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

Glossary

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

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

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

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

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

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

Major challenges for the IUCN Red List

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

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

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

Here, we systematically reviewed recently published methods that aim either at identifying correlates of extinction risk, or at predicting species' extinction risk categories for groups of species using modelling or automated calculation (considering papers published between 2001 and June 2021; see Supplementary Information). We then evaluated their utility from a practical perspective and discussed the main barriers to their uptake in Red Listing. Finally, we suggested how to bridge this important research-implementation gap, and highlighted potential future research directions.

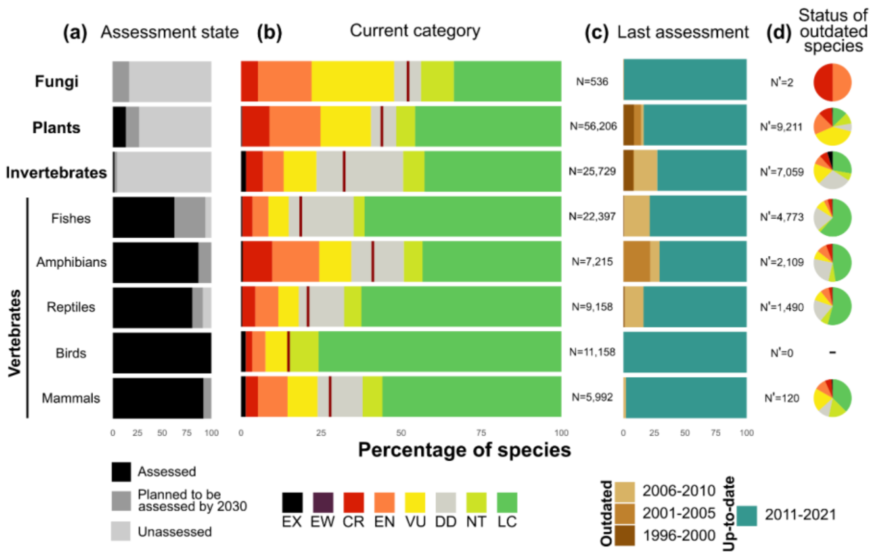

Figure 1. **Information on Red List assessments per taxonomic group**. (a): Proportion of described species that are currently assessed (as in https://www.iucnredlist.org/resources/summary-statistics), planned to be assessed by 2030 (calculated from [15]), or unassessed. (b): Proportion of assessed species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

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

Published methods to predict Red List categories

Four main objectives of published studies

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

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

Two main approaches to predict Red List categories

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

Criteria-explicit approach

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

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

It may perhaps be surprising that criterion E, which is related to quantitative estimates of extinction probability, is rarely considered in these studies. This criterion is also rarely used in assessments (currently only used for four species, always in combination with another criterion [1]). This scarce use of Criterion E results from the large amount of information required (e.g., demographic data or patterns of occupancy used to perform Population Viability Analyses; [19]), which is not available for a vast majority of species. This may also explain the lack of relevant multispecies studies targeting Criterion E. We found one single study attempting to apply criterion E on a large set of species [52], with extinction probability estimated from very limited information (generation length and past transition between categories), thus being unreliable at the species level.

Category-predictive approach

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

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

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

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

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

System and taxonomic biases

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

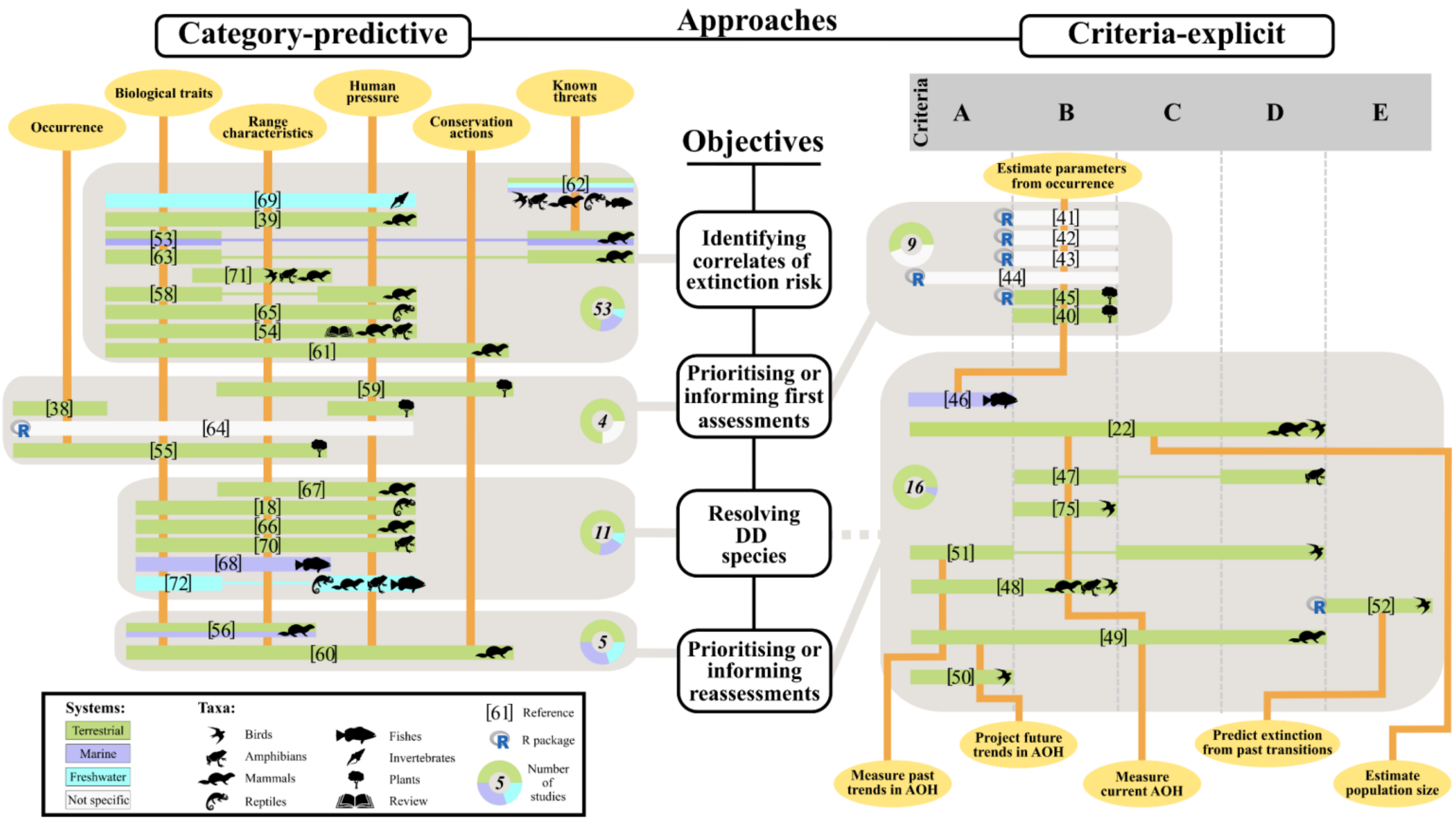

Figure 2: **Graphical summary of studies reviewed**, presenting the two approaches and the four objectives of studies developing modelling or automated calculation methods to predict Red List categories. All studies cited in the main text are reported in the figure in brackets (full references in Fig. 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.

From research to implementation

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

Overcoming barriers

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

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

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

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

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

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

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

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

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

Second, because of the heterogeneity in assessors' backgrounds, uptake of any new method requires easy use. This can be achieved by releasing methods through user-friendly online platforms, such as Shiny Apps (e.g., [45]), and ensuring their long-term maintenance and update with new data and methods. At the same time, any information provided should come with high transparency (so that assessors can understand basic assumptions and limitations of underlying methods), with explicit uncertainty bounds, and be open-source. In addition, platforms could benefit from allowing assessors to adjust some methodological choices (e.g., selecting variables to include in a given model) based on their expertise. However, this may come at the expense of consistency and may increase the risk of cherry-picking (e.g., assessors may be tempted to adjust methods to meet the output they expected).

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

Future research directions

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

Supporting assignment of Red List categories

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

Facilitating the application of criterion E: A wider use of criterion E would have two main advantages: direct incorporation of quantitative analyses in Red List assessments, and explicit consideration of longer time frames than all other criteria (up to 100 years in the future, regardless of generation length). Methods may build on allometry-driven parameters (e.g., [83]) and population density estimates [84] to inform extinction risk simulations on entire groups of species. Extinction probability could also be estimated by modelling the probability that a species' Area of Habitat disappears in the future, according to climate and land-use change projections [19].

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

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

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

Prioritising assessments or data collection

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

Prioritising reassessments: Given that reassessments rates are currently insufficient to provide updates every 10 years for most groups (Fig. 1C), the identification of species most likely to have changed their category is also relevant [22,60]. Additionally, a period of 10 years between assessments may be too long to detect rapid changes in some species' status (e.g., the Mount Gorongosa Pygmy Chameleon, *Rhampholeon gorongosae*, Least Concern in 2014 was Endangered five years later following rapid habitat loss; [1]). Identifying which species are most likely to have changed in status since the previous assessment could inform targeted reassessments and thus help to keep the Red List up-to-date. Similarly, it would be useful to develop tools that flag Data Deficient species for which recent increases in data availability may allow application of Red List criteria (e.g., through accumulation of new information on citizen science platforms).

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

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

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

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

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

- Temporal block validation is the most recommended method, if applicable (i.e., species have been assessed at least twice), where models are trained on Red List categories from past assessments and validated against current assessments. This is relevant only if changes in categories are "genuine" (i.e., not due to improved knowledge or other non-genuine reasons, this is specified in Red List data).
- Phylogenetical or spatial block validation, is the most recommended method when temporal block validation is not applicable, where each independent taxon or region is separately set aside (i.e., not used in model training) and used for validation (e.g., [65]).
- Other split sample validation methods randomly split the dataset into training and testing sets (e.g., [66]). This is the least recommended, as accuracy can be overestimated due to the autocorrelation in training and testing samples [92].

● For both approaches, we advise systematically reporting confusion matrices and measures of accuracy (i.e., proportion of species correctly categorised), sensitivity (proportion of threatened species correctly categorised) and specificity (proportion of non-threatened species correctly categorised), as they provide key and complementary information [93]. Models with high sensitivity are particularly useful to identify species likely to be threatened, while models with high specificity can rule out species unlikely to be threatened. A model with intermediate specificity and sensitivity is less informative. Additionally, exploring how geographically / taxonomically consistent model performance is may provide important insights on model limitations.

● For both approaches, we advise subsetting the species used for validation, keeping only the most accurate assessments, to avoid underestimating the accuracy of the developed methods. We suggest selecting species:

- With up-to-date assessments
- Threatened by processes accounted for in the modelling (e.g., species threatened by habitat loss when validating methods based on Area of Habitat).
- With high certainty in Red List category, although in practice it may be difficult to identify such assessments.

Concluding Remarks

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

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

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

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