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LETTER

Predicting IUCN Extinction Risk Categories for the World's Data Deficient Groupers (Teleostei: Epinephelidae)

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Abstract

Groupers are highly susceptible to human-induced impacts, making them one of the most threatened fish families globally. Extinction risk assessments are important in endangered threatened species management, however the most comprehensive—the International Union for Conservation of Nature (IUCN) Red List—cannot classify approximately one-third of grouper species due to data deficiency. We used an ordinal analytical approach to model relationships between species-level traits and extinction risk categories. We found that larger species and those with shallower maximum depths and smaller geographic ranges had higher extinction risk. Using our best fitting model, we classified data deficient grouper species into IUCN's extinction risk categories based on traits. Most of these species were predicted to be of least concern. However, 12% were predicted to be endangered or vulnerable, suggesting that they may be of conservation interest. Importantly, we provide a quantitative method for overcoming data gaps that can be applied to conservation of other species.

Introduction

The International Union for Conservation of Nature (IUCN) Red List is regarded as the most objective and authoritative system available for classifying species in terms of their risk of extinction (Rodrigues *et al.* 2006). Assessments must be backed up by data and species for which insufficient data are available to make an assessment of extinction risk are termed data deficient (Mace *et al.* 2008). Since species in the data deficient category could fall into any of the other Red List categories, genuinely threatened species may be neglected by conservation programs due to their uncertain conservation status (Bland *et al.* 2015a). Therefore, there is an urgent need to prioritize research on data deficient species and to generate data that will accurately assign them into a threat category. Unfortunately, due to both time and financial limitations, funds are rarely directed to filling these gaps (Hoffman *et al.* 2008).

The realization that there is not enough time nor enough resources to collect basic data on all data deficient species before extinctions may occur (Howard & Bickford 2014; Bland *et al.* 2015b) has resulted in a growing number of studies aimed at overcoming uncertainty regarding the conservation status of data deficient species. The approaches within these studies vary widely. Some authors have used a subset of the criteria used in Red List assessments to evaluate extinction risk of data deficient species (Morais *et al.* 2013), while others have used alternative data sources to reevaluate previous assessments (Good *et al.* 2006; Sousa-Baena *et al.* 2014). Others still have modeled correlations between existing species' trait data and extinction risk among data sufficient species to predict the conservation status of data deficient species (Bland *et al.* 2015a). Sophisticated models for predicting conservation status of data deficient species also incorporate phylogenetic and environmental information along with traits (Bland *et al.* 2015b; Jetz & Freckleton 2015). However, there is a trade-off between model complexity and data availability. Data deficient species are, by definition, poorly studied. Hence, they often lack phylogenetic, spatial, or trait information, which may hamper the use

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of data-hungry modeling approaches. This is especially the case with marine taxa, which are considerably less well studied on average than nonmarine taxa. As a result, marine species have double the proportion of data deficient species as their nonmarine counterparts (Webb & Mindel 2015).

A commercially important group of marine fishes for which approximately one-third of species are data deficient are the groupers (Epinephelidae). Consisting of 163 species, groupers are an iconic family of marine predators that occur on coral reefs worldwide. Groupers have high market prices, and are consequently heavily targeted by commercial, recreational, and artisanal fisheries (Sadovy de Mitcheson *et al.* 2013). Groupers are also popular among recreational divers, providing nonextractive economic value to the tourism industry and influencing the economic viability of marine-protected areas (Rudd & Tupper 2002). Their economic importance aside, groupers play a critical ecological role in moderating the abundance (Stallings 2008) and behavior (Madin *et al.* 2010) of prey species, with numerous indirect effects on ecosystems. Therefore, the loss of grouper species has substantial socioeconomic and ecological implications.

Groupers possess a series of life history traits that make them the teleost family with the highest number of threatened species on coral reefs (McClenachan 2015). Despite the wide recognition that groupers are vulnerable to high fishing pressure, catches have been increasing unabatedly for more than 50 years (Sadovy de Mitcheson *et al.* 2013). This fact has raised concerns about their potential risk of extinction. As a result, since 1998, the IUCN Grouper and Wrasses Specialist Group (GWSG) has been assessing the threat status of all taxonomically valid grouper species using the Red List criteria (Sadovy de Mitcheson *et al.* 2013). Among them, a relatively high proportion of species (30%) are considered to be data deficient (Sadovy de Mitcheson *et al.* 2013).

Data deficient species contribute to considerable uncertainty in global patterns of extinction risk and conservation prioritization. The use of preexisting biological data to model the conservation status of data sufficient species to predict the status of data deficient species has been proven a very cost-effective methodology relative to comprehensive risk assessments (Bland *et al.* 2015b). Here, we modeled correlates of extinction risk among species of one the most threatened families of marine fishes using an ordinal regression approach that accounts for biological traits that influence extinction risk in reef fishes, that is, body size, maximum depth of occurrence, breadth of habitat use, geographic range size, and aggregative spawning behavior. We then used the best fitting model to estimate the probabilities of data deficient species being assigned into each of the Red List categories.

Materials and methods

Data collection

Data on the Red List categories of grouper species were taken from Craig *et al.* (2011), which are based on the most recent assessment made by the GWSG at the time of writing. For this study, we focused on five key ecological traits that are most likely to influence the extinction risk of groupers. First, large body size has often been linked to elevated extinction risk in reef fishes (Jennings *et al.* 1999; Bender *et al.* 2013). Second, shallow water marine environments have being increasingly exposed to human impacts that threaten fish populations (Bridge *et al.* 2013). Fishes capable of utilizing deep-reef habitats are considered to be at lower risk of local extinction than fishes confined to shallow habitats (Lindfield *et al.* 2014). Third, species with large geographic range sizes are generally at less risk than those that occur in restricted ranges, as a broad distribution permits a large population size and/or a buffer against habitat loss, therefore, able to withstand local extirpation without risk of global extinction (Hawkins *et al.* 2000). Fourth, species that form spawning aggregations are likely to be vulnerable to overfishing, as evidenced by the loss of aggregations of commercially important species in many locations due to unsustainable fishing (Sadovy de Mitcheson & Colin 2012). Fifth, species that occupy a large range of habitats may be expected to be more resilient to disturbance than habitat-specific species. Here, habitat generalists included species that use other habitats in addition to structural reefs (soft bottoms, seagrass/macroalgae beds, mangroves, and estuaries). Our analysis also includes species distributions among three distinct regions: the Indo-Central Pacific, the Atlantic, and the Tropical Eastern Pacific, to allow for tests of the effect of regional variation in the predictive factors.

Data on body length, maximum depth, and multihabitat use were obtained from Craig *et al.* (2011), Robertson & Allen (2012), Robertson & Van Tassel (2012). Geographical range sizes were calculated as the total area of all constituent polygons in each species' distribution map available from the IUCN Red List spatial database (IUCN 2015).

Species that form spawning aggregations were obtained from Sadovy de Mitcheson & Colin (2012). They provide lists of species that form spawning aggregations delineated by quality of evidence. We tested the effect of forming spawning aggregations on groupers' extinction risk at two levels of data quality. One model considered aggregators only the species in which spawning aggregations were confirmed by direct evidence (Table S1). A second, less conservative model, broadened the definition of aggregators by including species in which information on

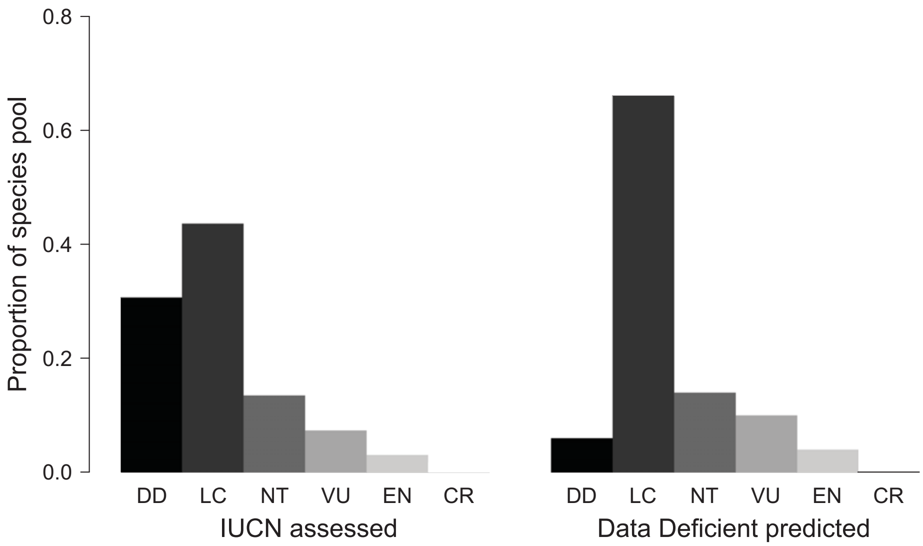

Figure 1 Distribution of assessed and predicted extinction risk. Extinction risk distribution for International Union for the Conservation of Nature (IUCN) assessed (left, $n = 163$) and CLMM predictions for data deficient (right, $n = 50$) groupers as percentage of the species pool in each of the IUCN extinction risk categories. DD, data deficient; LC, least concern; NT, near threatened; VU, vulnerable; EN, endangered; CR, critically endangered.

Table 1 Parameters of the final CLMM with the IUCN Red List category as an ordinal categorical response variable, including significant interactions between biogeographic region and range size and depth

Variable	Estimate	*SE*	*z* Value	*P* value
Body size	3.441	0.636	5.410	**<0.001**
Region				
IWP	6.607	3.398	1.944	0.051
TEP	−1.176	6.858	−0.172	0.863
Range size	−0.0006	0.0002	−2.558	**0.010**
Max. depth: ATL	0.092	0.552	0.168	0.866
Max. depth: IWPICP	−1.433	0.673	−2.128	**0.033**
Max. depth: TEP	−0.021	1.570	−0.014	0.988

Coefficient estimates of fixed variables, standard error (*SE*), test statistic (*z* value), and probability (*P* value) are included. Coefficient in bold indicates that p-value is significant ($P < 0.05$).

spawning aggregations is derived from indirect evidence (Table S2).

Data analysis

In order to investigate the relationship between species traits and extinction risk, and subsequently estimate the probability for data deficient species to be assigned to each Red List category, we used cumulative link mixed-effects modeling (CLMM). CLMM's are ideal for analyzing ranked categorical response variables, such as the IUCN Red List categories, because they preserve the variance structure of the original ordinal ranks of the categorical response variable. This approach prevents information loss, such as happens with aggregated binomial classifications (e.g., pooling categories in threatened vs. nonthreatened species), as well as avoids elevated type I error rates caused by assuming that differences between adjacent risk levels are equivalent, such as when transforming categorical data to a numeric index for multiple regression (e.g., from 1 to 5).

The response variable in our model is the species Red List category as an ordered categorical factor (least concern [LC] < near threatened [NT] < vulnerable [VU] < endangered [EN] < critically endangered [CR]). Fixed variables were body size, maximum depth, geographic range, formation of spawning aggregations, and broad-habitat use. Biogeographical region was also included as a fixed factor to test regional variability in the predictor variables. Finally, we included taxonomic genus as a random effect in our models to account for potential effects of shared ancestry.

For model selection, we did a backward stepwise removal of nonsignificant fixed-effect terms from the full model, based on log-likelihood ratio tests. The models were fitted using the function "clmm" from the package "ordinal" (Christensen 2013) in R (R Core Team 2015). We used the coefficients of our final model to estimate the Red List category of the data deficient species.

Overall model fit was quantified using the percentage of categorized species that were correctly classified by our final model (percentage correct classified, PCC). Because of the small sample size of our training set

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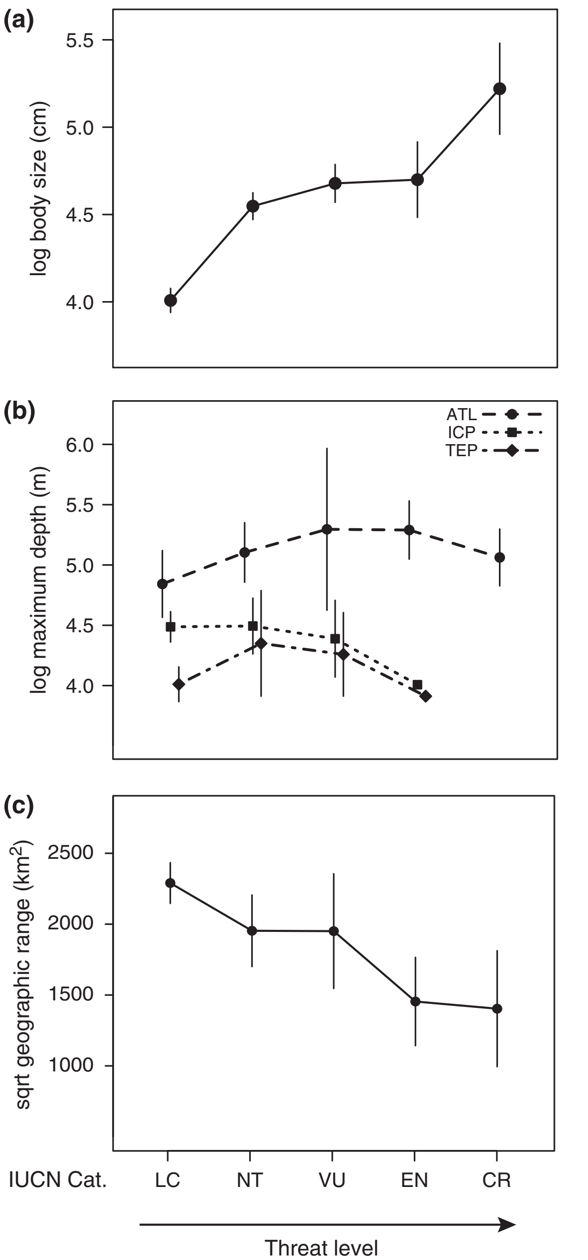

Figure 2 Average maximum body size (a), maximum depth (b), and geographic range size (c) of groupers in each Red List category. In (b), the data were grouped by biogeographical region to illustrate the interaction detected in the model. ATL, Atlantic; ICP, Indo-Central Pacific; TEP, Tropical Eastern Pacific; DD, data deficient; LC, least concern; NT, near threatened; VU, vulnerable; EN, endangered; CR, critically endangered.

(113 spp.), we tested the model fit both using the whole training set Additionally, we tested the model fit and with the data set split into two subsets (75% for training; 25% for testing). For the divided data set, we randomly drew 1,000 samples for the testing set from the list of all data sufficient species and calculated the mean PCC and *SE*. Model estimates were recalculated for each sample. We defined specificity and sensitivity as the combined percentage of correct classifications among nonthreatened (LC, NT) and threatened (VU, EN, CR) categories, respectively. Cohen's kappa statistic (function "kappa2" in R package "irr"; Gamer *et al.* 2012) was used to measure the agreement between predicted and actual categorizations while correcting for agreement caused by chance (Hand 2012).

Results

Among all 163 grouper species evaluated by the GWSG, 71 were classed as LC, 22 as NT, 12 as VU, 5 as EN, and 3 as CR. Fifty species were data deficient (Figure 1). Our analysis showed that body size and geographic range size were important predictors of extinction risk among groupers, with threatened status generally increasing with increasing body size and decreasing range sizes across all regions globally (Table 1; Figure 2). We also found a significant interaction between biogeographic region and maximum depth (Table S1). A negative relationship between maximum depth of occurrence and threatened status was observed only in the Indo-Central Pacific (Table 1).

Including only species with direct evidence for spawning aggregation in the aggregation formation category resulted in a similar result as including species with indirect evidence for spawning aggregation as well (Table S2). In neither case was spawning aggregation a significant predictor of extinction risk.

The range of trait values and the modeled relationship between traits and extinction risk were the same among data deficient and data sufficient species (Figure S1). The overall accuracy of our model is satisfactory (Table S3; PCC 74%; Cohen's kappa = 0.52, $P < 0.001$) given that it predicted species classification into five categories, although the accuracy varied among categories (LC = 87%; NT = 54%; VU = 41%; EN = 60%; CR = 66%). We caution that model performance tests based on the full training set may overestimate accuracy estimates, however our choice is justified based on the low sample size and high imbalance among response categories (Table S4).

The uncertainty of predictions for data deficient species increased with extinction risk (Table S5), a likely result of the progressively lower number of species in the higher risk categories. Only three data deficient species for which neither maximum depth of occurrence or geographic range size was available were not assigned a

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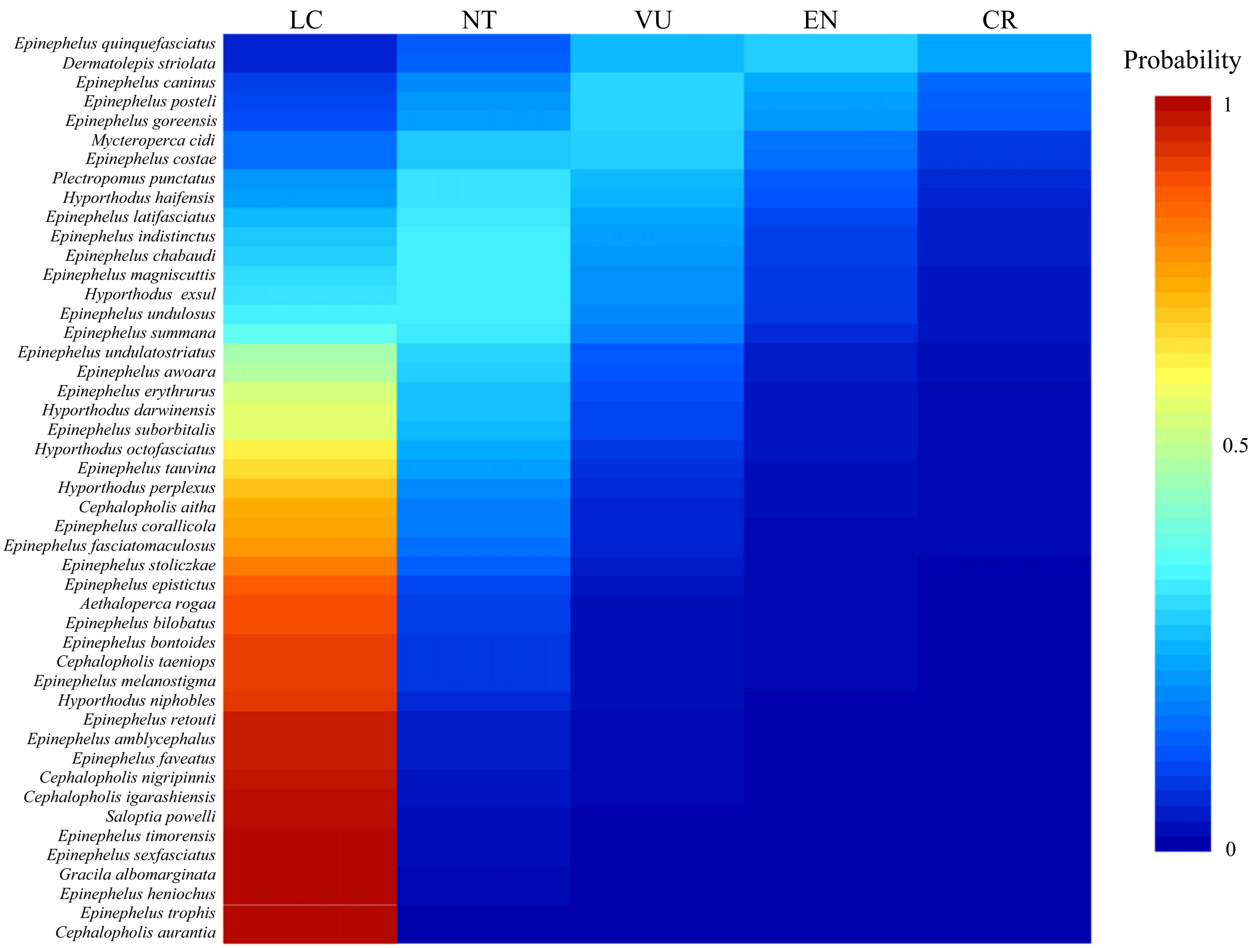

Figure 3 Probability distributions for data deficient species to be assigned into each of the IUCN's Red List categories. Three species (*Epinephelus chlorocephalus*, *E. lebretonianus*, and *E. polystigma*) were not predicted to an extinction risk category because they lack data on the maximum depth of occurrence or geographic range size. LC, least concern; NT, near threatened; VU, vulnerable; EN, endangered; CR, critically endangered.

predicted category. Among those categorized, two are predicted to be EN, four to be VU, nine NT, and 32 of LC (Figure 3).

Discussion

In this study, we used a novel method to estimate the threat status of data deficient grouper species. The method, which can be broadly applied to other taxonomic groups in any system type, models relationships between species' traits and extinction risk categories for IUCN-assessed species. In general, data deficient groupers were predicted to be slightly less threatened than data sufficient species. Sixty-four percent of the data deficient species are predicted to be of LC, which is roughly one-third more of the percentage of data sufficient species in that same category. Twelve percent ($n = 6$) of the data deficient species are predicted to be EN or VU and may therefore be of particular conservation interest.

Our analysis also highlights traits of groupers that are associated with extinction risk. In general, large body size was correlated with grouper endangerment. Large marine animals tend to have limited intrinsic rebound potential (Jennings *et al.* 1999; Bender *et al.* 2013), and large fish species are more likely to be targets for fishing (Levin & Grimes 2002). Even moderate artisanal fishing effort has been shown to deplete local stocks of some of the largest groupers in the Tropical Eastern Pacific (Sáenz-Arroyo *et al.* 2005) and in the Western Atlantic (Giglio *et al.* 2015).

The negative relationship between extinction risk and maximum depth of occurrence, which is predicted

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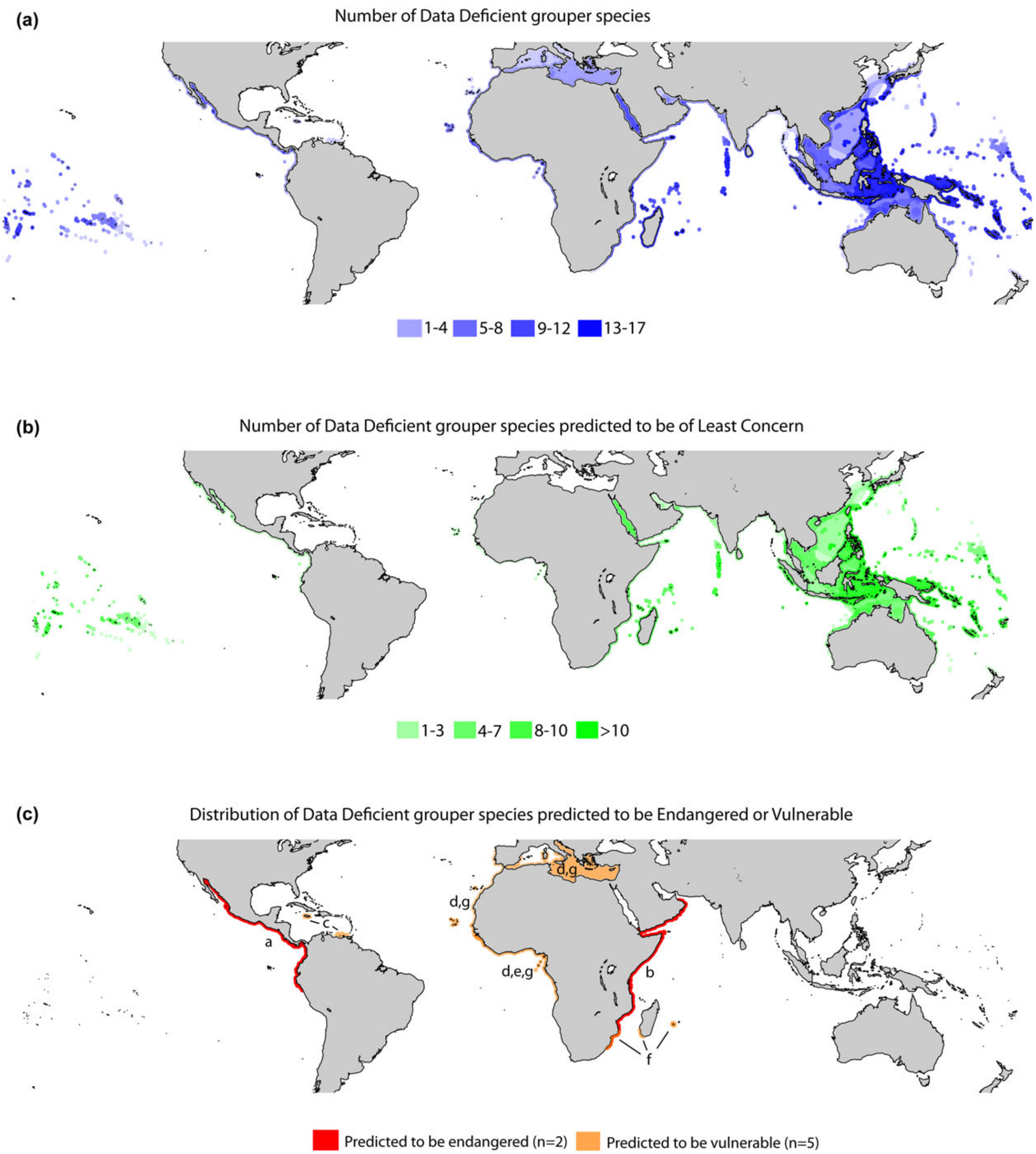

Figure 4 Maps of the distribution of all data deficient, data deficient predicted to be least concern, data deficient predicted to be vulnerable and data deficient predicted to be endangered species. (a) Total number of data deficient species. (b) Total number of data deficient species predicted to be least concern. (c) Distribution of data deficient species predicted to be vulnerable or endangered; a: *Epinephelus quinquefasciatus*, b: *Dermatolepis striolata*, c: *Mycteroperca cidi*, d: *E. costae*, e: *E. posteli*, f: *E. goreensis*, and g: *E. caninus*.

under the "depth refuge" hypothesis, was significant only in the Indo-Central Pacific. This may be explained by the contrasting geographical settings and differing fishing practices among regions. The vastness of the Indo-Central Pacific, and its extensive network of archipelagos, offers many refuges where fishing is limited to artisanal subsistence, often performed with depth-restrictive equipment (e.g., spearfishing; Lindfield *et al.* 2014). In contrast,

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large-scale commercial harvest of groupers is common in the Atlantic, where large fleets with advanced fishing equipment, such as bottom longlines (Russell *et al.* 1988), allow commercial fishers to fish at greater depths than artisanal fishers.

The formation of spawning aggregations, which is largely assumed to be a primary driver of extinction risk among groupers, was not a significant predictor for threatened status. Apparently, reproductive aggregations are linked to extinction risk only when associated with large-bodied species.

Although conservation prioritization must consider important socioeconomical factors in addition to observed or predicted extinction risk (Possingham *et al.* 2002; Miller *et al.* 2006), the latter is a key input variable for priority setting. Therefore, identifying species of conservation concern among data deficient groupers is considered high priority research for their management (Sadovy de Mitcheson *et al.* 2013). Along with continued protection of species already recognized as being at risk, there needs to be a selective mechanism for pinpointing the data deficient species that are likely to be at most risk before their population declines go unnoticed. An important outcome of the analytical approach used here is the probability estimates for a species being within each of the Red List categories (Figure 3, Table S5), which allow ranking of data deficient species both among and within categories. This fine-scale categorization of extinction risk among data deficient species has important implications for management, policy and conservation planning. For example, it has been suggested that the areas with higher numbers of data deficient species should be prioritized in order to tackle data deficiency (Brito 2010). However, doing so may lead to misplaced effort if the goal is to maximize protection of threatened species. For example, while the Coral Triangle in SE Asia is the global hotspot for data deficient groupers, none of the data deficient species predicted to be threatened by our model occur in the Coral Triangle. Instead, they are found in the Western Indian Ocean, the Tropical Eastern Pacific, in the Eastern Atlantic, and in the Mediterranean Sea (Figure 4).

To date, most models aimed at predicting the conservation status of data deficient species have been based on machine-learning methods (MLM). This approach is well suited to data sets with many hundreds or thousands of species, as is the case of broader taxonomic groups with good coverage by IUCN assessments such as mammals and amphibians (Howard & Bickford 2014; Bland et al. 2015a; Jetz & Freckleton 2015). However, predicting the status of data deficient species among narrow taxonomic groups (single families or genera) or groups for which data are available for just a small subset of the species remains challenging. The performance of MLM is limited by low sample sizes, especially when small data sets are associated with highly imbalanced response categories (Table S6), because MLM split the data during the analyses, progressively diminishing observations available for the next node construction (Elith *et al.* 2008).

In addition, inconsistent conclusions about the traits explaining variation in extinction risk among species are derived from the use of comparative models of broad taxonomic and geographic scope (Cardillo & Meijaard 2012). For these reasons, it has been suggested that the most powerful and informative comparative models of extinction risk will be those of narrow scope, restricted to relatively lower taxonomic groups (Fisher & Owens 2004). Our approach provides an alternative method to MLM when predicting the conservation status of narrow taxonomic groups or groups in which only a few subsets of species have been assessed by IUCN. We must caution, however, that our model provides lower sensitivity relative to specificity. This means that it is more prone to incorrectly predict species to be nonthreatened than the converse. However, the quantification of this uncertainty for each species Red List category combination (Figure 3; Table S4) is an important advantage over MLM in this case.

Data deficiency is a major hindrance to conservation planning in taxonomic groups with a large proportion of data deficient species. Despite the precautionary recommendation that data deficient species should be afforded the same degree of protection as threatened taxa (Mace *et al.* 2008), this is often not the case in practice (Hoffmann *et al.* 2008). This can result in genuinely threatened species receiving little conservation attention until their populations decline substantially (Howard & Bickford 2014). Modeling risk status of data sufficient species is a very cost-effective way to identify high-risk data deficient species for preferential reassessment within a reasonable time frame (Bland *et al.* 2015b). The method presented here provides one simple, defensible way to overcome this pressing conservation problem.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Figure S1. (A) Boxplots of the significant explanatory variables in data sufficient ($n = 113$) and data deficient species ($n = 50$). (B) Modeled relationships among significant explanatory variables and data deficient species.

Table S1. Model selection for a) the effect of including the interaction of region with each variable and b) the effect of dropping variables in a backward stepwise manner

Table S2. Model selection for a) the effect of including the interaction of region with each variable and b) the effect of dropping variables in a backward stepwise manner

Table S3. Confusion matrix of the training data predictions and accuracy measures for the selected CLMM predicting the IUCN Red List conservation status category in groupers ($n = 113$)

Table S4. Accuracy measures (PCC) for the training data predictions of the selected CLM on the full training set and on the model calibrated on a 75% training set and 25% validation set. The split set was randomly drawn 1,000 times to calculate the mean and standard error (*SE*)

Table S5. Estimates of probabilities of data deficient species being classed in each Red List category

Table S6. Confusion matrix for the training data predictions and accuracy measures for the machine-learning* model predicting the IUCN Red List conservation status category in groupers ($n = 113$)

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(This link will take you to the article abstract).

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