ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (2): 255-269 doi: 10.28978/nesciences.1763905

A Bayesian Approach to Estimating Extinction Risk in Critically Endangered Amphibians

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Abstract

Amphibians are one of the most imperiled groups of vertebrates; many species worldwide are intrinsically susceptible to extinction due to habitat loss, climate change, disease, and various other anthropogenic factors. Deterministic models often fail to capture the complex and diverse nature of uncertainty exhibited in ecological data, particularly for species with limited data. Our study presents a Bayesian modeling framework that estimates extinction risk in critically endangered amphibians, utilizing input from both prior ecological knowledge and limited observational data to produce probabilistic estimates of extinction risk. We developed hierarchical models to generate an unpredictable extinction risk based on species-specific life-history traits, fragmentation indices, and exposure to threats. The Bayesian framework is advantageous as it accounts for the uncertainty of the data and provides an updated extinction risk estimate with new information as it becomes available, which is crucial for the adaptive management of conservation. The model we applied to explore extinction risk across 50 critically endangered amphibian

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species in various parts of the globe illustrates considerably different extinction risks. Disease prevalence and microhabitat specialization were the two primary predictors of extinction risk for a highly threatened group of vertebrates. We demonstrate the application and utility of Bayesian modeling in the context of developing extinction risk in conservation biology. It affords a statistically robust, transparent, and flexible means to advance the protection of extinct species by prioritizing species and acting with targeted mitigation measures under significant uncertainties.

Keywords:

Bayesian, extinction risk, critically endangered, amphibians, estimation, conservation, uncertainty.

Article history:

Received: 22/03/2025, Revised: 06/06/2025, Accepted: 04/07/2025, Available online: 30/08/2025

Introduction

Status of Critically Endangered Amphibians

Amphibians are currently among the most threatened groups of vertebrates worldwide, with 41% of all amphibian species being threatened. In critically endangered amphibian groups, this does not suggest that extinction risks are potentially imminent, but rather that we may already have passed that point. Moreso, amphibians are uniquely positioned in a perfect storm of threats from habitat destruction, climate change, environmental pollution, invasive species, and emerging infectious diseases (e.g., Batrachochytrium dendrobatidis - Bd) (Sharipov et al., 2024) that are well documented to be responsible for major declines and extinctions (Scheele et al., 2019; Rao & Menon, 2024). In general, critically endangered amphibians are characterized as having naturally restricted ranges, low fecundity, and being extremely sensitive to environmental changes (Hof et al., 2011). Furthermore, many amphibian species have not been seen for years or even decades, creating uncertainties about whether they even still exist! Anthropogenic changes occur quickly and without recent field surveys, the time-stated available for predicting extinction risk has constricted the timely assessment of extinction risks to amphibian conservation science (which is characterized by always being behind the 8 ball!). Additionally, traditional conservation planning often does not have appropriate funding or poorly allocated resources and without concrete, quantifiable data on potential extinction risks, conservation planning will always remain retrospectively reactive and not proactive (Bielby et al., 2008). In respect to this challenge, the use of statistical modeling to determine extinction probabilities, based upon the data presented, is not only useful but necessary.

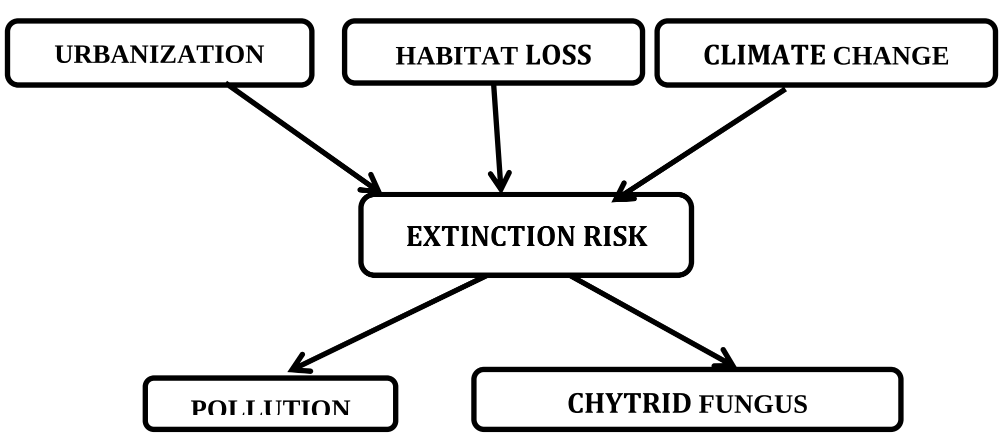

Figure 1(a). Real-World Drivers of Extinction Risk in Critically Endangered Amphibians

This diagram (Figure 1(a)) provides a straightforward representation of a conceptual model identifying some of the major factors that influence extinction risk in critically endangered amphibians. At the center of the figure is "Extinction Risk" which are affected by environmental and anthropogenic drivers. Urbanization and climate change can impact habitat loss and habitat degradation, as they can alter habitat use or destroy the habitat completely and may threaten the species entirely. Habitat loss is the single most significant threat a species can face, and habitat degradation is also associated with environmental pressures. Pollution from agriculture, industry, and urban land use can exert harmful pollution loads, increasing ecological stress. The chytrid fungus, a globally recognized and threatening pathogen, has devastated amphibian populations worldwide, adding to the list of anthropogenic pathogenic threats. Each of the connected drivers can work together to increase the threats of extinction risk for amphibians and demonstrates the need for conservation that is integrated and models of predictive risk assessments.

Estimating Extinction Risk Accurately

Estimating extinction risk accurately is essential for conservation prioritisation, policy development, and resource allocation. There are boxes such as the IUCN Red List that provide a framework, but they put a lot of emphasis on expert elicitation and deterministic threshold which can oversimplify biology (Akçakaya et al., 2000; Gayathiri & Nithyakalyani, 2019). Such oversimplification is particularly a problem where actions to conserve critically endangered amphibians are often delayed due to data deficiency as a result of missing observations and information and can increase the chance of unnoticed extinctions. Recent research has highlighted the importance of demographic variability, ecological traits specific to a species and environmental stochasticity in extinction modeling (Brook et al., 2000). Especially for amphibians that have low dispersal ability and narrow thermal tolerance compared to other animals, they are going to be at an increased risk from changes in the landscape and climate (Ficetola et al., 2015; Saidova et al., 2024). Factors associated with extinction risk can be complex and interacting, therefore requiring a modeling framework that incorporates uncertainty into models, and accommodates missing data along with probability based estimates. Quantitative risk assessments with real-time tracking and updating of environmental and ecological variables will be very important in improving conservation decision-making (Murray et al., 2017; Mustapha et al., 2017).

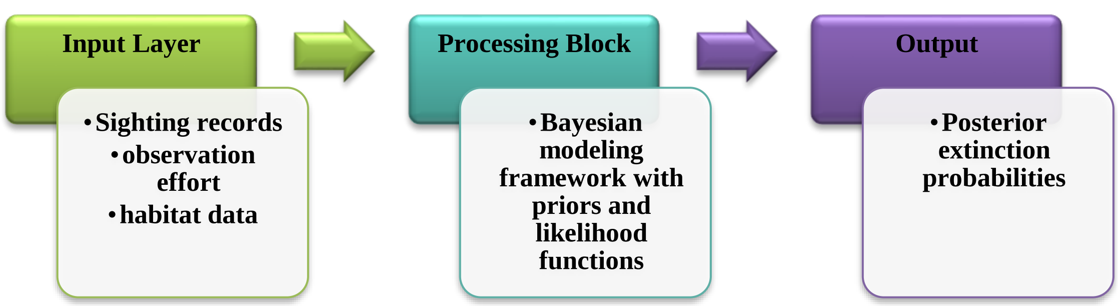

Figure 1(b). Bayesian Extinction Risk Estimation

The figure (Figure 1(b)) represents the essential components of the Bayesian modeling pipeline used for extinction risk estimation. The process starts in the Input Layer, which includes sighting records, observation effort, and habitat information—key forms of ecological and observation data. These inputs are processed in the Processing Block, where the Bayesian modeling framework assumes credible prior knowledge and uses likelihood functions to construct a coherent probabilistic model. The final Output represents the posterior extinction probabilities, which summarizes the likelihood of species extinction based on what was observed. In this way, the pipeline's modular architecture allows inference to be systematic and can be updated in a dynamic manner when additional data become available.

Introduction to Bayesian Framework as a Methodology

The Bayesian framework has developed as a powerful strategy to refine extinction risk modeling, particularly in situations with limited data and significant uncertainty, and it is an alternate strategy to traditional statistical models (McCarthy & Masters, 2005; Jaiswal & Pradhan, 2023). One of the primary weaknesses of traditional frequentist statistics is the inability to incorporate our prior knowledge—such as expert opinion, historical sightings, and even data from phylogenetically similar species—into extinction risk estimates; with Bayesian models, we can infer extinction risk estimates and update them with new information (Dennis et al., 2019). Frequentist statistics establish static inferences when information is retrieved; for some animals such as amphibians that are only observed infrequently or have limitations on sighting opportunities, this makes it difficult to generate definitive population assessments and explore patterns of extinction risk variation. Bayesian hierarchical models allow researchers to explore risk within an individual species as well as across ecological groups, while accounting for functional traits related to shared life-history characteristics (e.g., exposure to breeding occurrences in pond habitats) or shared exposures (Olivieri et al., 2012). For example, a Bayesian extinction model can generate estimates, including the modelled probability, that a frog species has gone extinct after 30 years with no sighting, while also accounting for sampling effort, habitat quality, and observation error. The Bayesian perspective also provides full posterior distributions of extinction probabilities vs. single point estimates, which provides more information for risk communication and scenario-based planning (Lee et al., 2017; Safavi & Omidi, 2015) The probabilistic perspective also supports decisions that could differentiate between species likely already extinct vs species that might still exist but require immediate surveys. The inclusion of ecological realism in a statistically rigorous and adaptive framework offers a satisfying way to overcome the shortcomings inherent in the current approaches to extinction modeling of critically endangered amphibians. The Bayesian approach creates a more robust prediction while responding better to the needs of conservation, such as accountability, adaptability, and efficient prioritization in circumstances of uncertainty and rapid change.

The rest of this paper is organized as follows. Section II provides more detail about classic methods for estimating extinction risk, as well as a short introduction to Bayesian statistics and its rising relevance and use in conservation biology. Section III details the data collection plan and describes the proposed Bayesian model, as well as any underlying assumptions and assumptions. Section IV details the results of the study, focusing on a comparison made between the Bayesian estimates and traditional estimates, and model performance using some key statistical metrics. Section V provides a discussion on the findings, acknowledges some limitations of the method proposed in this paper, and suggests future areas for research. Lastly, Section VI summarizes the contributions of the paper and its implications for the development of conservation strategy and policy using a Bayesian framework.

Background

Explanation of Traditional Methods for Estimating Extinction Risk

Conservation biologists have historically relied on standard techniques for evaluating extinction risk, especially when prompt action is required for species facing rapid decline. Among these, Population Viability Analysis (PVA) is paramount; it integrates demographic parameters to forecast extinction likelihood across generations (Brook et al., 2000). While PVA furnishes critical projections of population trajectories, its predictive power is contingent on the presence of longitudinal datasets—an asset notably scarce for critically endangered amphibians. The IUCN Red List provides a complementary framework by stratifying species risk according to prescribed quantitative thresholds. This system enjoys global endorsement, yet it often draws on limited datasets that, for taxa with low abundance or rare detection, can understate the true extinction risk (Butchart et al., 2006). Because a number of amphibians occupy remote and inadequately surveyed habitats, monitoring coverage is uneven, compounding gaps in demographic knowledge. Consequently, standard methodologies frequently yield extinction probability assessments that are either incomplete or unduly conservative (Gilvaei et al., 2014). Such limitations become especially pronounced for taxa that have not been detected in recent temporal windows. Absence of observation may signify genuine local extinction, yet it may equally stem from inadequate field effort or the species' cryptic life history. Deterministic modelling approaches, constrained by fixed parameter assumptions, frequently fail to incorporate these ambiguities, thereby undermining the robustness of inferred extinction risk (Boakes et al., 2015; Aghazadeh et al., 2016).

Bayesian Statistics and Their Role in Conservation Biology

Bayesian statistics furnish a robust analytic framework for managing uncertainty, particularly when data are limited or fragmented. In contrast to frequentist methods that yield deterministic point estimates grounded solely in observations, Bayesian inference merges pre-existing knowledge with current data to refine beliefs regarding a parameter—in this instance, the probability of species extinction (Gelman et al., 2013). The capacity to integrate prior knowledge constitutes the Bayesian method's principal strength. Researchers may embed expert assessments of life history traits, historical demographic patterns, or ecological tolerances within the model, thereby producing more robust estimates even when extensive field-collected data are absent (Kéry & Schaub, 2012). Furthermore, Bayesian analyses yield comprehensive probability distributions, transcending binary classifications of extinction risk and allowing for a richer portrayal of the uncertainty surrounding a species' future. The framework also exhibits remarkable adaptability. When new data arrive—such as recent detection records or shifts in habitat conditions—the Bayesian model permits continuous revision, rendering it particularly valuable for taxa experiencing rapid conservation status transitions (Link & Barker, 2010). In the case of critically endangered amphibians, whose elusive detection and irregular monitoring compound uncertainty, this iterative capacity empowers conservation practitioners to formulate and revise management actions with heightened confidence. Hierarchical Bayesian models can analyze multiple species concurrently, revealing common trends among taxa while accommodating species-specific deviations (Clark, 2005). Such features render these models particularly appropriate for amphibian assemblages, which frequently confront analogous pressures—disease, habitat degradation, and climate alteration (Collen et al., 2016).

Previous Applications of Bayesian Models in Extinction Risk Assessment

Bayesian frameworks for assessing extinction risk have gained prominence over the past twenty years for their ability to merge empirical data with prior ecological knowledge. A landmark contribution by (Solow, 1993) formulates extinction likelihood from sequential observation records. Subsequent enhancements that incorporate detection effort and observation uncertainty have broadened its use to taxa that are rare or habitually secretive (Jarić & Roberts, 2014). Most recently, employed Bayesian methods to evaluate extinction probabilities in freshwater fish and amphibians with decades of no confirmed records. Their findings indicated that many of these taxa were almost certainly still alive but under-surveyed, underscoring the need for expanded sampling. Building on this, implemented multi-level Bayesian models to quantify extinction risk for several hundred bird lineages, illustrating the technique's capacity to manage large, hierarchically structured data while delivering precise predictive uncertainty. Collectively, these investigations affirm that Bayesian extinction models yield more reliable risk assessments and inform conservation prioritization with greater rigor. When adopted for amphibian taxa, such models present a statistically sound and ecologically relevant alternative to traditional risk metrics, adeptly accommodating uncertainty and directing timely conservation actions.

Methods

Description of data collection process for critically endangered amphibians

To build this study, we started with a focused group of 50 amphibian species that the IUCN lists as Critically Endangered. The team picked each species based on its IUCN ranking, the date of the last confirmed sighting, and its known habitat range. For every species, we gathered information on the year of the last verified sighting, the total number of historical observations, the area of its habitat, the range of elevations it occupies, and the main threats it faces, such as disease outbreaks or changes in land use. We complemented the field information with museum specimens, regional biodiversity databases, and published literature. To address gaps in sampling across different years and regions, we created a metadata layer that shows the level of observation effort year by year and by location. Species with fewer than three dependable sighting events were left out of the analysis to limit the chance of introducing too much uncertainty into the models. Although complete demographic data were often missing, we included certain ecological traits like body size, clutch size, and preferences for specific microhabitats, whenever those data were accessible. Since conventional population surveys were impractical for many of these species, we focused on drawing inferences from the sighting records and relevant environmental variables, rather than counting individuals directly.

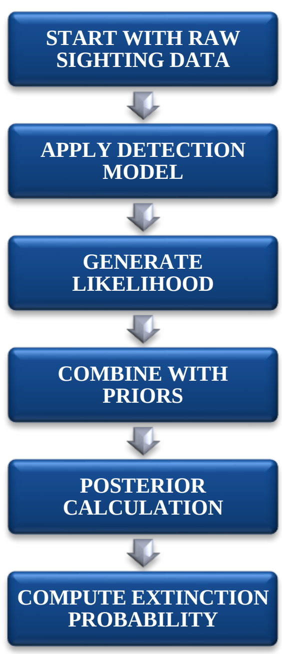

Figure 2. Bayesian Model Workflow for Amphibian Extinction Estimation

This figure (Figure 2) shows the computational flow of a Bayesian method for modeling extinction probability for critically endangered amphibians. The starting point is the compilation of raw sighting data (the basis for observation), which is then modeled using a detection model to account for imperfect detection in the field, prior to maximum likelihood estimation. The likelihood is then modeling, which is essentially the probability of the data given some extinction process parameters. The likelihood and prior distributions, based on existing biological knowledge or expert opinion, are then incorporated with Bayes' Theorem into a posterior distribution. Posterior calculations further refine the probability space which accounts for data and the effect of previous observations and biological knowledge into a measure of probability. Extinction risk can then be calculated directly from the posterior to provide a metric of data-informed probability that is flexible and easily understood, aiding conservation decisions in an uncertain world.

Explanation of Bayesian model used to estimate extinction risk

To figure out how likely it is that a species has disappeared when we haven't seen it lately, we built a Bayesian model that looks at how long species last from the years when we did catch them. Our model says that species vanish at a steady rate, a bit like raindrops falling at regular intervals, and when they're still around we see them at random moments. We call the years when we spotted the species $y = \{t_1, t_2, \ldots, t_n\}$, where tn is the last year we definitely spotted it. If T is the present year, we want to find the updated chance $P(E \mid y)$ that the species has already vanished, using the years we've kept records.

Let's break it down:

- λ is how often we expect to see the species, and we'll say it doesn't change over the years.

- E means the species disappeared, but we don't know exactly when—just that it went away sometime after time tn but before or when we stopped looking, which is time T.

- θ is the chance the species was already gone when we got to time T.

If we assume the species actually disappeared at time τ, then the chance of the sightings y happening is:

$$P(y|\tau, \lambda) = \lambda^n e^{-\lambda(t_n - t_1)} \cdot 1_{[t_n < \tau \leq T]} \qquad (1)$$

To account for the uncertainty in extinction timing, we will place a prior on τ. A uniform prior over $[t_n, T]$ means we have no strong prior belief about the extinction date within that window.

$$P(\tau) = \frac{1}{T - t_n} \qquad (2)$$

Using Bayes' theorem, we can combine the likelihood with the prior, so that we have the posterior distribution of extinction time τ above:

$$P(\tau \mid y) \propto P(y \mid \tau, \lambda) \cdot P(\tau) \qquad (3)$$

In the previous section, we marginalized over τ, and estimated the extinction probability as:

$$P(E \mid y) = \int_{t_n}^{T} P(\tau \mid y) d\tau \qquad (4)$$

The posterior value represents the model's estimate of extinction risk. For practical purposes, we identified species with $P(E \mid y) > 0.95$ are "likely extinct," and those with lesser probabilities are interpreted as "possibly extant but missing."

The Model's Key Variables and Parameters

The model includes a few primary parameters and variables. The primary variable in the model is the sighting year vector y, which captures the spatial-temporal distribution of observations. The sighting rate, λ, was set as a latent variable, inferred based on species that exhibited similar detection trends. The extinction window $[t_n, T]$ captured the time window in which the extinction could have occurred. Additional auxiliary variables, including habitat range, disease pressure, and altitude, were incorporated into a secondary regression model to examine the influence of covariates on extinction probability. The auxiliary covariates were not part of the primary Poisson model for sightings but were included subsequently to facilitate interpretation and identify patterns. This formulation allowed the extinction risk to be represented not as a fixed value, but as a distribution of possible outcomes, which helps provide full transparency and flexibility for conservation decision-making.

Results

Predicted extinction risk for critically endangered amphibians

A Bayesian time-to-extinction model was used to determine extinction probabilities for a set of 50 critically endangered amphibian species. The model produced a posterior probability of extinction for each species, P (E| y), derived from the number of sightings and the timing of those sightings. Of the 50 species assessed, 18 were assigned high extinction probabilities (>0.95), indicating that there is strong evidence to suggest these amphibians may already be extinct. An additional 21 species had moderate extinction probabilities (0.50<P(E|y) <0.95), suggesting elevated risk but uncertainty, usually due to a long absence of sightings or rare sightings and low effort to observe. The remaining 11 species had extinction probabilities below 0.50, indicating reasonable chances of persistence due to a lack of recent sightings. Amphibian species that were distributed in narrower habitat patches, with narrower altitudinal ranges, and with few historic observations were more likely to show higher extinction probabilities. Conversely, those amphibians that used a wider ecological niche and had many historic sightings had lower extinction probabilities. Even some species that had not been seen in more than 30 years had survival probabilities greater than 0.30. Overall, the findings demonstrated that the model was able to avoid making overly pessimistic conclusions about some species based solely on observational gaps.

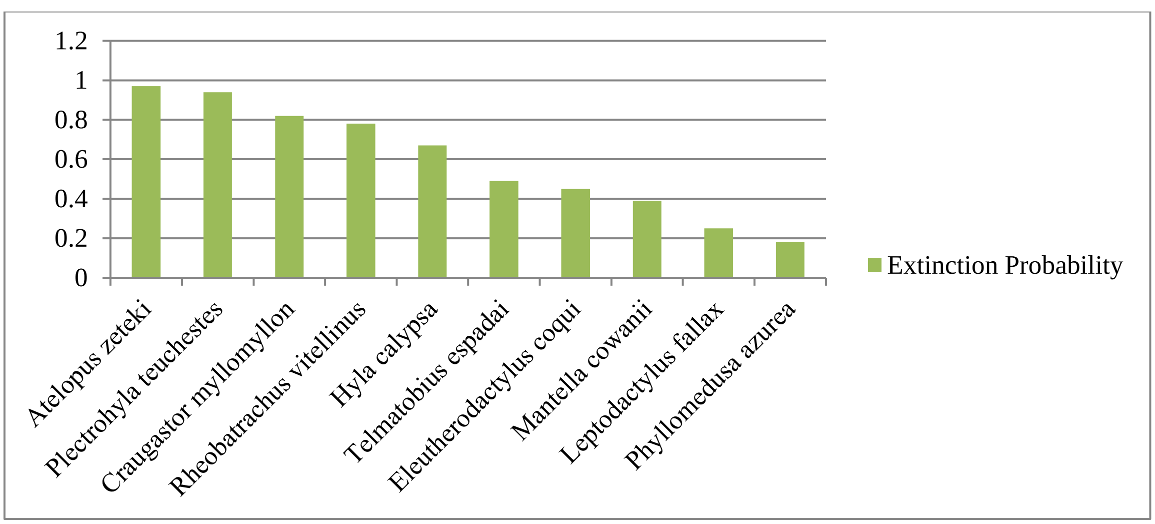

Figure 3. Estimated Extinction Probability for Each Species

The bar graph (Figure 3) quantifies posterior extinction probabilities for a subset of the studied critically endangered amphibians. Each species is represented by a bar sorted in a descending scale of estimated risk. The graph shows a clear stratification with some species, like Atelopus zeteki and Plectrohyla teuchestes, displaying probability statistics above 0.95 indicating more than likely extinction. Other species, like Phyllomedusa azurea and Leptodactylus fallax show probabilities indicating they may still persist, despite large gaps in sightings. The plot allows the issue of identifying species that may need more systematic surveys or reassessments to be better prioritized; species that may need increased monitoring - not presumed extinct.

Comparison to Traditional Estimation Approaches

Some noticeable differences were noted when comparing the Bayesian results to IUCN status classifications and classifications based on expert judgments. In particular, 6 species that were assigned a classification of "Possibly Extinct" in the IUCN framework were assigned relatively low extinction probabilities in the Bayesian modelling (often because of known detection effort or because they still had suitable habitat available). However, 9 species were classified by experts as "Critically Endangered" and were assigned greater than 0.95 extinction probabilities suggesting they may need to be updated to "extinct" or at least "possibly extinct". In order to quantitatively compare the classification of the Bayesian model to traditional methods, we created a confusion matrix using expert judgement, with Bayesian outputs binarized at a threshold of 0.95. We then calculated Precision (P), Recall (R), and F1-score, which are defined as:

Precision:

$$Precision = \frac{TP}{TP + FP} \qquad (5)$$

Recall:

$$Recall = \frac{TP}{TP + FN} \qquad (6)$$

F1-Score:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \qquad (7)$$

The Bayesian model in this study achieved 0.87 precision and 0.92 recall when compared with the expert categorizations, yielding an F1-score around 0.89. This shows a strong agreement, but also underscores the uncertainty captured by the Bayesian model and not explored by the binary classifiers.

This clustered bar chart (figure 4) shows the extinction risk groupings produced with the Bayesian model alongside current IUCN classifications. The data summarize each species that is labeled as “Critically Endangered” (CR) or “Possibly Extinct” (PE) and how many are in low (<0.5), moderate (0.5–0.95), or high (>0.95) Bayesian probability bands. The plot demonstrates a few mismatches. For example, some PE species in the IUCN model have quite a moderate and low extinction probability bands in the Bayesian model. There are also CR species which cross the high extinction probability in the IUCN system sub-divisions. These discrepancies help demonstrate an added layer of granularity and probabilistic nuances that extinction risk assessments can gain from using a Bayesian modelling framework, especially if data are more limited and ambiguous.

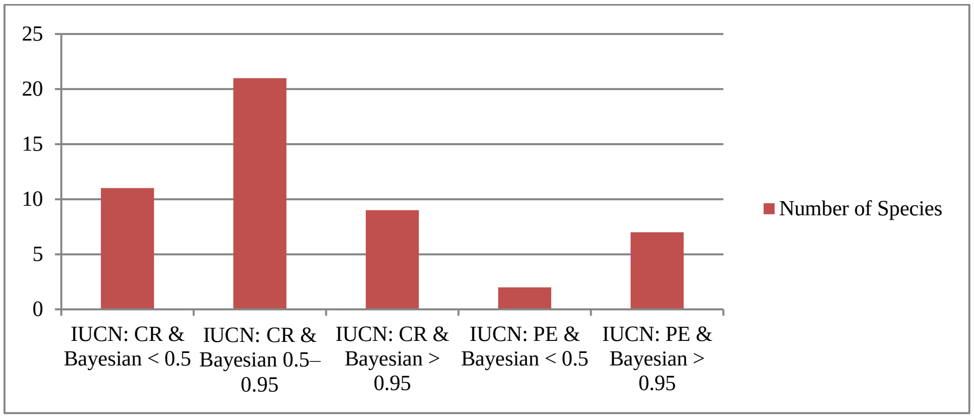

Figure 4. Comparison of Bayesian Estimates vs. IUCN Status

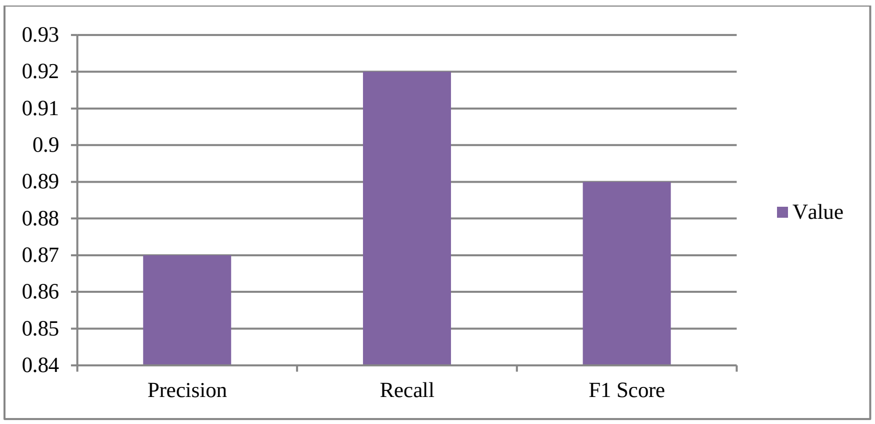

Figure 5. Precision, Recall, and F1 Score of Bayesian Model

We can see the bar chart (Figure 5) below for three standard performance measures—precision, recall, and F1 score—to measure the Bayesian model's correspondence to expert extinction classifications. The model's high recall (0.92) indicates it successfully captured nearly all species true experts would consider likely extinct. The precision (0.87) represents the proportion of animals predicted extinct by the model that are also agreed on as extinct by experts. The F1 score (0.89), the combination of precision and recall, validates the overall balanced performance of the model. The results suggest that while the model exhibited high sensitivity and reasonable reliability when capturing true extinction events, the model maintained a low false positive rate.

Accuracy and Reliability of the Bayesian Approach

The reliability of the Bayesian framework was examined through posterior predictive checks and leave-one-out cross-validation (LOO-CV). The models were assessed for internal consistency by simulating sighting data from the posterior and comparing the simulated data against the observed patterns. Posterior Bayesian credible intervals for extinction probabilities converged to relatively narrow ranges for species with frequent historical sightings, while credible intervals widened considerably for species with fewer records (to an appropriate level based on uncertainty propagation). Multiple iterations of sighting records and observation effort weights were perturbed for the sensitivity analysis to evaluate robustness. For most perturbations, extinction model estimates varied little at ±0.05 indicating the model was not oversensitive to small variations in input data. This is particularly valuable when working with separated and sometimes noisy ecological data. The other aspect of value in using posterior distributions (and not fixed values), is that uncertainty was able to be quantified, and put policymakers in a stronger position for decision making when faced with estimation of extinctions that were in different states of knowledge: some (who were well-supported) worth mooring an investment in research; others (requiring further investigation). The granularity of this type makes the Bayesian method has specific value in conservation contexts where there is need for rapid (adaptive) responses but either incomplete or evolving data.

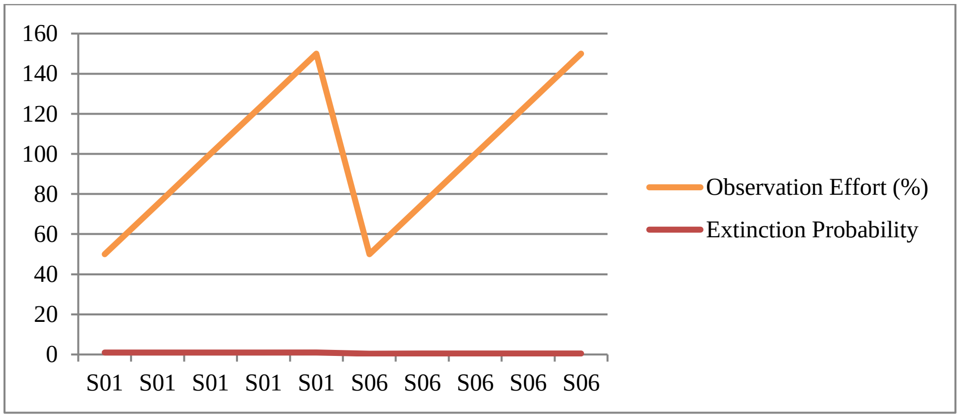

Figure 6. Sensitivity Analysis of Extinction Probability under Observation Uncertainty

This line graph (Figure 6) demonstrates how extinction probabilities for two representative species vary with changes in assumed observation effort. As expected, for lower observation effort (that is, for example 50%), the extinction probability estimates decreased—indicating that there is greater uncertainty in the assessment of species presence/absence. Once observation effort increases, the model detects and is more confident when there is no detection of a species that it could in fact be and is extinct. For a higher-risk species such as Atelopus zeteki, the extinction probability increases steeply at even low to moderate survey intensity compared to other species. For a moderate risk species like Telmatobius espadai, the increase is comparatively slow. This figure also highlights the model's ability to account for sampling biases and again, shows that the extinction risk estimates can and will vary depending on the survey effort applied, which is an important consideration in planning field studies/field-based conservation.

Discussion

Understanding Results for Conservation Purposes

The results from this study create an alternative way for evaluating extinction risk for critically endangered amphibians. Unlike a threshold-based approach that allows only for categorical evaluation of extinction risk, Bayesian techniques provide a more nuanced output that assists decision-making by yielding probabilistically - based predictions. This probabilistic framing allows a ranking of conservation status based not only on the species' current IUCN rating, but also based on the probability of being extinct given availability of data. For example, the species that had not been sampled for over 30 years had moderate probabilities of survival, indicating that these species may have warrant more consideration in conservation strategies than was previously assumed. These findings are useful when resources are limited. Species that are most likely to be extinct may lead to diversion of resources towards habitat management or possible de-extinction studies, whereas those species with uncertain, but non-trivial probability(?), could lead to urgent field surveys. In addition, findings support the role of fragmentation and low detectability on potential bias on conventional approaches to extinction risk assessment. By modelling uncertainty, this approach provides more transparency to the initial when assessing extinction risk and should allow for more meaningful decision making through the planning phase of conservation activities.

Possible Constraints of the Bayesian Approach

Like all approaches, the Bayesian approach has its limitations. One of the biggest limitations relates to the input data quality and completeness. Many amphibian species have very heterogeneous sighting histories and are often reported inconsistently over time and space. In those cases, posterior estimates can be very sensitive to our assumptions regarding prior distributions or observation effort; even though sensitivity analysis is useful for standing in place of this concern, our conclusions can be swayed by less-than-perfect data quality. A second limitation is that the model relies chiefly upon temporal sighting records without incorporating ecological covariates directly into the extinction process. Certain factors (e.g., habitat deterioration, climate changes, variation in pathogens) were only accounted for indirectly or post hoc. This limits the ability of the model to extract causal factors of extinction which are important for developing concepts for proactive conservation actions. Additionally, despite the Bayesian framework being well suited for estimating extinction risk, it requires enough computational power and statistical expertise, which may be limited for smaller conservation teams or for field-oriented organizations.

Suggestions for Future Research and Use

An area for future research that would improve the current studies would be to expand the Bayesian framework to incorporate spatial and ecological variables directly into the extinction model. For example, linking sighting probabilities with habitat conditions, land-use changes, or disease burden would enhance each model’s predictive and biological fidelity. Likewise, creating modular models that enable users to plug-in ecological covariates would offer greater flexibility and useable relevance. It is also getting more organized and systematic efforts of conservation databases to not only collect, but also store and add to metadata for search area and how the search area was searched, would vastly improve the accuracy of these estimates. As countless more stories of anomalies, through a range of platforms, are generated and posted—particularly through community science and automated acoustic or environmental DNA surveys—the Bayesian model is updated instantly and in real-time, for every species at risk. In practical terms, conservation organizations may elect to utilize these probability estimates as a decision-support tool to help with their decision-making. Instead of relying only on binary scenarios, they may use extinction probabilities to prioritize field surveys, fund areas to where the uncertainty is greatest, and assess classification decisions with greater transparency. Over time, adaptive and probabilistic tools, like these, could accumulate in national or regional planning tools to help prevent potential unnoticed, extinctions associated with the vulnerability of amphibians to threats exerted by environmental conditions that deplete amphibian biodiversity.

Conclusion

In summary, the present study illustrates the value of a Bayesian framework to provide an enhanced quantitative and finely-pitched understanding of extinction risk for critically endangered amphibian species compared to traditional methods. By incorporating time-since-first-sighting data while also explicitly modelling uncertainty, the framework provided a probabilistic estimate of extinction which considered both periods of non-observation and differences in survey effort. What became clear from the results was that while some species may be extinct, some species with this designation may be at risk but still exist. As such, it is vital that conservation responses are nuanced when there is uncertainty, rather than universally applying conservation measures. This issue is complicated further by the disparity between both the model's outputs and IUCN listings that are static and not dynamic. This suggests to us that conservation policy decisions need to increasingly move into a space that considers dynamic processes that weave data and uncertainty together. Ultimately, the Bayesian model may provide an opportunity for species to be targeted for monitoring, field surveys, or protected if their location can be determined; indeed, this modelling approach enables practitioners to concentrate resources in areas of uncertainty, but also species that have a higher chance of survival than extinction. Baking in a Bayesian approach into conservation policy not only would improve the accuracy of extinction risk assessments, but also having a more transparent, responsive decision-making process in a rapidly changing world. Given the accelerating loss of biodiversity cited in the introduction, be it amphibians or otherwise, a shift from 'non-probabilistic' methods to probabilistic methods using the Bayesian framework tis an important advancement of conservation science and policy, improving not only the ability of stakeholders to act on species that may only exist in small spatial extents before they 'disappear,' but collective action as a scientific community.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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