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Using publicly available data to conduct rapid assessments of extinction risk

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Abstract

The IUCN Red List plays a key role in setting global conservation priorities and is populated via rigorous, time-intensive assessments. Here, we test rapid preliminary assessments of plant extinction risk using one Red List metric: Extent of Occurrence (EOO). We developed REBA (Rapid EOO-Based Assessment) to harvest and clean data from the Global Biodiversity Information Facility, calculate each species' EOO and assign EOO-based Red List categories. We validated REBA classifications against 1671 North American plant species already on the Red List and found ~87% overlap between REBA's classifications and the IUCN's. However, REBA's false-negative rate for species outside the Least Concern category was substantial (~68%). To elucidate factors that might drive such a high rate of under-classification, we used hierarchical Bayesian models to show that certain plant types (e.g., Geophytes) and threats (e.g., Invasive and Other Problematic Species, Genes, and Diseases) increased the probability of under-classification. While REBA requires further refinement, it has yielded valuable insight into how preliminary assessment methodologies may become more effective.

KEYWORDS

conservation priorities, EOO, extent of occurrence, GBIF, IUCN Red List, least concern, North America, plants, prioritization, rapid assessment

1 | INTRODUCTION

The International Union for the Conservation of Nature's (IUCN; www.iucn.org) Red List is one of the most widely used frameworks to assess extinction risk. The Red List assessment process places extant species into one of six extinction risk categories: Critically Endangered (CR), Endangered (EN), Vulnerable (VU), Near Threatened (NT), Least Concern (LC), or Data Deficient (DD). To date, more than 134,000 species have been evaluated, including about 55,000 vertebrates, 54,000 plants, 25,000 invertebrates, and 450 fungi and protists. This represents only a small proportion of globally described species, particularly for invertebrates, but the extent and quality of these assessments are a remarkable achievement considering the relatively limited resources available.

As is the case with all extinction risk assessments, there are certain concerns and biases associated with the Red List's methodology. The representation of plants on the Red List, for example, suffers from biases that affect

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conservation science more generally (Di Marco et al., 2017; Nic Lughadha et al., 2020), as the proportion of described plant species evaluated on the Red List is well below that of vertebrates (13% and 75%, respectively, as of 2021; https://www.iucnredlist.org/resources/summary-statistics, table 1a). Of plants that are assessed, these are primarily trees, taxa of particular interest to IUCN Specialist Groups, and species linked to commercial and horticultural interests (Bachman et al., 2019; Brummitt et al., 2008; Sharrock, 2020). Furthermore, research shows that the Red List may be vastly underestimating plant extinctions, a concerning finding given that the modern rate of plant extinction is at least 500 times greater than the background rate (Humphreys et al., 2019).

Red Listing can also be hampered by features of the assessment process itself. For example, the time it takes for an assessment to be prepared can be substantial—in one non-botanical case, it took 17 workshops and 300 experts to assess approximately 1000 of the world's ray and shark species (le Breton et al., 2019). Furthermore, many assessed species fail to receive mandated regular reassessments; 17% of all assessments were already out of date (>10 years old) on the 2012 Red List, with the median age of Red List assessments estimated to reach 36 years by 2050 (Rondinini et al., 2014). Lengthy extinction risk assessments and delays in reassessment mean that species in need of urgent conservation attention may not benefit from timely management action.

To address these limitations, several tools have been developed to facilitate rapid preliminary extinction assessments (Nic Lughadha et al., 2019), particularly for plants (Bachman et al., 2020; Callmander et al., 2005; Davis et al., 2006; le Breton et al., 2019; Miller et al., 2013; Utteridge et al., 2005). However, only a small subset of these rapid assessment frameworks have examined the factors that might influence classification success or have been tested on large suites of species across broad geographic scales (Pelletier et al., 2018; Stévart et al., 2019; Zizka et al., 2021). Many of these tools rely upon a single criterion from the full IUCN assessment, Criterion B, which focuses on geographic range and is cited in more than 60% of all IUCN assessments (le Breton et al., 2019). Criterion B relies predominantly upon two measures: Extent of Occurrence (EOO) and Area of Occupancy (AOO), and also incorporates measures of population/spatial declines, extreme population fluctuations, and/or population fragmentation. EOO is related to geographic range and measures "the degree to which risks from threatening factors are spread spatially across the taxon's geographical distribution," while AOO correlates with population size and approximates a species' resistance to stochastic events (IUCN Standards and Petitions Committee, 2019; le Breton et al., 2019). Both have thresholds that dictate species classification (i.e., if EOO < 100 km^2, a species could be classified as CR).

Here, we use a publicly available biodiversity database to gather plant occurrence records for Red Listed species on a continental scale and analyze the resulting data using a rapid, EOO-based assessment (hereafter: "REBA") to assign species a Red List category. In addition, we fit statistical models to highlight plant traits and threats that affect the probability of under-classification with REBA (i.e., placing a species into a lower extinction risk category than assigned by the full IUCN Red List assessment process). Overall, we assessed the concordance between our simplified, automated classifications and the existing full IUCN classifications for 1671 North American plant species. Our results demonstrate the potential benefits of a rapid preliminary assessment method while highlighting how difficult it can be to construct one that is reliable across broad use cases. Methods such as these may eventually serve as a prioritization tool for optimizing resources and effort toward producing full IUCN assessments.

2 | METHODS

2.1 | Automated red list classification

The REBA workflow begins by using the R package rGBIF (Chamberlain & Boettiger, 2017) to query the Global Biodiversity Information Facility (GBIF) for georeferenced plant occurrence records, which we cap at 50,000 per species to reduce computation time. rGBIF pulls occurrence records for each species in reverse chronological order, extracting the most recent records first. To clean the data, we filtered records to only include "HUMAN_OBSERVATION" or "OBSERVATION" record types, helping to eliminate records that might be georeferenced to a museum location rather than the location of sample collection. We then used a suite of functions within the R package CoordinateCleaner (Zizka et al., 2019) to remove occurrence records that were potentially inaccurate representations of wild plant collection localities. These cleaning steps included: removing occurrences with identical latitude and longitude values; removing occurrences that were georeferenced to country centroids, country capitals, the GBIF headquarters, or known biodiversity institutions; and removing occurrences that did not lie over land. Next, REBA uses the R package rCAT to conduct an EOO-based Red List classification (Moat & Bachman, 2020). REBA relies exclusively on EOO as there is precedent for such an approach (Davis et al., 2006; Miller et al., 2013), and we believe that a metric designed to measure the spatial spread of risk itself (EOO) is more relevant in this case than one designed to approximate a species' insurance against that risk (AOO). rCAT calculates EOO as the area of a minimum-convex polygon drawn around known occurrence records (a minimum of 3 is required) and uses IUCN-defined thresholds to classify species as CR, EN, VU, NT, or LC, with EOO values of <100, < 5000, <20,000, <30,000, and ≥30,000 km^2, respectively. In previous comparisons of rapid assessment methodologies, rCAT has proven consistent and comparatively reliable (Nic Lughadha et al., 2019; Zizka et al., 2021).

2.2 | Testing REBA on North American plant species

We tested REBA's efficacy on the 2662 North American plant species on the Red List. We gathered data on extinction risk, "Plant Type", and "Threats" from the IUCN using the Red List's advanced search feature (https://www.iucnredlist.org/search; accessed March 23, 2020). After removing 97 species with no GBIF occurrence records and 29 with no representation in the GBIF taxonomic hierarchy, we initially harvested 15,560,079 occurrence records representing 2536 plant species. While all of these species are found in North America, not all are native to the continent. Non-native species identified as part of the North American flora by the IUCN were retained for this analysis. As such, all species assessed in this analysis are hereafter referred to as "North American species".

After cleaning the data as described above, we eliminated records from the year of or years following the IUCN's assessment date to ensure REBA was not influenced by data unavailable during the original Red List assessment process. This left us with 5,970,793 records from 1882 unique plant species. We joined these occurrence data with Red List assessment data by species, and, after eliminating species with fewer than 3 cleaned occurrence records, REBA produced EOO-based Red List classifications for 1687 plant species (16 of which were classified by the IUCN as DD) across 5,970,512 occurrence records (derived occurrence dataset 10.15468/dd.df4evh registered via GBIF.org on July 21, 2021).

To visualize REBA's accuracy, we generated a tile plot illustrating the overlap between Red List Category classifications generated by the IUCN and by REBA. We then calculated the number of "correctly" classified species (i.e., REBA matched the existing Red List classification), over-classified species (i.e., REBA produced a higher extinction risk category than the existing Red List classification), and under-classified species (i.e., REBA produced a lower extinction risk category than the existing Red List classification).

2.3 | Statistical modeling

In the extinction assessment context, under-classification is the major error of concern since it could lead an analyst using a rapid classification tool to discount real biological threats to the organism in question. To better understand how and where REBA succeeds and fails, we derived two data subsets to model the effects of "Plant Type" and "Threats" on the probability of under-classification—that is, those species classified into a lower extinction risk category by REBA than they actually inhabit on the Red List. These analyses excluded DD species by necessity, as REBA does not generate DD classifications. The first data subset contained all non-DD species that had 'Plant Type' data available from the IUCN (n = 1671 plant species). We modeled the probability of under-classification among different "Plant Types", which were previously defined by the IUCN (https://www.iucnredlist.org/resources/classification-schemes, Plant and Fungal Growth Forms Classification Scheme). Species used in the REBA pipeline fell into 19 of the 24 IUCN "Plant Type" categories. We combined some categories to bolster sample sizes within categories, and these combinations are justified both biologically and by the IUCN's "Plant Type" classification guidelines. For example, IUCN has multiple "Tree" categories differentiated by size (i.e., "Tree—size unknown", "Tree—large", "Tree—small"), but admits that the categories based on size are "sub-types which may be dropped at some point in the future." Thus, we combined these categories into one "Tree" category. Size-based sub-categories for both "Succulent" and "Shrub" categories were combined for similar reasons. We also combined the "Vine", "Epiphyte", and "Lithophyte" categories due to low sample sizes, which we thought was biologically reasonable because plants of these types often grow on atypical substrates and tend to climb. Finally, the single "Moss" species in our dataset was combined with the "Hydrophytes" because the plants in these categories both require a close association with moist habitats for survival. The second data subset represented all non-DD species that had "Threats" data available from the IUCN (https://www.iucnredlist.org/resources/classification-schemes, Threats Classification Scheme; n = 453 plant species). All 12 of the original IUCN "Threats" categories were represented in unmodified form in our analysis.

To more completely understand the factors that lead REBA to generate under-classification errors, we created an additional data subset of only NT and threatened (VU, EN, and CR) species. First, we recognized that our data contained a preponderance of LC species ($n = 1575$), which, by definition, cannot be under-classified by REBA as there is no category representing a lower extinction risk. Furthermore, only species outside of the LC category have data specifying which Red List criteria were used to determine their Red List classification. Thus, using the two previously described data subsets, it was difficult to address the question of whether REBA was more effective for species that were listed according to Criterion B (one might hypothesize that a rapid assessment method based upon a Criterion B metric, EOO, would be better at classifying species actually listed according to that Criterion). So, to account for our data's LC inflation and to allow us to best model the effect of listing under Criterion B on the probability of under-classification, we derived a subset of the non-DD data that further excluded LC species and therefore contained only those plants classified as NT, VU, EN, or CR by the IUCN. This non-LC data subset contained 96 species, and each of these species had associated "Plant Type" and "Threats" data. For simplicity, we refer to this dataset hereafter as the "Non-LC" dataset. Thus, in total, we derived three distinct datasets: all non-DD North American species with "Plant Type" data ($n = 1671$), all non-DD North American species with "Threats" data ($n = 453$), and the Non-LC dataset, wherein all species had "Plant Type" and "Threats" data ($n = 96$).

We then constructed four separate multilevel Bayesian models (one fit to the "Plant Type" dataset, one fit to the "Threats" dataset, and two fit to the Non-LC dataset) with a binomial outcome distribution where under-classification was the outcome of interest. All models included the number of occurrence records available for a species as a fixed effect. Two models included "Plant Type" categories as varying effects (one each for the "Plant Type" and Non-LC datasets), and the remaining two included "Threats" categories as varying effects (one each for the "Threats" and Non-LC datasets). The two models that were applied to the Non-LC dataset also included "Listing Under Criterion B, Sub-Criterion B1" and "Listing Under Criterion B, Sub-Criterion B2" as binary fixed effect predictors. In sum, these models estimate the effect of number of occurrence records, "Plant Type", "Threats", and listing under Criterion B on REBA's probability of under-classification. We specified and fit our models using the "ulam()" function within the rethinking R package (Carpenter et al., 2017; McElreath, 2020). We fit each model using four independent MCMC chains, specifying 7500 total iterations per chain, 2500 of which were considered warmup. As a result, our statistical inferences are based on 20,000 posterior samples from each model (5000 post-warmup samples per chain with four chains total). After model fitting, we inspected parameter trace plots and R-hat values to confirm convergence and good model fits (Gelman & Rubin, 1992). We report parameter estimates using posterior means and 99% highest posterior density intervals (HPDIs).

2.4 | Counterfactual plots of classification accuracy

We visualized our model results with counterfactual plots (McElreath, 2020). Here, we imagine using REBA for a species with a given "Plant Type" or "Threats" classification across a range of arbitrary occurrence record sample sizes, where the implied probability of under-classification is informed by the full posterior parameter distributions from fit models. We plotted the implied probability of under-classification using three occurrence record sample sizes: 100, 1000, and 10,000 records. These visualizations help provide a more intuitive way of understanding our statistical models in that they combine inference about all relevant model parameters (number of occurrence records, "Plant Type", and "Threats") and are translated onto the probability scale (by contrast, raw parameter posterior distributions are on the log-odds scale).

3 | RESULTS

REBA correctly classified 1457 of 1671 (87.19%) non-DD North American plant species in our dataset. An overwhelming majority of correct classifications (99.38%) were for LC species (Figure 1), and REBA correctly classified 91.94% of LC species in our dataset. However, in describing REBA's error rate, we choose to focus on non-LC species, as LC species are of lowest conservation priority yet represent the vast majority of species in our dataset. As such, inclusion of LC species into our error calculations would obscure REBA's classification behavior with more threatened taxa. Therefore, when characterizing REBA error, we considered the 96 plant species in our Non-LC dataset (which was composed only of NT, VU, EN, and CR species). Only 9 (9.38%) of those 96 species were correctly classified by REBA. REBA's non-LC false negative rate can be determined by examining all those non-LC species that were under-classified. Thus, REBA's non-LC false negative rate was 67.71% (65 under-classified species out of 96, with 57 of those under-classified species placed into the least threatened LC category).

In the Bayesian model fit to the full "Plant Types" dataset, "Geophytes" contained the highest proportion of

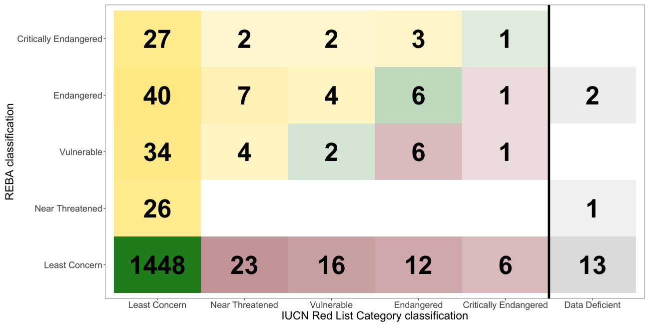

FIGURE 1 To the left of the bold line, each tile represents an intersection of IUCN threat category classifications: Those assigned by the IUCN and those assigned using REBA. Green tiles along the diagonal represent matching classifications, where both the IUCN and REBA classified species into the same categories. Yellow tiles above the diagonal are those we over-classified, where REBA placed species into a higher extinction risk category than that produced by the IUCN's classification. Red tiles below the diagonal represent those species we under-classified, where REBA placed species into a lower extinction risk category than that produced by the IUCN's classification. Tile transparency is a function of the number of species associated with that classification combination. Gray tiles to the right of the bold line represent the threat categories into which we classified 16 DD species using REBA

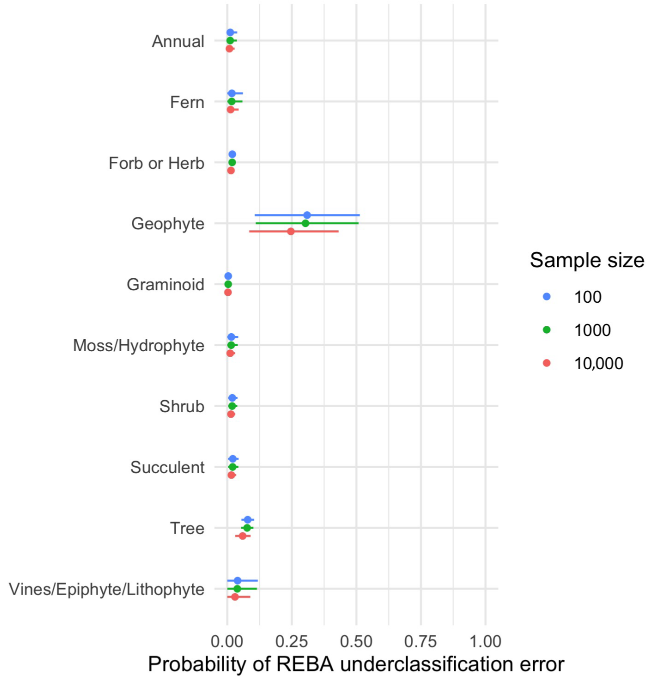

FIGURE 2 95% HPDIs for the implied probability of REBA under-classification across plant types and occurrence record sample sizes. Distributions for the implied probability of under-classification were derived from raw parameter posterior distributions from the Bayesian model fit to the full "Plant Type" dataset

under-classified species among "Plant Types" ($n = 10$, 21.74%; Table S1, Figure S1) and exhibited the strongest positive effect on the probability of under-classification (mean value on log-odds scale [99% HPDI]: 2.83 [1.48, 4.20]; Figure 2). "Annuals", "Ferns", and "Graminoids" contained no under-classified species ($n = 0$, 0%; Table S1, Figure S1), and "Graminoids" exhibited the strongest negative effect on the probability of under-classification (−2.46 [−6.84, −0.28]; Figure 2). The number of occurrence records had a minimal effect on under-classification as it overlapped with 0 in the 99% HPDI (−0.29 [−0.92, 0.19]; Figure 2). However, the posterior mean was negative, indicating that more available data would be expected to reduce the probability of an under-classification error.

In the Bayesian model fit to the full "Threats" dataset, "Geological Events" had the highest proportion of under-classified species ($n = 1$, 100%; Table S2, Figure S2)—however, this category applied to only a single species. "Transportation and Service Corridors" had the second-highest proportion of under-classified species ($n = 9$, 26.47%; Table S2, Figure S2). "Invasive and Other Problematic Species, Genes and Diseases" exhibited the most positive effect on the probability of under-classification (0.51 [−0.12, 1.26]; Figure 3). "Other Options" had the lowest proportion of under-classified species (n = 1, 14.29%; Table S2, Figure S2); "Climate Change and Severe Weather" had the second-lowest proportion of under-classified species ($n = 17$, 15.74%; Table S2, Figure S2) and exhibited the largest negative effect on under-classification based on our fit model (−0.02 [−0.72, 0.64]; Figure 3). As in the "Threat" model, the number of occurrence records had relatively little effect on the probability of under-classification (−0.05 [−0.66, 0.42]; Figure 3), but again the posterior mean was negative.

In the "Plant Types" model fit to the Non-LC dataset, "Geophytes" contained the highest proportion of under-classified species among "Plant Types" ($n = 10$, 100.00%), alongside "Moss/Hydrophytes" and Vines, Epiphytes, and Lithophytes, which each had 1 under-classified species in the Non-LC dataset; "Annuals", "Ferns", and "Graminoids" contained no under-classified species ($n = 0$, 0%). "Geophytes" exhibited the strongest positive effect on the probability of under-classification (3.55 [0.24, 10.05]; Figure 4); "Shrubs" exhibited the strongest negative effect on the probability of under-classification (−0.63 [−2.30, 1.11]; Figure 4). Here, the number of occurrence records had a more substantial effect on under-classification as 99.1% of the parameter's posterior probability mass was >0 (1.27 [−0.08, 3.27]; Figure 4), indicating that more available data would be expected to increase the probability of an under-classification error.

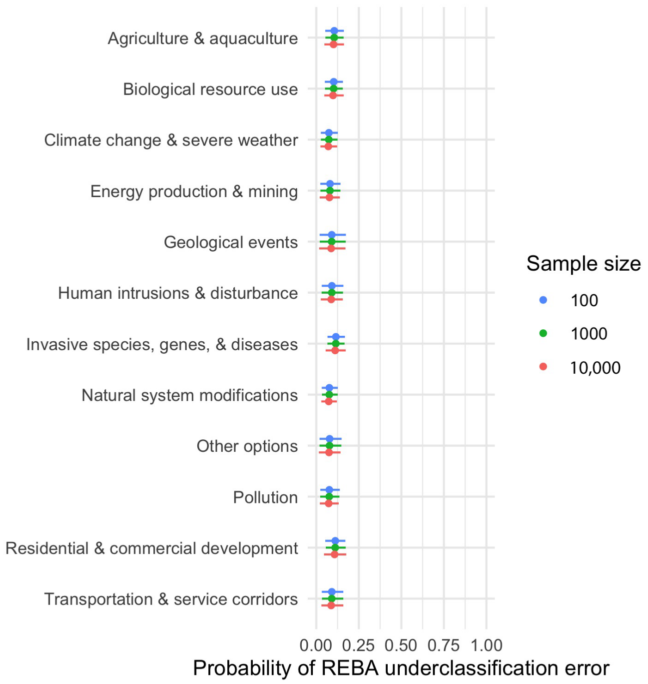

FIGURE 3 95% HPDIs for the implied probability of REBA under-classification across threats and occurrence record sample sizes. Distributions for the implied probability of under-classification were derived from raw parameter posterior distributions from the Bayesian model fit to the full "Threats" dataset

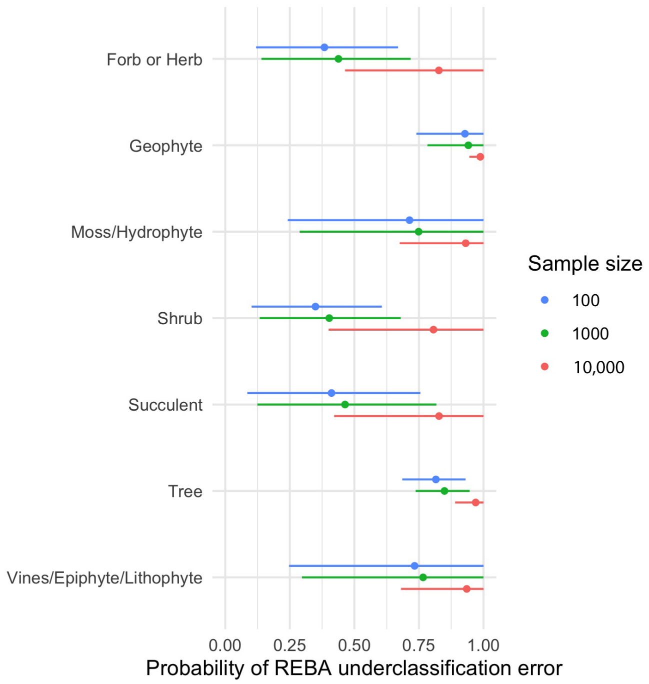

FIGURE 4 95% HPDIs for the implied probability of REBA under-classification across plant types and occurrence record sample sizes. Distributions for the implied probability of under-classification were derived from raw parameter posterior distributions from the Bayesian model fit to the "Non-LC" dataset

Classification under Sub-Criterion B1 (0.30 [−1.40, 2.01]) and under Sub-Criterion B2 (−0.56 [−1.95, 0.80]) had minimal effects on under-classification as they overlapped substantially with 0 in the 99% HPDI.

In the "Threats" model fit to the Non-LC dataset, "Geological Events" contained the highest proportion of under-classified species among "Threats" (n = 1, 100.00%)—however, this category again applied to only a single species. "Biological Resource Use" had the second highest proportion of under-classified species (n = 30, 76.92%) and exhibited the strongest positive effect on the probability of under-classification (0.29 [−0.36, 1.62]; Figure 5). "Human Intrusions and Disturbance" exhibited the strongest negative effect on the probability of under-classification (−0.32, [−1.85, 0.33]). The number of occurrence records had a positive posterior mean and, in this case, did not overlap with 0 in the 99% HPDI (1.44 [0.03, 3.50]; Figure 5), indicating strong evidence for a positive relationship between the amount of data and the likelihood of under-classification. Classification under Sub-Criterion B1 (−0.37 [−1.84, 1.08]) and under Sub-Criterion B2 (0.01 [−1.15, 1.18]) had minimal effects on under-classification as they overlapped substantially with 0 in the 99% HPDI.

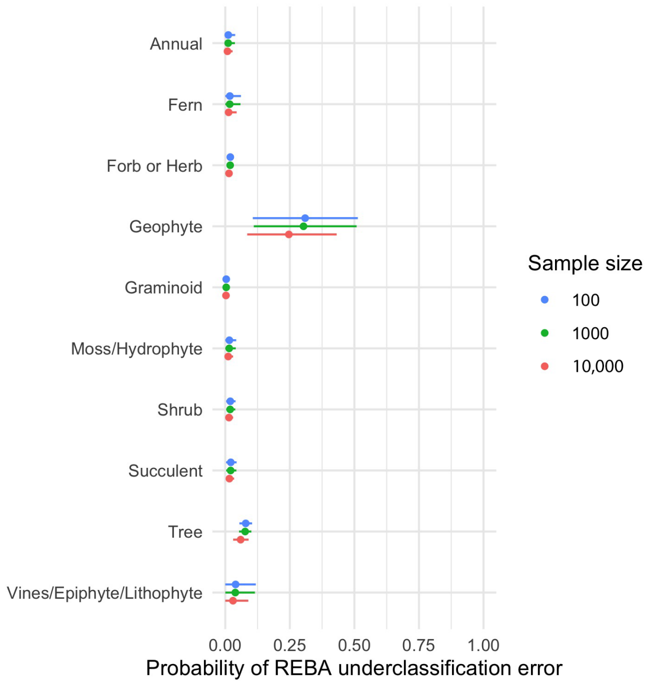

FIGURE 5 95% HPDIs for the implied probability of REBA under-classification across threats and occurrence record sample sizes. Distributions for the implied probability of under-classification were derived from raw parameter posterior distributions from the Bayesian model fit to the "Non-LC" dataset

4 | DISCUSSION

REBA can quickly produce preliminary Red List assessments on a continental scale that match existing Red List assessments approximately 90% of the time. However, REBA's failures likely bar it in its current state from contributing to permanent assessments and are worth exploring in greater detail. REBA's false-negative rate with non-LC species (>67%) is particularly troubling—the workflow is not only failing to correctly classify species associated with higher extinction risk, but is categorizing many of those species actually at risk of extinction into a category with the lowest risk of extinction (LC). Such a high false-negative rate with a critical subset of species means that this tool is too risky to deploy in real-world scenarios at this point, despite its success in identifying species of LC.

A closer look at those species facing the highest risk of extinction that were misclassified may shed light on some of the complications REBA struggles to overcome. REBA under-classified eight of the nine North American species listed by the IUCN as CR, labeling six as LC: five *Fraxinus* species threatened by the Emerald Ash Borer (*Agrilus planipennis*) and the American Chestnut (*Castanea dentata*), which is threatened by the chestnut blight caused by *Cryphonectria parasitica* (although it should be noted that under-classification is the only type of misclassification error possible for CR species, which cannot, by definition, be placed into a more threatened category). These are widespread species, and their large EOOs mask the tremendous risk that invasive species and disease represent across their ranges. These particular types of threats may frustrate the REBA workflow, particularly for species with large EOOs. These matches observations made in other tests of similar methods (Bachman et al., 2020).

Interestingly, the results from the models used to analyze the Non-LC dataset may provide additional clarity as to why these and other threatened species were under-classified. Our results suggest that listing under Criterion B has little influence on REBA's accuracy, but parameter estimates from both models applied to the Non-LC dataset indicate that as more occurrence records are used in the EOO calculation, the probability of an under-classification error is expected to increase. This supports what was found in the above examination of the most threatened species that REBA under-classified—more occurrence records tend to result in "false negative" classifications. Meanwhile, the effect of the number of occurrence records on under-classification in the full dataset suggested the opposite trend: there, more data tends to decrease the probability of under-classification. This makes some intuitive sense; LC species made up the majority of our dataset, and cannot be under-classified. Each additional occurrence record represents a potential increase in calculated EOO, and large EOO values produce LC classifications. Therefore, across the full dataset, the more data available to REBA for a given species, the more likely it is to produce an LC classification that, as a result of the strong LC bias in our dataset, is more likely to be correct, thereby reducing the overall probability of under-classification.

Our intention with REBA is to provide an avenue for preliminary batch assessments of large groups of species, but, should they ever be used to inform a full Red List assessment by the IUCN, each preliminary REBA assessment must be reviewed by a working group expert on that particular taxa. This human element is absolutely critical in all assessments, preliminary or otherwise, and is what makes the full IUCN process so effective—we envision human oversight as the critical check and balance on any automated assessment's false-negative potential. REBA is methodologically similar to the Rapid Least Concern workflow described by Bachman et al. (2020), which relies on rGBIF and rCAT to generate batch analyses of up to 100 species and subsequently submit reports directly to the IUCN describing species that fall into the LC category based on Rapid Least Concern's analysis. Other examinations of the accuracy of preliminary assessment methodologies have achieved lower false-negative rates by taking additional steps or using methodologies different from REBA. For example, Stévart et al. (2019) were able to lower their false negative rate from 37.88% to 9.81% by aggregating extinction risk categories together into broader groups and incorporating metrics of rarity into their assessment, while Darrah et al. (2017) used a modeling approach and achieved an accuracy similar to REBA's but with a sensitivity of 88%.

By incorporating facets that drive success in these other methods, such as decreasing the resolution of REBA's predictions from individual categories to broader "Threatened" and "Non-Threatened," this workflow's next iteration may prove to be more successful than its first. While it may have failed in terms of sensitivity, the under-classification modeling that accompanied this test has produced valuable information that could guide essential human scrutiny. Future working groups reviewing EOO-based preliminary assessments may turn a more critical eye toward Geophytes, which were frequently under-classified and exerted the strongest effect on the probability of under-classification; they may feel more confident in rapid classifications of Annuals, Ferns, and Graminoids, of which no species were under-classified. However, this guidance requires additional confirmation from future studies and could be more robustly rooted in specific biological facets of the various plant types that may contribute to under-classification. Results from the "Threats" models provide less clarity and are less easily interpreted, however, as there were more species labeled with multiple Threats than there were those with multiple "Plant Types" (the mean number of 'Plant Type' per species was 1.31 while for "Threats" it was 2.44). This increased overlap made it more difficult to accurately parse the individual effects of each "Threat" on under-classification. This becomes more clearly visible when comparing Figures 2 and 3, which show that different "Threats" did not influence the probability of under-classification as strongly as did "Plant Type".

An additional bias may be present in the geographic focus of this analysis. North America does not host especially high levels of plant species richness, but its floral community is well represented on the IUCN Red List (Bachman et al., 2019). Furthermore, national differences in the ways data are shared and funding is allocated inevitably spatially bias distributional databases, particularly GBIF (Beck et al., 2014). As such, REBA's application to the flora of other regions that are not as comprehensively assessed may be further complicated by limited data availability. Certain facets of REBA's methodology may also prove detrimental when dealing with data-poor species or regions. The choice to filter harvested GBIF occurrence records exclusively to those of "HUMAN_OBSERVATION" and "OBSERVATION" record types were designed to reduce the likelihood of mislabeled outliers, but could severely limit sample sizes outside of data-rich taxa or regions. Future users of the REBA workflow could easily modify these filters to suit their preferences.

Further refinement of REBA is necessary, but the future of this method across broader spatial and taxonomic applications is bright. While it may be inadequate in its current form, REBA's limitations only serve to highlight the pressing need for robust preliminary assessment methodologies. The precipitous global decline of biodiversity is well-monitored by the rigorous IUCN Red List assessment process. However, the speed of the extinction crisis outpaces the speed of assessment. We have neither the time nor the resources to thoroughly evaluate every species, and rapid assessments represent a crucial frontier for accelerating and focusing the full Red List assessment process. The need for action is immediate—there is little time to waste.

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CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

DATA AVAILABILITY STATEMENT

All R code used in the REBA workflow is documented and publicly accessible via a GitHub repository (https://github.com/eveskew/plant_rapid_assessment). Further, this entire codebase and larger data files not hosted on GitHub (i.e., all raw GBIF occurrence records and the final cleaned occurrence record dataset) are archived on Zenodo (Levin et al., 2021). Finally, as noted in the Methods section, the cleaned occurrence record dataset has been registered as a derived dataset with GBIF (10.15468/dd.df4evh).

ETHICS STATEMENT

This manuscript presents original research in a complete and honest fashion, with proper attribution to all co-authors. It has not been submitted for publication elsewhere.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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