# *Prioritizing the reassessment of data deficient species on the IUCN Red List*

Article

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# Prioritizing the reassessment of data-deficient species on the IUCN Red List

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## Abstract

Despite being central to the implementation of conservation policies, the usefulness of the International Union for Conservation of Nature (IUCN) Red List of Threatened Species is hampered by the 14% of species classified as data-deficient (DD) because information to evaluate these species' extinction risk was lacking when they were last assessed or because assessors did not appropriately account for uncertainty. Robust methods are needed to identify which DD species are more likely to be reclassified in one of the data-sufficient

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IUCN Red List categories. We devised a reproducible method to help red-list assessors prioritize reassessment of DD species and tested it with 6887 DD species of mammals, reptiles, amphibians, fishes, and Odonata (dragonflies and damselflies). For each DD species in these groups, we calculated its probability of being classified in a data-sufficient category if reassessed today from covariates measuring available knowledge (e.g., number of occurrence records or published articles available), knowledge proxies (e.g., remoteness of the range), and species characteristics (e.g., nocturnality); calculated change in such probability since last assessment from the increase in available knowledge (e.g., new occurrence records); and determined whether the species might qualify as threatened based on recent rate of habitat loss determined from global land-cover maps. We identified 1907 species with a probability of being reassessed in a data-sufficient category of >0.5; 624 species for which this probability increased by >0.25 since last assessment; and 77 species that could be reassessed as near threatened or threatened based on habitat loss. Combining these 3 elements, our results provided a list of species likely to be data-sufficient such that the comprehensiveness and representativeness of the IUCN Red List can be improved.

**KEYWORDS**
amphibians, ecological knowledge, extinction risk, fish, IUCN Red List, mammals, Odonata, reptiles

Priorización de la reevaluación de las especies con datos deficientes en la Lista Roja de la UICN

**Resumen:** No obstante que es fundamental para la implementación de políticas de conservación, la utilidad de la Lista Roja de Especies Amenazadas de la Unión Internacional para la Conservación de la Naturaleza (UICN) está limitada por el 14% de especies clasificadas con datos deficientes (DD) debido a que la información para evaluar el riesgo de extinción de estas especies no existía cuando fueron evaluadas la última vez o porque los evaluadores no consideraron la incertidumbre apropiadamente. Se requieren métodos robustos para identificar las especies DD con mayor probabilidad de ser reclasificadas en alguna de las categorías en la Lista Roja UICN con datos suficientes. Diseñamos un método reproducible para ayudar a que los evaluadores de la lista roja prioricen la reevaluación de especies DD y lo probamos con 6,887 especies DD de mamíferos, reptiles, anfibios, peces y Odonata (libélulas y caballitos del diablo). Para cada una de las especies DD en estos grupos, calculamos la probabilidad de ser clasificadas en una categoría con datos suficientes si fuera reevaluada hoy a partir de covariables que miden el conocimiento disponible (e.g., número de registros de ocurrencia o artículos publicados disponibles), sustitutos de conocimiento (e.g., extensión del rango de distribución) y características de la especie ((e.g., nocturnidad); calculamos el cambio en tal probabilidad desde la última reevaluación a partir del incremento en el conocimiento disponible (e.g., registros de ocurrencia nuevos); y determinamos si las especies podrían calificar como amenazadas con base en pérdidas de hábitat recientes a partir de mapas globales de cobertura de suelo recientes. Identificamos 1,907 especies con una probabilidad >0.5 de ser reclasificados en una categoría con datos suficientes; 624 especies cuya probabilidad aumentó en >0.25 desde la última evaluación, y 77 especies que podrían ser reclasificadas como casi en peligro con base en la pérdida de hábitat. Combinando estos 3 elementos, nuestros resultados proporcionaron una lista de especies probablemente con datos suficientes de tal modo que la exhaustividad y la representatividad de la Lista Roja de la UICN pueden ser mejoradas.

**PALABRAS CLAVE**
Anfibios, conocimiento ecológico, Lista Roja UICN, mamíferos, Odonata, peces, reptiles, riesgo de extinción

# INTRODUCTION

The International Union for Conservation of Nature (IUCN) Red List of Threatened Species (hereafter red list) is a central tool in biodiversity conservation, guiding policy implementation and biodiversity monitoring from local to global scales (Betts et al., 2020; Rodrigues et al., 2006; Stuart et al., 2010; Williams et al., 2021). An accurate, updated, and comprehensive red list is crucial for biodiversity conservation, but decades of insufficient funding (Juffe-Bignoli et al., 2016; Rondinini et al., 2014) have dramatically limited assessment and reassessment rates (Cazalis et al., 2022). For example, 14% of all assessed species ($n$ = 20,469) are currently classified as data-deficient (DD), meaning assessors were unable to evaluate their extinction risk (IUCN, 2022). These DD species potentially include imperiled taxa (Bland et al., 2015; Borgelt et al., 2022; de Oliveira Caetano et al., 2022), and these taxa may not be included in conservation legislation and policy because such instruments target only formally threatened species. A designation of DD also introduces uncertainty in monitoring of extinction risk trends of comprehensively assessed taxa (Bland et al., 2017; Butchart & Bird, 2010). Assigning an alternative category (hereafter, data-sufficient category [DS]) to species currently classified as DD is therefore a high priority (Bland et al., 2017).

Species are typically assessed as DD when "there is inadequate information to make a direct, or indirect, assessment of its risk of extinction based on its distribution and/or population" (IUCN, 2012). The number of DD species may be inadvertently inflated when assessors ineffectively use indirect information (e.g., habitat loss within the range of a species) or are more cautious than required by IUCN's guidelines (IUCN Standards & Petitions Committee, 2022). For birds, systematic efforts to use all indirect information (in addition to all direct information owing to the popularity of birds) have reduced the proportion of DD species to 0.4% ($n$ = 47) (IUCN, 2022), such that the status of remaining DD species may only be resolvable by the collection of new in situ information (Butchart & Bird, 2010). Conversely, many groups likely include DD species that could be reassessed as DS if assessors had more systematic access to recent direct and indirect information on species' distributions, populations, and trends.

Multiple studies have attempted to predict the red-list status of DD species through category-predictive or criteria-explicit approaches (Cazalis et al., 2022). Category-predictive approaches establish correlative models that link extinction risk of DS species with relevant characteristics of the species (e.g., showing that narrow-ranged species exposed to high human pressure are more likely threatened). These models are then used to predict the red-list category of DD species (Bland & Böhm, 2016; Bland et al., 2015; Borgelt et al., 2022; Zizka et al., 2021, 2022). However, use of such approaches to inform red-list assessments has been limited because their predictive ability for categories other than least concern is low (Di Marco, 2022). Additionally, because these correlative approaches are not explicitly based on red-list criteria, their results lack the required justification of the criteria that are triggered and are therefore of limited value to assessors (Cardillo & Meijaard, 2012; Cazalis et al., 2022).

Criteria-explicit studies mirror the process of assessments by automatically calculating parameters that are used to apply red-list criteria. For example, geospatial data have been used to measure trends in area of habitat (AOH) from global land cover (Santini et al., 2019) or global forest cover (Tracewski et al., 2016) to apply criteria on population reduction and create a list of DD species that could be reclassified as threatened under criterion A2 under certain assumptions. However, these approaches are not sufficient to prioritize reassessments because land-cover products provide a partial view of extinction risk drivers (i.e., habitat loss).

An avenue better aligned with red-list assessors' needs may be the identification of species likely to become DS if they were reassessed, which would help assessors prioritize reassessments. This identification can be done by training models to predict species' probability of being DS from variables that directly represent available knowledge (e.g., amount of available occurrence data), proxies of available knowledge (e.g., road density within species range), or the ecological characteristics of a species that make them difficult to monitor (e.g., nocturnality). The main difference between identifying likely DS species and the category-predictive approach is that covariates are not expected to correlate with species' extinction risk but with knowledge available to assessors. If such models can accurately predict which species are DS, they could in turn be used to predict the DD species with the highest probability of being classified in a DS category if reassessed and DD species for which such probabilities have substantially increased since the last assessment. This would allow ranking of species based on current information (e.g., a species could be prioritized due to the large number of occurrence records) and on the gain in information since the last assessment (e.g., a species could be prioritized because the number of occurrence records increased), thus providing valuable complementary information for prioritizing reassessments. We devised a reproducible method to prioritize reassessment of DD species based on 3 complementary analyses and applied it to DD species of mammals, reptiles, amphibians, freshwater and marine fishes, and dragonflies and damselflies (Odonata) (6887 species total).

## METHODS

We modeled the probability of a species being classified as DS and used this model to determine the probability of DD species being classified as DS if reassessed (pDS). We used the same model to predict by how much the probability of being DS increased for a DD species since last assessment (ΔpDS). We also calculated change in AOH ($\Delta_{AOH}$), based on 2 global land-cover products for each terrestrial DD species, and identified some species that potentially qualify as threatened or near threatened based on our data and collated additional information to guide assessors' work. We combined the results of these 3 analyses in a single priority index.

We applied our method to animal groups on the IUCN Red List with at least 10% of species classified as DD (e.g., excluding birds in which DD species are too few to build a model; ~0.4% of all bird species [IUCN, 2022]) and with published range maps for at least half of the species in a group. From these groups, we selected species with available range maps, which are needed to calculate many of our covariates. We eventually removed all species for which at least 1 covariate could not be calculated. We included 5663 mammals (14% DD), 8294 reptiles (13% DD), 7051 amphibians (15% DD), 14,023 fishes

(19% DD) (including Actinopterygii, Chondrichthyes, Myxini, Cephalaspidomorphi, and Sarcopterygii), and 4511 Odonata (29% DD). We refer to these 5 groups as *broad taxonomic groups*. We used species' current red-list category (IUCN, 2022) to separate species into DD and DS and excluded those categorized as extinct or extinct in the wild.

## Covariates

We gathered covariates relevant to predicting species' probabilities of being DS (Table 1). Detailed methods of covariate calculation, source, and rationale are in Appendix S3. First, we gathered direct measures of available knowledge: number of occurrence records available from the Global Biodiversity Information Facility (GBIF) and for fishes from the Ocean Biodiversity Information System (OBIS); proportion of the species' range covered by GBIF records; density of occurrence records for the broad taxonomic group within a focal species' range, as a proxy for sampling effort; number of articles in Web of Science mentioning the focal species' name as recorded on the IUCN Red List; number of known species' traits; spatial overlap among DD species in the broad taxonomic group occurring in the range; whether the species is present in at least 1 zoo or aquarium; and time since description of the species. Second, we retrieved a number of knowledge proxies: average gross domestic product (GDP) and frequency of armed conflicts in species' countries of occurrence; remoteness of species range; road density in species range; human population size in species range; proportion of rural population in species range; and fishing intensity in species range (marine fishes only). Third, we determined ecological characteristics of species: habitat preference; order of magnitude of range size; elevation or depth of occurrence; main realm of occurrence; and other potentially relevant traits that we could readily retrieve from existing trait data sets that use the IUCN Red List taxonomy (body mass and nocturnality for mammals, body length for amphibians). Finally, we retrieved the name of the expert group (red-list authority) responsible for coordinating assessments and reviews of each species (e.g., IUCN SSC Chameleon Specialist Group for all chameleons) to control for possible differences in assessment approaches among expert groups working on different taxa (de Oliveira Caetano et al., 2022). Four variables were calculated for 2 time steps: time of assessment (to fit the model) and present time (to predict pDS). These temporal variables were number of GBIF records, coverage of GBIF records, number of published scientific articles, and time since description. All data used to create the different models are provided in Appendix S1 and codes are available at https://zenodo.org/record/8019681.

## Modeling data sufficiency

We modeled independently the probability of species in each of the 5 broad taxonomic groups being DS. Mammals classified as strictly marine on the red list (i.e., 73 cetaceans, 1 dugong, 2 seals) were removed from the analyses because they could not be modeled with terrestrial species (covariates such as human density, remoteness, and elevations could not be calculated) and there were too few DD species to be modeled independently ($n = 3$). Conversely, strictly marine reptiles (i.e., 48 species of sea snakes, including 20 DD) were modeled with terrestrial reptiles because they are mainly coastal species (Appendix S3). For fishes, we fitted 2 models: all species occurring in freshwater domain ($n = 10{,}160$) and all species occurring in marine domain ($n = 4987$). There were 942 species included in each model (e.g., anadromous or catadromous species) (Appendix S7).

For each broad taxonomic group and domain, we fitted a Random Forest model with 1000 trees with the ranger function from the ranger R package 0.13.1 (Wright & Ziegler, 2017). For temporal variables, we used values from the year of last assessment. Because our samples were unbalanced, we used the class.weights argument to attribute to DD species a weight corresponding to the proportion of DS species and to DS species a weight corresponding to the proportion of DD species. We measured the relative importance of covariates with the impurity_corrected argument, which provides a sampling-size-corrected measure of the Gini impurity index.

We measured model performance with a taxonomic block validation. To that end, we iteratively fitted models, putting aside 1 family from the training data and then predicting the probability of being DS for the species in that family. We calculated performance metrics based on a binary categorization of the probability of being DS: sensitivity (proportion of DS species correctly categorized), specificity (proportion of DD species correctly categorized), and true skill statistic (specificity + sensitivity − 1) (TSS) (Allouche et al., 2006). Performance metrics were calculated across all species (rather than per family and averaging values across families) to limit the influence of families with very few DD species because a family with a single DD species will have a specificity of 0 or 1 depending on whether that single species is correctly or incorrectly predicted (Appendix S6). We used 2 different threshold rules to assign binary values (DD or DS) to probabilities and chose the thresholds that maximized TSS and maximized TSS with sensitivity >0.9. The latter rule minimized false negatives (i.e., DS species incorrectly predicted as DD). This is a desirable property of our method because it limits the number of species excluded from prioritization because they are predicted to remain DD even though they could be reassessed as DS. In addition, we measured variation in performance metrics among families (Appendix S6).

Prior to model fitting, we verified the correlation between all continuous covariates, considering that pairs of covariates with a Pearson's correlation coefficient >0.7 could affect parameter estimates (Dormann et al., 2013). Only the number of GBIF records and the number of articles in Web of Science on Odonata were correlated (0.79) (Appendix S4). However, this did not affect the predictive performance of our model (full model: TSS = 0.67; model excluding the number of GBIF records: TSS = 0.64; model excluding the number of articles in Web of Science: TSS = 0.67) or the shape of the relationship, so we kept both covariates in our model because they have strong independent rationale and were important for the temporal analysis.

**TABLE 1** Variables used to predict the probability of data-deficient (DD) species being data-sufficient.[a]

| Variable | Group | Type | Short definition | Temporal[b] | Rationale | Source |
|---|---|---|---|---|---|---|
| Number of Global Biodiversity Information Facility (GBIF) records | All | Numeric | Number of records found for the species name; for fishes, maximum number of records between GBIF and Ocean Biodiversity Information System (OBIS) | Yes | Species with many GBIF records regularly observed and thus more likely to be well known; GBIF records can directly improve assessment (e.g., measuring extent of occurrence) | Chamberlain et al., 2022; Provoost & Bosch, 2021 |
| Coverage of GBIF records | All | Numeric | proportion of ∼80-km grid cells with ≥1 record | Yes | GBIF records less informative when concentrated in very small part of species' range | Chamberlain et al., 2022 |
| Intensity of GBIF sampling effort | All | Numeric | Median density of records for broad taxonomic group in the range | No | Species in heavily sampled regions likely to be better known, even if they are not often reported (e.g., limited records in intensively sampled areas might indicate rarity) | Chamberlain et al. 2022 |
| Number of Web of Science articles | All | Numeric | Number of search hits for species' name in Web of Science | Yes | Published data can provide useful information for assessments (e.g., population monitoring, point locality data, population size estimates) | |
| Trait availability | Mammals + amphibians | Numeric | Number of traits available in 2 combined trait databases | No | High number of traits available for a species is a direct indicator species is well known (e.g., morphologically, demographically) | Lucas et al., 2023, preprint; Soria et al., 2021 |
| Spatial overlap with DD species | All | Numeric | Overlap of species' range with DD species from the broad taxonomic group measured as the proportion of red-list gridded distributions from DD species | No | Cluster of DD species can indicate poor knowledge of the region | IUCN, 2022 |
| Presence in zoos and aquaria | All | Binary | Whether at least 1 specimen is known in zoos or aquaria | No | May lead to better knowledge on the species from individuals kept in captivity | Species 360, 2021, p. 360 |
| Time since description | All | Numeric | Difference between 2022 and the year reported in the species taxonomy authority | Yes | Species recently described have less time to accumulate data; species may have been described with more in-depth information | IUCN, 2022 |

(Continues)

**TABLE 1** (Continued)

| Variable | Group | Type | Short definition | Temporal[b] | Rationale | Source |
|---|---|---|---|---|---|---|
| Gross domestic product (GDP) | All | Numeric | Median GDP of species' red-list countries of occurrence | No | Countries with high GDP might be more likely to fund biodiversity monitoring | World Bank, 2021 |
| Frequency of armed conflicts | All | Numeric | Median number of years of armed conflict in species' red-list countries of occurrence in last 20 years | No | Monitoring less likely in regions where armed conflicts are frequent | Gleditsch et al., 2002; Pettersson et al., 2021 |
| Remoteness | All | Numeric | Median travel time to cities across species' range (terrestrial) or median distance to nearest port (marine) | No | Species close to human populations more likely to be observed regularly | Basher et al., 2019; Weiss et al., 2018 |
| Road density | Terrestrial + freshwater species | Numeric | Highest quartile of road density in species' range | No | Species' distribution where road density is high more likely to be well sampled | Meijer et al., 2018 |
| Human population density | Terrestrial + freshwater species | Numeric | Human population density across species' range | No | In areas of high human population density, species more likely to be observed and thus better known | Florczyk et al., 2019 |
| Proportion of rural population | Terrestrial + freshwater species | Numeric | Proportion of rural inhabitants in species' range | No | Humans living in rural areas might be more likely to encounter species and gather knowledge than humans living in urban areas | Florczyk et al., 2019 |
| Marine fishing | Marine fishes | Numeric | Median of log-transformed number of fishing hours across specie's range | No | Species in heavily fished areas more likely to be caught; catch records can contribute to assessments (e.g., occurrence data or population dynamics data) | Kroodsma et al., 2018 |
| Habitat preference | Terrestrial + freshwater species | Categorical | Cluster of preferred habitat (e.g., forest specialist, forest generalist, nonforest specialist, nonforest generalist, rocky) | No | Difficult to sample some habitats (e.g., caves, forests); specialists thus likely less known | IUCN, 2022 |
| Range size (order of magnitude) | All | Numeric | Order of magnitude of area of range polygons | No | Species with large ranges more likely to be observed and thus well known; order of magnitude used to minimize influence of range size underestimation common with DD species | IUCN 2022 |

(Continues)

**TABLE 1** (Continued)

| Variable | Group | Type | Short definition | Temporal[b] | Rationale | Source |
|---|---|---|---|---|---|---|
| Median elevation | Terrestrial + freshwater species | Numeric | Median elevation across range | No | High elevation more difficult to sample | National Geophysical Data Center, 1999 |
| Water depth | Marine fishes | Numeric | Discrete depth class based on habitat preferences: 1 (0–200 m), 2 (200–1000 m), 3 (1000–4000 m), 4 (>4000 m) | No | Deep water more difficult to sample | IUCN, 2022 |
| Main realm | All | Categorical | Realm covering the biggest part of species range: 8 classes for terrestrial; 18 for marine | No | Some realms less studied than others over | World Wildlife Fund—US, 2004; The Nature Conservancy, 2012 |
| Body mass | Mammals | Numeric | Body mass from published database (includes some imputed data) | No | Large species usually easier to observe and monitor | Soria et al., 2021 |
| Nocturnality | Mammals | Binary | Strictly nocturnal species | No | Species harder to observe and monitor | Soria et al. 2021 |
| Body length | Amphibians | Numeric | Snout to vent length from cited database (including some imputed data) | No | Large species usually easier to observe and monitor | Lucas et al., 2023 |
| Red-list authority | Mammals + reptiles + fishes | Categorical | Name of the red-list authority: 36 classes for mammals, 13 classes for reptiles, 11 classes for fishes | No | Groups of assessors and reviewers might treat uncertainty in assessments slightly differently; thus, assessments differ for DD species | IUCN, 2022 |
| Taxonomic order | All | Categorical | | No | Some orders more likely than others to be DD (e.g., because they share specific traits or because species-level identification is harder in that group) | IUCN 2022 |

[a]Details in Appendix S3.
[b]Variables also used to estimate change in probability of being data-sufficient since last assessment.

## Predicting the probability of being DS

To predict pDS, we used the Random Forest model trained with all species after changing the temporal variables to their present-day values. For example, we used the current number of GBIF records rather than the records at the time of last assessment. For the 160 DD fishes that occur in freshwater and marine domains, we reported the highest probability from the 2 predictions. We considered this choice more cautious from a practical perspective because the risk here is prioritizing a species for reassessment that will remain DD (i.e., waste assessor time), whereas the opposite would risk not reassessing a species that could become DS (i.e., leave a species DD for years). To provide assessors with more information on why a species has high pDS, we identified variables contributing most to pDS for individual species with the breakDown R package 0.2.1 (Staniak & Biecek, 2019).

## Predicting change in probability of being DS

We calculated ΔpDS since last assessment as the difference between predictions based on models with the past- (last assessment) versus present-day values of the temporal variables (see distribution of the increase of temporal variables between last assessment and now in Appendix S5). For fishes occurring in freshwater and marine domains, we reported the change in the domain for which current probability pDS was the highest (most conservative). In rare cases where ΔpDS was negative (481 species had negative ΔpDS, median −0.0019, minimum −0.06), we used 0 because negative values do not result from a loss of knowledge but from the nonmonotony of some covariate effects (Figure 2).

## Measuring change in AOH

We expect that pDS and ΔpDS would mostly prioritize DD species that are relatively common and thus mostly not threatened (e.g., species with many GBIF records and large ranges in well-sampled regions). To increase the proportion of potentially threatened species in the prioritization, we specifically identified DD species that could be reassessed as threatened or near threatened based on habitat loss. This index is not needed to calculate data sufficiency per se, but could be very helpful in supporting reassessments of some species (Santini et al., 2019; Tracewski et al., 2016) and should thus be considered in reassessment prioritization.

To that end, we calculated $\Delta_{AOH}$ for all broad taxonomic groups, except fishes, to identify species that could likely be reassessed as threatened under criterion A2 based on population size reduction (IUCN, 2012; IUCN Standards & Petitions Committee, 2022). Assessors would need to check carefully whether the range map and habitat preferences we used (i.e., those from the last assessment) were representative.

To map AOH, we extracted species' preferences in terms of elevation and habitat type from the red-list data. We used the ESA-CCI land cover data 2.1.1 to extract pixels within the range that corresponded to a species' suitable habitat and the crosswalk between ESA-CCI and red-list habitat classification from Lumbierres et al. (2022). From those, we extracted cells within the species' elevational range based on elevation data from the National Geophysical Data Center (1999). We calculated AOH with a Mollweide projection in the R aoh package 1.0.0 (Hanson, 2022) at 2 time steps: current (from 2020 ESA-CCI data) and 10 years or 3 generations ago, whichever was longest, following red-list guidelines (IUCN Standards & Petitions Committee, 2022). We used a time frame of 10 years unless a generation length estimate was included in the red-list database (only included for mammals in our DD subset); thus, $\Delta_{AOH}$ may be underestimated for a few reptile and amphibian species with long generation times.

Because more detailed data were available for forests, we calculated change in forest cover for each terrestrial DD forest specialist (i.e., with only habitat class 1 suitable, disregarding 5, 9–13, 15, 17–18) with the Global Forest Change maps (Hansen et al., 2013). We used the gfcanalysis R package 1.6.0 (Zvoleff, 2020) to download and process the data. We calculated forest cover in 2021 within a species' range as the 30-m pixels covered by forest in 2000 (i.e., coverage value >0.25, which is the default of the threshold_gfc function) where there was no forest loss since 2000. We calculated forest coverage in the initial year (from 2000 to 2011, depending on generation length) with the same method but excluded cells that lost forest before the initial year. We did not consider forest gains, assuming that regenerated forests would not provide habitat of sufficient quality over the short study period.

For both AOH and forest cover, we then calculated change as the difference between current and initial values divided by initial coverage (negative values in case of habitat loss). When generation length was so high that the initial year was before the first year of land-cover products (i.e., 1992 for the ESA-CCI and 2000 for the Global Forest Change), we linearly extrapolated habitat loss. We kept the lowest (i.e., most negative) $\Delta_{AOH}$ among ESA-CCI and Global Forest Changes estimates and considered that species with $\Delta_{AOH} \leq -0.3$ could qualify as threatened under criterion A2(c). Although there is no strict quantitative threshold for near threatened, we considered species could potentially qualify as near threatened if $\Delta_{AOH} \leq -0.2$, which corresponds to the example given in the IUCN Red List guidelines (IUCN Standards & Petitions Committee, 2022).

## Prioritizing reassessments

We created an index to identify reassessment priorities:

$$\mathrm{PrioDS} = \begin{cases} 1, & \text{if } \Delta_{AOH} \leq -0.2, \\ 1 - \sqrt{0.5 \times \left[ \left(1 - \mathrm{pDS}\right)^2 + \left(1 - \Delta\mathrm{pDS}\right)^2 \right]}, & \text{if } \Delta_{AOH} > -0.2, \end{cases} \tag{1}$$

where pDS is the current probability of being DS, ΔpDS is the change in probability of being DS since last assessment, and

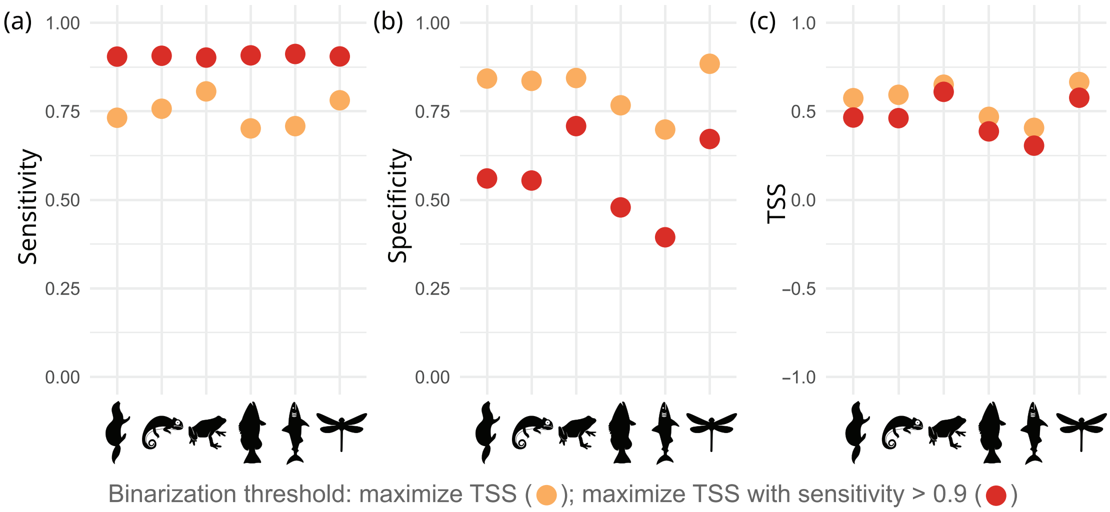


**FIGURE 1** Performance of the Random Forest models in predicting data-sufficient (DS) species by group (mammals, reptiles, amphibians, freshwater fishes, marine fishes, Odonata) relative to (a) sensitivity (proportion of DS species correctly categorized), (b) specificity (proportion of data-deficient species correctly categorized), and (c) true skill statistic (TSS) (specificity + sensitivity – 1) resulting from a taxonomic block cross-validation with 2 different binarization rules. Variation in performance among families is shown in Appendix S6.

$\Delta_{AOH}$ is the AOH change in the last 10 years or 3 generations. The PrioDS ranges from 0 to 1; higher values indicate higher reassessment priority. The value is 1 if $\Delta_{AOH} \leq -0.2$ (i.e., maximum priority because the species could likely be reassessed as near threatened or threatened based on that information). Otherwise, the value is based on pDS and ΔpDS. The index gives equal importance to pDS and ΔpDS and takes a value of 1 when both pDS and ΔpDS are 1 and value of 0 when both are null. We then used the index values to create a priority list of the 10%, 25%, and 50% of species with the highest priority score and mapped the distribution of these priority species.

## Application and performance of the priority list

All analyses were based on IUCN Red List 2021-3, but we used version 2022-2 to perform an ex post validation of our models. In this new version, 180 DD species included in our analyses were reassessed, of which 73 remained DD and 107 were changed to DS. We checked the agreement between the new category (i.e., remained DD or became DS) and the PrioDS score. This provided an independent validation of our approach and proposed priority list, although it was based on a small sample size and, importantly, reassessments were conducted without information resulting from application of our method.

# RESULTS

Our models showed good performance at predicting DS species of mammals, reptiles, amphibians, and Odonata from taxonomically independent samples (Figure 1; Appendix S8), although there was some important variation among families (Appendix S6). When we used the threshold that maximized TSS to assign binary values to predictions, we obtained a TSS of >0.5 for these 4 groups. Odonata had a maximum of 0.67 and a specificity slightly higher than sensitivity. Models for fishes performed slightly worse with a TSS of 0.47 and 0.41 for freshwater and marine fish species, respectively. Using the threshold that maximizes TSS with a sensitivity >0.9 (i.e., to ensure we correctly identified species that could be reassessed as DS) led to a drop in specificity (0.39 for marine fishes and 0.71 for amphibians), but TSS remained relatively high (0.31 for marine fishes and 0.61 for amphibians).

The most important variables for predicting species probability of being DS differed among taxa (Figure 2; Appendix S9). Overall, direct measures of available knowledge were among the most important variables, especially the number of GBIF records, which was among the 3 most important variables for all taxonomic groups and the most important for 3 groups, coverage of GBIF records, and trait data availability (among the 4 most important variables for the 2 groups for which it was measured). Some proxies of knowledge were also particularly important, especially the spatial overlap with DD species, which was among the 4 most important variables for all groups except mammals and marine fishes. Countries' median GDP (for freshwater fishes) and time since description of the species (for marine fishes and mammals) were also important. Finally, the most important ecological characteristic was order of magnitude of range size, which was among the 4 most important variables for 4 groups (with a positive effect on the probability of being DS), whereas habitat preferences, nocturnality, and body size did not strongly influence the probability of being DS.

Using these group-specific models, we found that 27% of DD species (1907 of 6887) had a high probability of currently

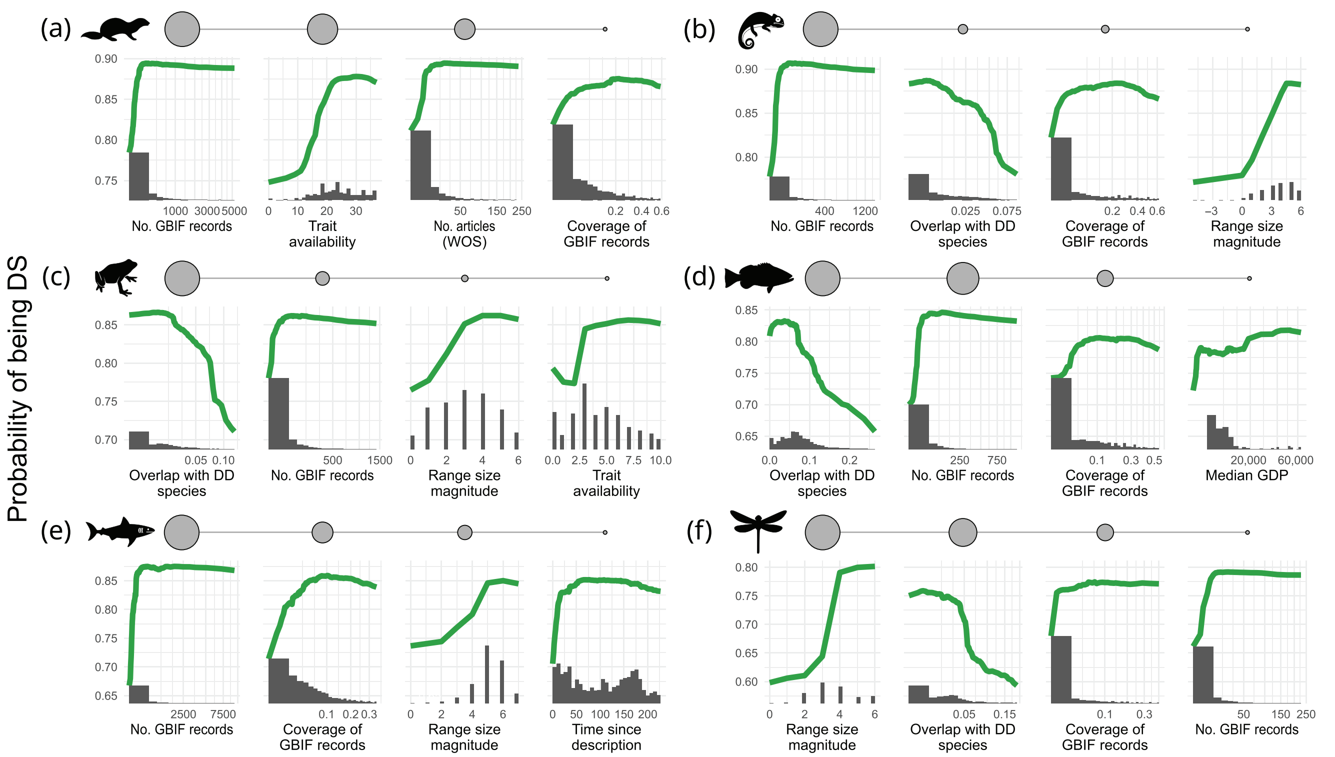


**FIGURE 2** Main effects of the 4 most important covariates on the probability of being data-sufficient (DS), measured as partial dependence per group for (a) mammals, (b) reptiles, (c) amphibians, (d) freshwater fishes, (e) marine fishes, and (f) Odonata by decreasing importance of covariates (bubbles, relative importance of covariate; bars, covariate distribution; lines, partial dependence; GBIF, Global Biodiversity Information Facility; GDP, gross domestic product; WOS, Web of Science; covariate calculation and units described in Table 1). Plots are limited to the 95th quantile of the covariate on the right for visualization purposes and are transformed to the square root where it helps visualization.

being DS (pDS > 0.5) (Figure 3), for example, *Zamenis lineatus* (Figure 4a). Moreover, 624 species had considerably increased probabilities of being DS since last assessment (ΔpDS > 0.25) due to, for example, many new GBIF records (Figure 3), for example, *Elattoneura campioni* (Figure 4b). Although pDS and ΔpDS were correlated (Pearson's correlation coefficient of 0.68), there was great variation in ΔpDS for the same pDS, often ranging from 0 (i.e., no new information since last assessment) to a value close to pDS (i.e., all information gained since last assessment).

In the final step of our method, assuming that distribution and species preferences data were accurate, we identified 5 mammals, 14 reptiles, 5 amphibians, and 5 Odonata species with an estimated loss of >30% of their AOH in the last 10 years or 3 generations (i.e., $\Delta_{AOH} \leq -0.3$); thus, they would be considered threatened under criterion A2: 24 vulnerable, 3 endangered, and 2 critically endangered (Figure 3), for example, *Hypsugo vordermanni* (Figure 4c; Appendix S1). An additional 11, 28, 9, and 35 species, respectively, could be considered as near threatened based on an estimated AOH loss of 20–30% (Figures 3 and 4c; Appendix S1).

Calculated PrioDS values suggested that priority DD species for reassessment were mainly concentrated in Latin America and Southeast Asia (Appendix S10).

The independent validation of predictions (for 180 species based on the recently released version 2022-2) showed higher priority scores for species reassessed as DS (mean [SD] = 0.39 [0.17] vs. 0.24 [0.12] for species that remained DD after their reassessment) (unilateral $t$ test: $t = -6.97$, $p < 10^{-10}$) (Figure 5). Our method performed particularly well for amphibians ($n = 107$); PrioDS was on average double for species reassessed as DS than species reassessed as DD (0.39 [0.16] vs. 0.19 [0.10]; $t = -7.53$, $p < 10^{-11}$). Results for reptiles ($n = 45$) also showed a significant difference in PrioDS (0.36 [0.11] vs. 0.28 [0.12]; $t = -2.35$, $p = 0.01$). Results for fishes ($n = 24$) confirmed that this group was not as accurately predicted (0.31 [0.12] vs. 0.29 [0.11]; $t = -0.38$, $p = 0.36$). Results for mammals ($n = 1$) and Odonata ($n = 3$) included only species reassessed as DS with relatively high priority scores. Results were similar for pDS and ΔpDS independently; ΔpDS was a better predictor of amphibian species reassessed as DS (Appendix S11).

## DISCUSSION

We are the first to predict the probability of a species being DS with the aim of being of practical value for red-list assessors. Our covariates showed strong predictive power of species classification as DD or DS during taxonomic block validation, performing well (TSS > 0.5) for all groups but fishes, and thus suggesting our method is a powerful tool for prioritizing reassessment, at least of terrestrial DD species. The

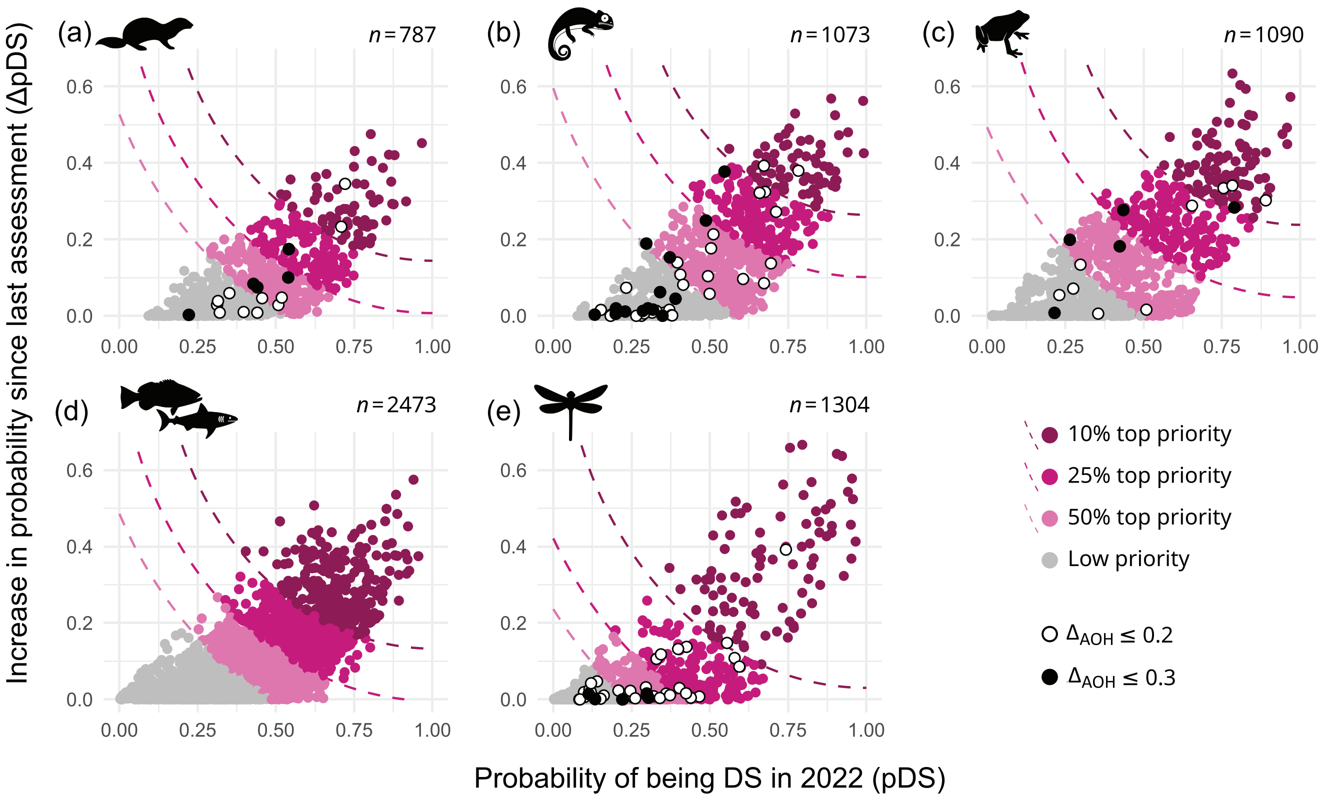


**FIGURE 3** Predicted probability of species being data-sufficient (DS) currently (2022) and increase in probability of being DS since the last assessment for currently data-deficient species per group: (a) mammals, (b) reptiles, (c) amphibians, (d) fishes, and (e) Odonata (colors and isoclines, priority of species for reassessment based on percentage of species that can be reassessed; e.g., purple circles, 10% of species with the highest probability of being data-sufficient; black circles, species that could be reassessed based on change in area of habitat [AOH] in the terrestrial realm only and with a priority index value of 1; solid circles, species with $\Delta_{AOH} \leq -0.3$ that potentially qualify as threatened; open circles, species with $\Delta_{AOH} \leq -0.2$ that potentially qualify as near threatened).

independent validation enabled by the recent update of the IUCN Red List showed that our method performed well for the 107 amphibian species and 45 reptiles we examined, with newly DS species showing higher priority scores than species retaining DD status. However, the sample size of this validation is relatively low and thus cannot be seen as a direct test of our method because assessors did not have access to our results (which could potentially have contributed to additional species being reassessed as DS). The actual performance and utility of our method can be measured only after assessors use it and see if fewer species remained DD with rather than without our information. This is particularly true for $\Delta_{AOH}$, which has been useful in the past (Santini et al., 2019; Tracewski et al., 2016) but could not be tested with our method outside of a real assessment process.

The most important variable for predicting the probability of species being DS was the number of GBIF records available at the time of the last assessment, which provides information directly applicable in assessments (Bachman et al., 2020). Across all broad taxonomic groups, the probability of being DS was low for species with no GBIF records, greatly increased as the first records were gathered, and plateaued when a few tens of records were available (Appendix S12), highlighting the utmost importance of increasing the collection and availability of primary occurrence records for poorly known species (Shirey et al., 2019).

Other direct indicators of available knowledge were also important, such as number of articles published on a species, which can be directly used in IUCN Red List assessments (Bird et al., 2020), and trait data availability (for the 2 groups for which it was measured) (González-Suárez et al., 2012). Several proxies of knowledge were also important predictors. The spatial overlap with DD species reduced the probability of being DS, highlighting the geographical clustering of DD species (Appendix S10). This means that a DD species co-occurring with many other DD species is less likely to be reassessed as DS, for example, because the region has been poorly sampled or little contextual information is available on threats. In fewer cases, species described very recently were more likely to be DD, indicating that it takes time to gain knowledge on a new taxon (Morais et al., 2013).

Finally, some ecological characteristics were important predictors; for example, species with small range sizes were more likely to be DD (Bland & Böhm, 2016; Butchart & Bird, 2010). This effect might be partly driven by underestimation of range size for DD species (example in Figure 4b) and thus means species known from a small area are more likely to be DD (even if their true range size may be larger). Variables

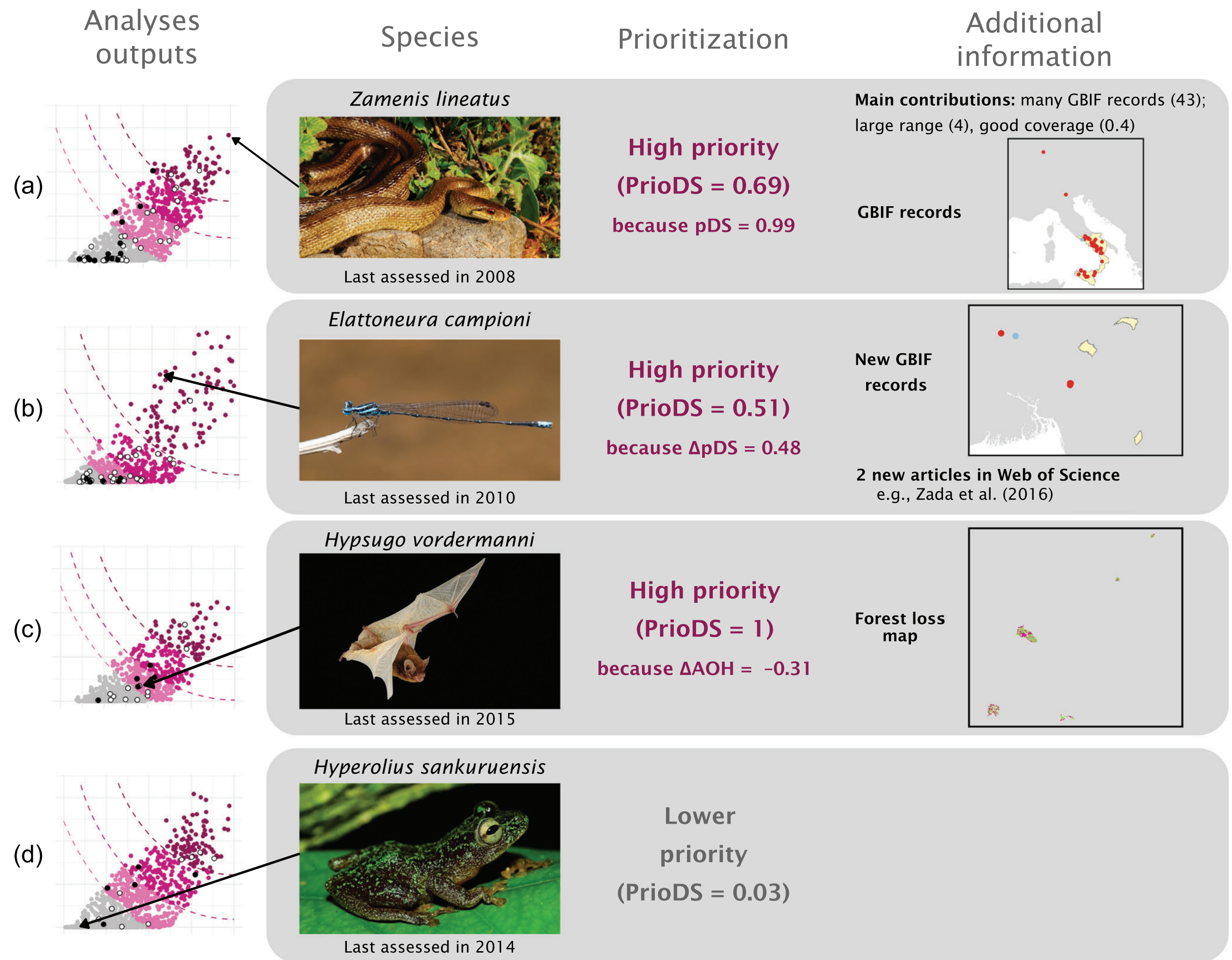


**FIGURE 4** Reassessment priority for 4 example species currently classified as data-deficient that have different types of available information: (a-c) species with a high priority for reassessment (PrioDS) because of (a) a high probability of being data-sufficient (pDS); (b) a large increase in probability of being DS (ΔpDS); (c) a relatively large decrease in AOH ($\Delta_{AOH}$); and (d) species with a low reassessment priority (analyses output, see Figure 3) (PrioDS, index of reassessment priority) (yellow, species' range; blue, records gathered before last assessment; red, records gathered after last assessment; green, current forest; red, forest lost in the last 16 years or 3 generations for the species). Additional information column shows examples of information made available to assessors that include the primary variables that explain model results, maps of records from the Global Biodiversity Information Facility or AOH loss, and list of articles available in Web of Science. Photos by (a) Benny Trapp, (b) Shantanu Joshi, (c) Chien C. Lee, and (d) Jos Kielgast.

describing human distribution (e.g., population density, road density, or travel time to cities) and variables related to species elevation or marine depth preferences were not among the most important predictors (Appendix S9). This could be due to the exclusion in our method of some poorly known species for which the distribution has not been mapped; these species may occur in more remote areas than other DD species. It could also be that our models did not identify remoteness as important because they had a more direct way of measuring availability of knowledge for the species (i.e., number of GBIF records).

The predicted probability of being DS if the DD species is reassessed today (pDS) should help identify species that currently share many characteristics with DS species (e.g., in terms of distribution, available knowledge, traits) and invite assessors to reconsider the status of these species. The snake *Zamenis lineatus*, for instance, was predicted to have one of the highest probabilities of being DS, mainly because of the high number and coverage of GBIF records, its large range, and the fact that it overlaps with few DD species (Figure 4; Corti et al. (2009)). It could thus be of high reassessment priority because its last assessment was 14 years ago. Notably, several of the GBIF records for *Z. lineatus* were well outside the known range of the species, a problem with georeferenced occurrences from public data repositories (Maldonado et al., 2015) that can be ameliorated with the use of automated tools to filter data (Arlé et al., 2021; Zizka et al., 2019), although this would significantly increase calculation time.

The dragonfly *Elattoneura campioni* was last assessed in 2010, when no articles in Web of Science and no GBIF records were available (the species was not reported since 1967 according to

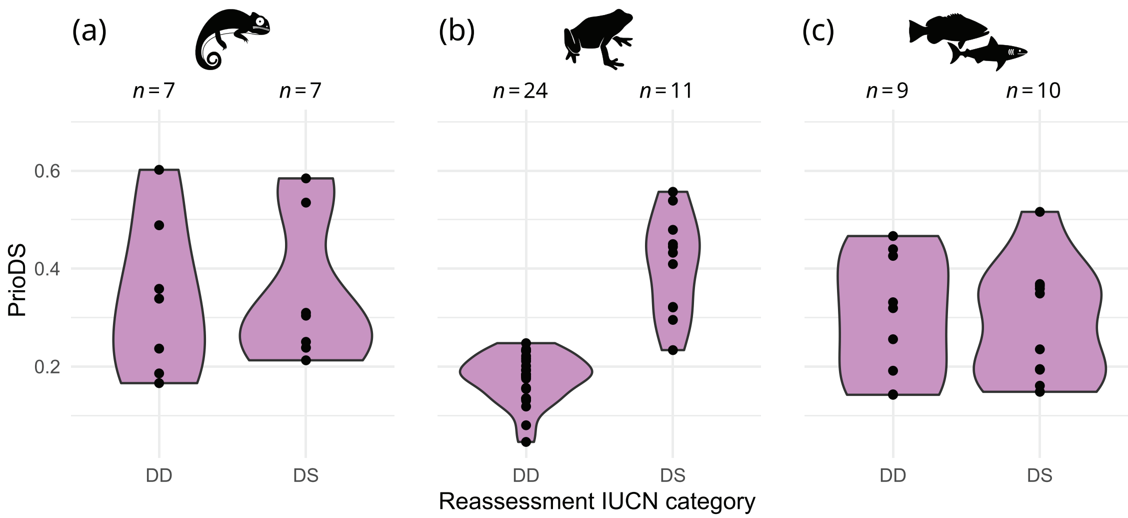


**FIGURE 5** Comparison of priority-for-reassessment scores (PrioDS) for the 180 data-deficient (DD) species reassessed in a data-sufficient (DS) category ($n = 107$) or as DD ($n = 73$) in an update of the International Union for Conservation of Nature (IUCN) Red List subsequent to our analyses by group (reptiles, amphibians, fishes) (circles, raw data; polygons, distribution of raw data).

the last red-list assessment [Sharma & Dow, 2010]), resulting in a probability of 0.06 of the species being DS at that time (Figure 4). Even though the probability of being DS was only intermediate based on current data (pDS = 0.54), our results suggest that the probability strongly increased since last assessment (ΔpDS = 0.48), indicating that the species is of higher reassessment priority than a species with similar pDS but lower ΔpDS. Indeed, the number of GBIF records for this species is now 29 and suggests the species is more widespread than previously thought. Two articles mentioning the species were published since the last assessment, providing additional records and information on species habitat (Mujumdar et al., 2021). This index of change in probability of being DS is important because we found that gain in information greatly varied among species independent of the time since last assessment (Appendix S5). It could still gain relevance if more temporal variables, measuring the availability of data directly usable by red-list assessors, were included in the model (e.g., number of specimens in museums, records in citizen science platforms that do not contribute to GBIF, articles published in non-English journals) (Amano et al., 2021; Bachman et al., 2019; Nic Lughadha et al., 2019).

The species prioritized based on the 2 abovementioned parameters are more likely to be species with relatively large ranges, that are not rare (e.g., with more GBIF records), and that will thus most likely be reassessed as least concern. Although this is important to reduce the uncertainty around the proportion and distribution of threatened species, it is also very important that our prioritization helps assessors identify those DD species that are threatened with extinction (Bland et al., 2015; Howard & Bickford, 2014). To do so, we included in our methods a calculation of species' $\Delta_{AOH}$ (Brooks et al., 2019; IUCN Standards & Petitions Committee, 2022) based on land-cover time series that provide direct input for red-list assessments (IUCN Standards & Petitions Committee, 2022; Santini et al., 2019; Tracewski et al., 2016). We identified 112 species that lost >20% of their AOH in the last 10 years or 3 generations and may thus potentially qualify as threatened or near threatened. For instance, the last assessment of the bat *Hypsugo vordermanni*, conducted in 2015, mentions that the species lives in forest and may be restricted to mangroves, but that information on population dynamics is lacking to assess extinction risk (Görföl et al., 2016). The loss of 31% of forest habitat within its range ($\Delta_{AOH} = -0.31$), as we calculated, could be sufficient to classify the species as vulnerable under criterion A2c based on a decline in population size inferred from habitat reduction. To use this result, assessors should evaluate the completeness of the published range map (i.e., that it includes sites of occurrence and inferred or projected presences) and habitat preferences of the species; consider the likely relationship between habitat loss and population decline; and acknowledge that the land-cover maps and habitat crosswalks we used can have misclassification errors. Although change in AOH may be important in prioritizing reassessment of potentially threatened species, we acknowledge it only relates to a subset of the reasons to classify a species as threatened and could in the future be supplemented by other indices of threat that can be directly used by assessors.

Based on the outputs pDS, ΔpDS, and $\Delta_{AOH}$, we created a priority index (PrioDS) that can be used to create a priority list for reassessment. Assessors can choose a threshold in PrioDS, depending on their resources and the rate of false positives and negative they are willing to accept (e.g., a group with very limited resources will select only species of the highest priority, which will likely include mostly species that can be reassessed as DS, but will be incomplete [Appendix S8]).

Our method provides outputs assessors can use directly to prioritize and inform reassessments (Figure 4). This contrasts with previous studies that aimed to reduce the number of DD species by estimating their extinction risk (Bland & Böhm, 2016;

Borgelt et al., 2022; Howard & Bickford, 2014) but that were not widely used by assessors (Cardillo & Meijaard, 2012; Cazalis et al., 2022). Although being so far restricted to groups with polygon range maps, it could in principle be extended to groups with point data but no polygon range maps (most of vascular plants and some invertebrates) by adding an automated approximation of polygon range maps from points (e.g., by using alpha hulls), which would enable spatial covariates to be calculated. This would be feasible only if point coverage within the species distribution is adequate.

To maximize its utility, our method will have to be effectively shared with assessors. For example, integrating it in an interactive platform (e.g., as a Shiny App [Bachman et al., 2020]) would allow assessors to create their priority list from their own criteria (e.g., choosing if they want to use PrioDS or if they want to give more weight to pDS or ΔpDS individually or a single variable of interest, such as the new number of GBIF records) and filtering conditions (e.g., species last assessed before a given year, from a given family or region). Such a platform could also provide easy access to the additional information provided by our method (e.g., list of published articles, map of GBIF records, or map of change in AOH [Figure 4]), which may be used by assessors as supplementary decision support in their assessments.

Allowing flexibility in the use of the outputs and updating them regularly (e.g., the number of GBIF records can increase rapidly for some species) will be key to the uptake of our method by the IUCN Red List community (Cazalis et al., 2022). It should help assessors make better use of their limited time and resources by targeting the reassessment of DD species that will most likely be reassessed in a DS category. It should also help them find and make use of "whatever information is available and relevant to make assessments," as required by the guidelines (IUCN Standards & Petitions Committee, 2022). Eventually, we expect our approach to reduce the proportion of DD species on the IUCN Red List, which would reduce the uncertainty of products based on the red list and help focus research efforts on the remaining DD species, thus helping future conservation efforts be based on more robust foundations.

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## SUPPORTING INFORMATION

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