Applying habitat and population-density models to land-cover time series to inform IUCN Red List assessments

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Abstract

The IUCN Red List categories and criteria are the most widely used framework for assessing the relative extinction risk of species. The criteria are based on quantitative thresholds relating to the size, trends and structure of species’ distributions and populations. However, data on these parameters are

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sparse and uncertain for many species and unavailable for others, potentially leading to their misclassification, or classification as Data Deficient.

Here we propose an approach combining data on land-cover change and species-specific habitat preferences, population abundance and dispersal distance to estimate key parameters (extent of occurrence, maximum area of occupancy, population size and trend, and degree of fragmentation) and hence IUCN Red List categories.

We demonstrate the applicability of our approach for non-pelagic birds and terrestrial mammals globally (~15,000 species), generating predictions fairly consistent with published Red List assessments, but more optimistic overall. We predict 4.2% of species (467 birds and 143 mammals) to be more threatened than currently assessed, and 20.2% of Data Deficient species (10 birds and 114 mammals) to be at risk of extinction. However, incorporating the habitat fragmentation sub-criterion reduced these predictions 1.5-2.3% and 6.4-14.9% (depending on the quantitative definition of fragmentation) of threatened and Data Deficient species respectively, highlighting the need for improved guidance to Red List assessors on applying this aspect of the Red List criteria.

Our approach can be used to complement traditional methods of estimating parameters for Red List assessments. Furthermore, it can readily provide an early warning system to identify species potentially warranting changes in their extinction risk category based on periodic updates of land cover information. Given that our method relies on optimistic assumptions about species distribution and abundance, all species predicted to be more at risk than currently evaluated should be prioritized for reassessment.

Introduction

The International Union for Conservation of Nature (IUCN) Red List of Threatened Species is the most authoritative and widely used framework to assess the extinction risk of species (Rodrigues et al. 2006; IUCN 2017a). Species are assessed using five criteria with quantitative thresholds relating to the size, trends and structure of species’ distributions and populations (Mace et al. 1992; IUCN 2017b). The assessments result in species being listed under one of seven categories, from Least Concern to Extinct (or Data Deficient if insufficient information is available to apply the criteria). The Red List now covers >90,000 species, and a key challenge is to re-assess the status of a large proportion of these species periodically and consistently with up-to-date data to identify conservation priorities. Re-assessments currently rely on information from published and unpublished sources and expert knowledge, but collating relevant data from the literature and from experts for hundreds or thousands of species across wide geographic areas can render the process slow and costly (Rondinini et al. 2014). To increase efficiency, a more systematic, quantitative and comprehensive approach is needed to support and complement the painstaking work of Red List assessors.

Assessing species extinction risk requires intense and regular data-gathering, using all available sources of information. Although data would ideally be scaled up from data collected on the ground (Pereira et al. 2013), such measurements are relatively costly and time-consuming. Furthermore, in situ observations are typically biased geographically and taxonomically due to a number of factors, such as the availability of research funding, emphasis on charismatic species, the location of research institutions and researchers, security issues and accessibility (Wilson et al. 2007;
Boakes et al. 2010; Fleming & Bateman 2016). Because of this, there is increasing need for new technology, models and datasets to update, improve and increase the consistency of assessments for large numbers of species.

The main drivers of biodiversity loss today are overexploitation and habitat loss (Hoffmann et al. 2010; Joppa et al. 2016). Overexploitation is challenging to model in a predictive framework (Benítez-López et al. 2017), but habitat loss can be inferred indirectly using remote sensing data and particularly land cover data (Pettorelli et al. 2014). Land cover change influences the availability in suitable habitat and, consequently, the potential population size of species. Within the Climate Change Initiative (CCI) of the European Space Agency (ESA), the CCI Land Cover partnership has recently released an annual global land cover time series covering 24 years from 1992 to 2015 at a resolution of 10 arc-seconds (~300 meters) (ESA 2017). Further, land cover maps from 2016 to 2019 are now being developed in the framework of the Copernicus Climate Change Service (C3S 312b- lot5; C. Lamarche personal communication). These datasets provide an unprecedented opportunity to quantify the effect of land cover change on species’ habitat distribution and fragmentation in the recent past.

Land cover change data and information on species’ habitat preferences can be coupled to assess how land cover change alters the extent of suitable habitat of species and influences their risk of extinction under the Red List criteria (Buchanan et al. 2008; Rondinini et al. 2011; Bird et al. 2012; Tracewski et al. 2016; Visconti et al. 2016). For example, recent remotely sensed images of forest cover have been used to assess extinction risk and its recent changes for forest-dependent species (Buchanan et al. 2008; Tracewski et al. 2016). Such studies have typically focused on criteria A (reduction in population size) and B (small and fragmented/declining range) (e.g. Tracewski et al. 2016), while few have considered criterion C1 (small and declining population, e.g. Buchanan et al. 2008), or D1 (very small population e.g. Visconti et al. 2016).

Here we demonstrate for all non-pelagic birds (10,378 species) and terrestrial (i.e. non-marine) mammals (4,835 species) globally how Red List criteria can be evaluated by coupling land cover time series, species’ habitat preferences, and statistical predictions of species population density and dispersal distance. We use maps of species’ distributions and information on species’ habitat preferences from the IUCN Red List and land cover time series data from the ESA to estimate species’ potential distributions and change in these over time. We then estimate the potential population size in suitable habitat and the level of population fragmentation following IUCN Red List guidance. We then assess the extinction risk of species under six IUCN Red List criteria (A2, B1, B2, C1, D1 and D2).

Methods

Red List Criteria

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In the IUCN Red List, species are assessed against all criteria for which suitable data are available, and are listed at the highest category under which they qualify (IUCN 2017b). Accordingly, here we assessed all species under six criteria that can be informed by land cover and land cover change and classified them in the most threatened category in which they qualified. These included criteria A2 (population reduction in the last 10 years or three generations, whichever is longer), B1 (small Extent of Occurrence, EOO) and B2 (Area of Occupancy, AOO), both in combination with subcriterion “a” (severe fragmentation), and “biii” (continuing decline in area, extent and/or quality of habitat), C1 (Small population size and decline), D1 (Very small population size) and D2 (very small AOO and plausible threats). Altogether, these criteria are currently used for the classification of 68% of threatened birds and 84% of threatened mammals. These criteria permit the classification of species into three threatened categories: Vulnerable (VU), Endangered (EN) and Critically Endangered (CR).

If the species does not qualify under any of these categories, the species is classified as Least Concern (LC) or Near Threatened (NT). However, in this study we did not consider the NT category as it lacks explicit quantitative criteria akin to those for the threatened categories and has thus been applied less consistently across different taxa.

Input data

We considered all non-pelagic birds and terrestrial mammals with data on habitat preferences, for a total of 10,378 bird and 4,835 mammal species. We excluded pelagic birds (N=362) because they spend most of the time in the open ocean far from land, and only return to very specific locations on land to breed, typically on rocky islands, or coastal cliffs, where land-cover change is generally not the major threat, and for which the land-cover change analysis is therefore not particularly informative as well as being extremely sensitive to the resolution used. We used the area of a minimum convex polygon encompassing the distribution maps from the IUCN Red List (IUCN 2017a, BirdLife International and Handbook of the Birds of the World 2017) to estimate the EOO (Joppa et al. 2016; IUCN 2017b). For migratory birds where polygons are classified into “resident”, “breeding range” and “non-breeding range”, the EOO was equal to the smallest between two minimum convex polygons encompassing the “resident” and “breeding range”, or the “resident” and “non-breeding range”(IUCN 2017b). Then, we clipped the EOO maps by suitable habitat for each species based on habitat preferences coded against the IUCN habitats classification scheme (IUCN 2018). We used habitats listed in level 2 of the scheme that were coded as ‘suitable’ for each species and excluded land at unsuitable altitudes within species ranges using data on altitudinal preferences from the IUCN Red List and the EarthEnv-DEM90 digital elevation model (Robinson et al. 2014). To reclassify the suitable habitat and calculate the ‘extent of suitable habitat’ (or ESH in previous studies) we used land cover data downloaded from https://www.esa-landcover-cci.org/ (ESA 2017) and we matched it to the IUCN habitat classification scheme in level 2 following the crosswalk (conversion table) presented in Table S2. There were 536 bird and 74 mammal species for which altitudinal or habitat preferences did not result in any suitable habitat within the range, indicating possible errors in either the habitat preferences classes, altitudinal tolerances, or the match between IUCN and ESA CCI categories. This was particularly an issue for insular bird species. Therefore we excluded these species, resulting in a final dataset of 9,842 birds and 4,761 mammals.

Each species’ ESH was used in two ways relevant to the application of Red List criteria (Fig. S1): First, an upper estimate of the potential Area of Occupancy (AOO) was estimated by resampling the ESH from 300 m to 2 km resolution so that any 2 km cell intersecting at least
one 300 m cell contributes to the AOO. This follows the standardized procedure to harmonize assessments across taxa with distributional data mapped at different resolutions (IUCN 2017b). Second, we estimated the potential population size within the ESH using population density models based on trait information (body mass and diet), local environmental conditions (primary productivity and climatic conditions) and taxonomic information at the level of the models’ random effects (See Appendix S1 for a detailed explanation of the procedure; Santini et al. 2018). Although the AOO and the suitable habitat used to estimate abundance are derived from the same habitat suitability maps (ESH), it is possible that their trend is inconsistent, for instance when AOO is insensitive to changes in the amount of habitat within each 2x2 km grid cell.

**Red List Assessment**

Under criterion A2, population changes should be calculated over a period of three generations or ten years, whichever is longer. Currently, ESA land cover maps are available for the period 1992-2015. We took 2015 as the present, and identified the start point for estimating trends as three generations or ten years prior to 2015, whichever was earlier. If the three-generation period was longer than 24 years, we calculated the change from 1992 and normalized the change as:

\[
\text{%Change} = \frac{\text{Change}(2015 - 1992) \cdot 3 \text{generations}}{24 \text{years}}
\]

Generation length data for all bird and mammal species were obtained from BirdLife International (2017) and Pacifici et al. (2013), respectively.

Criteria B1 and B2 were applied by comparing the EOO and ESH estimates with the EOO and AOO thresholds respectively (Fig. 1, Table S1). However, the application of these two criteria requires at least two sub-criteria to be met. Here we considered subcriterion “a” (severe fragmentation), and “biii” (continuing decline in area, extent and/or quality of habitat). Severe fragmentation is defined by the IUCN Red List as occurring when “increased extinction risks to the taxon results from the fact that most of its individuals are found in small and relatively isolated subpopulations” (IUCN 2017b). Accordingly, we considered species’ habitat to be fragmented if >50% of the ESH occurred in small and isolated patches (IUCN 2017b). ‘Small’ is not defined, and varies between species according to their typical population density and other characteristics. We therefore tested multiple criteria, with ‘small’ defined as: 1) fragments <100km²; 2) fragments supporting <100, <500, <1000, or <5000 individuals according to our population abundance models (Santini et al. 2018); 3) fragments supporting less than a viable population size according to Hilbers et al. (2016) using viability targets with five assumed proportions of the maximum population growth rate (0.2, 0.4, 0.6, 0.8, or 1; see Hilbers et al. 2016). Population viability estimates are only available for mammals (from Hilbers et al. 2016), so in total we tested five definitions for birds and 10 for mammals (Table S3). We defined ‘isolated’ following the approach described in Santini et al. (2014). Briefly, the approach consists in clustering habitat in contiguous habitat fragments, and then clumping those fragments within a median dispersal
distance (Fig. S2) (see Appendix S2 for dispersal distance estimation). The resulting clumps of habitat fragments are assumed to support demographically semi-isolated populations. Criteria C1 and D were applied by comparing population size estimates and population trends (C1 only) with their respective thresholds (Table S1).

Because empirical population density and dispersal distance estimates in bats are lacking, and their density can be highly clumped in space due to the location of roosting sites, we did not predict density and dispersal in bats and only classified them under criteria B1 and B2. Furthermore, because of the intrinsic uncertainty in the application of this criterion, we present the results considering fragmentation separately from the main results.

Overall our method is based on conservative (optimistic) assumptions. First we assumed the suitable habitat (ESH) to be entirely occupied (AOO), noting that this is unrealistic. Second, our predicted abundance estimates are applied to the entire ESH and, as specified under criteria C and D, are assumed to only represent mature individuals, therefore likely over-estimating the number of these. Third, we assumed that fragmentation results only from the size of habitat fragments and their degree of isolation. Therefore our predictions are expected to be more optimistic than published Red List assessments based on empirical species-specific data on average.

We compared predicted Red List categories with published categories by testing the correlation between ordinal values with Goodman and Kruskal's Gamma statistics. We also compared the ability to detect threatened and non-threatened species using sensitivity, specificity and TSS (see Appendix S3).

We conducted all GIS analyses using a Mollweide equal-area projection in GRASS GIS v. 7.4 (GRASS Development Team 2017), and all further statistical analyses and data processing in R v. 3.5.1 (R Core Team 2018). The GRASS and R codes are available from the corresponding author upon request.

Results

Red List categories predictions

We predicted 745 bird (VU=399, EN=254, CR=92) and 501 mammal (VU=266, EN=206, CR=29) species to be threatened (Fig. 2). These species qualified as threatened primarily under criterion B1 (53.3%; 393 birds and 348 mammals), B2 (23.4%; 165 birds and 161 mammals), D/D1 (15%; 208 birds and 70 mammals), C1 (5.6%; 59 birds and 19 mammals) and A2 (2.7%; 25 bird and 12 mammals). Among Data Deficient species, we predicted 10 species of birds (18.9% of bird Data Deficient species) and 114 of mammal species (22.3%) to be threatened (Birds: VU=5, EN=3, CR=2; Mammals: VU=52, EN=52, CR=10) (Fig. 3). Predictions for Data Deficient were concordant with those produced by previous authors using alternative methods for 76.2% of birds and 56.6% of mammals (Appendix S4). Predictions for all species are presented in Table S5.
Applying the sub-criterion B1a or B2a (Severe Fragmentation) substantially reduced the number of species qualifying under criteria B1 and B2, and hence the number of species qualifying as threatened (3.3-5.1%). The extent of this reduction depends on the quantitative definition of fragmentation applied, but overall as the minimum population size per fragment increased, the number of species qualifying as threatened under criteria B1 and B2 decreased (see Table S3).

Comparison between predicted and published IUCN Red List categories

Our predictions tended to be more optimistic but fairly consistent with the Red List assessments (Fig. 2). The correlation with the published Red List categories was high, with birds having a G-K Gamma=0.75 (p-value<0.001) and mammals a G-K Gamma=0.74 (p-value<0.001). The sensitivity in predicting threatened categories was low both in birds and mammals (0.29 and 0.27) and the specificity was high (0.95 and 0.96), with a resulting TSS of 0.24 for birds and 0.23 for mammals. These values indicates a high Type II error and low Type I error, i.e. high chance of classifying a threatened species as non-threatened, but low chance of classifying a non-threatened species as threatened.

In birds, 467 species (4.7%) were predicted to be in higher (i.e. more threatened) Red List categories and 990 species (10%) in lower Red List categories. In mammals 143 (3%) were predicted in higher Red List categories and 862 (18.1%) in lower Red List categories. Birds that were predicted to be more threatened than on the Red List qualified as threatened under criteria B1 (n=276), D (n=125), B2 (n=99), C1 (n=46) and A2 (n=17). Mammals predicted to be in higher Red List categories qualified as threatened under B1 (n=86), B2 (n=52), D (n=17), C1 (n=7) and A2 (n=2). The mismatches between our predictions and published Red List assessments were taxonomically biased, especially in mammals (Fig. 4). Bird species that were consistently predicted to be less threatened than published on the Red List are ground-dwelling species (e.g. Eurypygiformes, Mesitornithiformes, Galliformes), large-bodied species (e.g. Bucerotiformes, Ciconiformes, Otidiformes), and birds of prey (e.g. Accipitriformes), which are threatened by hunting, poisoning, and collision with power lines and wind turbines. Mammal species that were consistently predicted to be less threatened than currently assessed on the Red List are mostly large-bodied species and species threatened by hunting and illegal trade (e.g. Proboscidea, Perissodactyla, Cetartiodactyla, Pholidota, Primates) (Fig. 4).

Among geographic regions, our models predicted lower extinction risk on average in the Saharo-Arabian and Australian region for birds, in the Madagascan and the Oceanian regions for mammals, and in the Oriental region for both birds and mammals. In mammals, the northern part of Alaska and Greenland also show high values, but these areas are only occupied by a small number of species (Fig. 5, Fig. S3). The difference between Red List assessments and our predicted categories was positively correlated with species’ body mass in birds and mammals (Fig. S4), indicating that our approach is more likely to underestimate...
the Red List categories of larger species compared with those of smaller species. Finally, the comparison between our predictions and published assessments is dependent on the assumptions made for the Area of Occupancy and population size (Appendix S5, Fig. S6). A sensitivity analysis of the effect of these two parameters on the predictions suggests that the number of threatened species might be much higher than currently predicted (Appendix S5, Fig. S7).

Discussion

Our results demonstrate how data on land-cover change coupled with information on species habitat preferences and modelled abundance can inform species assessments under the IUCN Red List. This procedure is particularly useful to detect species whose rate and degree of habitat loss may have been under-estimated. Further, it identifies Data Deficient species most likely to be threatened, thus targeting research designed to gather sufficient information to apply the Red List criteria. The same procedure can be applied to other taxonomic groups for which distributions have been mapped, habitat preferences documented, and abundance predictions can be made (e.g. Amphibians; Ficetola et al. 2015; Santini et al. 2018). Our predictions are fairly consistent with published Red List assessments, suggesting that the procedure is reliable for preliminary species assessments. However, our approach also classifies many species in higher or lower Red List categories than their published status, highlighting limitations and strengths in both the Red List and our predictive method.

Most mismatches between published and predicted status involve species predicted to be less threatened than they are classified on the Red List. These mismatches include many species for which the assumption of presence in suitable habitat is particularly over-optimistic, as several factors other than habitat type can determine their presence (Colwell & Rangel 2009). For example, some species show clumped distributions within suitable habitat due to the patchy distribution of key resources (Mayor et al. 2009), or else shift nomadically around their geographic range and thus only occupy a limited part of it at any given time (Runge et al. 2015). Similarly, some species are absent or rarer in areas subject to particular threats, such as over-exploitation, invasive alien species, pollution or human disturbance (Benitez-López et al. 2010, 2017; Hoffmann et al. 2010; Ripple et al. 2016). Pangolins (Pholidota), for instance, are the most heavily trafficked mammals in the world and are facing severe population declines due to over-exploitation in Asia and Africa. Pangolins can occur in a large variety of habitats including primary and secondary tropical forests, shrublands and grasslands, therefore their ESH is large, yet their AOO is likely to be considerably smaller (Ingram et al. 2017). Interestingly, our predictions for small species are more consistent with the published Red List than those for large species, probably because the latter are more often threatened by direct exploitation, whereas smaller species are more often threatened by habitat loss and degradation (Ripple et al. 2017).

Our analysis revealed a consistent bias toward under-estimation of risk in the predictions, or over-estimation in the assessments, of the Madagascan, Oriental and Oceanian regions in mammals, and in the Oriental, Saharo-Arabian and Australian regions in birds (Fig. 5, Fig. S3). These mismatches can be explained by a combination of factors including high hunting...
pressure (e.g. Oriental), threats from invasive species (e.g. Australian and Oceanian) or climate change (e.g. Saharo-Arabian) in these regions (Loarie et al. 2009; Benítez-López et al. 2017; Spatz et al. 2017). Mismatches between predictions and Red List assessments appear to be larger and more taxonomically and geographically biased in mammals (Fig. 4, Fig. S3). This may arise from underlying methods because bird assessments are all performed by BirdLife International, whereas mammal assessments are coordinated by the Global Mammal Assessment but in effect generated by the many specialist groups for different taxa worldwide. This can result in inconsistencies between different taxonomic groups, for example in the application of different criteria, use of different types of data sources, or in evidentiary vs. precautionary attitudes.

We consider our approach particularly useful for species and regions that receive less research attention (Donaldson et al. 2016; Verde Arregoitia 2016; Di Marco et al. 2017), as they are often assessed by a small number of experts, with a limited amount of data collated from old publications or anecdotal information. As an example, the Polar Bear Specialist Group includes 25 members (http://pbsg.npolar.no/en/), whereas the Small Mammals Specialist Group, which overall covers around >2800 species, only includes around 120 members (http://www.small-mammals.org/). This inevitably influences the quality of the assessments. Overall, most species on the Red List are not assessed against all criteria, owing to lack of data (IUCN 2017b). While considering only one or few criteria allows poorly known species to be assessed, it also makes the Red List sensitive to data availability. In fact, species assessed against more criteria are more likely to be classified as threatened. Because we simultaneously assess species under five different criteria that are based on up-to-date remote sensing information, it is possible that our approach identifies species that are genuinely threatened at present, but have not yet been assessed as such on the Red List. For example, many species that could classify as threatened based on B1 (i.e. EOO smaller than the required thresholds) are not classified as such on the Red List because they are considered to have stable population trends (subcriterion Biii). However, we classified some of these as threatened under B1 because land cover data indicate that they have lost habitat over the last 10 years or three generations. Two examples are the red-breasted pygmy parrot (Micropsitta bruijnii) and the Ethiopian striped mouse (Muriculus imberbis), which are poorly known and have restricted geographical ranges but are believed to be stable in terms of distribution and population size. Both species are currently classified as Least Concern, but our models predict that they have suffered a severe decline in ESH and population size, and should therefore qualify as Endangered (Table S5). Review of the Red List assessments for species such as these are now warranted and should involve targeted efforts to compile up-to-date information on their status.

A useful application of our approach is the preliminary assessment of Data Deficient species. While there are few Data Deficient birds (0.6% of species), around 14% of mammal species are classified as Data Deficient. Our approach identified several species in urgent need of conservation attention, such as the brown-banded rail (Lewinia mirifica) and Williamson's mouse-deer (Tragulus williamsoni), which are predicted to be Critically Endangered by our models. Our predictions for Data Deficient species are fairly consistent with those based on expert judgement and machine learning algorithms (Appendix S3; Butchart & Bird 2010; Bland et al. 2015). Our approach mostly relies on
changes in habitat availability over time, while Bland et al. (2015) primarily focus on species’ intrinsic vulnerability to extinction, therefore these two approaches offer different, and complementary, perspectives, in identifying species that require urgent monitoring and targeted research.

The number of species qualifying as threatened in our analyses is substantially reduced when the fragmentation sub-criterion is applied, depending on the threshold used to define ‘small’ fragments. However, this also raises the issue that the IUCN definition of habitat fragmentation is qualitative and can be interpreted in different ways (IUCN 2017b). As a consequence, the fragmentation sub-criterion is typically applied based on expert opinion, which may imply that many species currently listed under criterion B should not be considered as threatened. Our operative interpretation of the definition allows this criterion to be applied more objectively and consistently across species (Santini et al. 2014; Di Marco et al. 2016), but it is also sensitive to the land cover data resolution, which might be inappropriate for many species, and ignores the effect of barriers. This may result in excessively conservative assessments, perhaps explaining the reduced number of a species qualifying under this subcriterion. We therefore urge IUCN to provide more explicit guidance on how to apply this sub-criterion more objectively and consistently, including through quantitative approaches such as ours.

Our results show how the Red List framework can be applied using land cover maps coupled with information on habitat preferences and spatially explicit abundance models. Because this approach tends to underestimate species extinction risk, it implies that any species predicted to be more at risk than currently classified should be urgently re-assessed. We propose that this approach be integrated into Red List assessments to reduce taxonomic and spatial biases, and to address constraints in data availability. More importantly, as periodic updates of automatically processed satellite images become available, our approach can be automated to provide an early warning system to identify species potentially warranting urgent conservation actions.

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Fig. 1. Schematic framework for our analysis. All criteria are applied, but only the one(s) indicating the most threatened category is used. Species that do not qualify under any of the three threatened categories (CR =
Critically Endangered; EN = Endangered; VU = Vulnerable) are classified as non-threatened. $t = \text{time 1 (2015 – the longest between 3 generations and 10 years)}$ and time 2 (2015); Additional requirements: * = Subcriteria a (severely fragmented range) and b (continuing decline in area/extent and/or quality of habitat) must be met; ** = Decline is measured as continuing population decline $\geq 25\%$ over 3 years/1 generation for CR, $\geq 20\%$ over 5 years/2 generations for EN, $\geq 10\%$ over 10 years/3 generations for VU).

Fig. 2. Consistency between predicted and published IUCN Red List categories for birds (top) and mammals (bottom). LC = Least Concern, NT = Near Threatened, VU = Vulnerable, EN = Endangered, CR = Critically Endangered. Note that our predictions make no distinction between NT and LC, as no quantitative definition exists for NT.

Fig. 3. Predicted Red List categories for Data Deficient species. LC = Least Concern, NT = Near Threatened, VU = Vulnerable, EN = Endangered, CR = Critically Endangered.
Fig. 4. Mean difference between published and predicted IUCN Red List categories by taxonomic order, where Least Concern and Near Threatened = 0, Vulnerable = 1, Endangered = 2, Critically Endangered = 3. Positive values indicate that predicted Red List categories were lower than the current published categories on the IUCN Red List. Error bars encompass the 90% of the distribution of the differences.

Fig. 5. Mean difference between published and predicted Red List categories per grid cell at 0.5 degree resolution, where Least Concern and Near Threatened=0, Vulnerable=1, Endangered=2, Critically endangered = 3. Positive values indicate that predicted categories are on average lower than published categories. Cells with no difference on average (zero values) are shown in grey.