictive – Prioritising or informing reassessments

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