

Research Letters

Wallacean shortfall is not reasonable for omitting poorly known species from the climate change agenda

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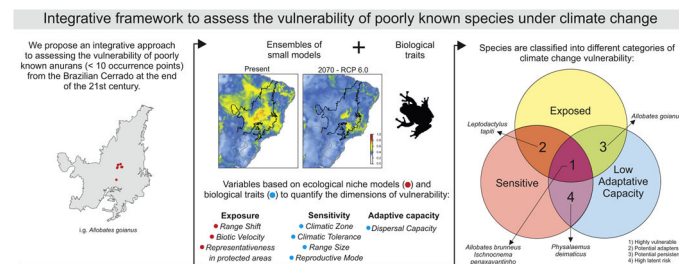
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HIGHLIGHTS

- Anthropogenic climate change threatens biodiversity and accelerates extinction risk.
- Poorly known species are traditionally omitted from the climate change agenda.
- We present an integrative framework to assess the vulnerability of poorly known species.
- Most poorly known species will show increasing vulnerability by 2070.
- Our low-cost techniques help complement existing extinction risk assessments.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change strongly affects species dynamics over spatial and temporal scales and serves as a major driver of future extinction risk. Conservationists have largely assessed the impacts of global warming on species with well-documented distributions; however, poorly known species have often been excluded from the climate change agenda because of the Wallacean shortfall (incomplete knowledge of species' geographic distributions). Here, we deconstruct this traditional argument by considering poorly known species in climate change research and proposing an integrative framework to assess their vulnerability by the end of the 21st century. By integrating trait-based and niche modeling approaches, we assessed the climatic vulnerability of seven poorly known anurans in terms of exposure, sensitivity, and adaptive capacity. The results showed that two species were classified as highly vulnerable, whereas three others were classified as potential adapters, potential persisters, or at high latent risk. These findings suggest that historically neglected species may face increasing vulnerability by the end of 2070. The study underscores the need to incorporate poorly known species in future climate change agendas, despite the persistent Wallacean shortfall.

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Introduction

Anthropogenic climate change has emerged as a major threat to biodiversity in recent decades (Bellard et al., 2012; Beyer and Manica, 2020). Predictions indicate a rapid increase in temperature and shifts in precipitation patterns by the end of the 21st century (Intergovernmental Panel on Climate Change [IPCC], 2023), with severe consequences for species survival (Manes et al., 2021). Climate change challenges organisms to remain in situ, disperse to new habitats, or adapt to novel conditions (Bellard et al., 2012). Consequently, species can exhibit varying levels of vulnerability depending on three dimensions: the rate and magnitude of climate change to which they are exposed (i.e., exposure), intrinsic biological traits shaping their climatic tolerance (i.e., sensitivity), and inherent capacity to adapt to novel climates (i.e., adaptive capacity) (Dawson et al., 2011; Pacifici et al., 2015). Understanding how these factors drive the species vulnerability is fundamental for predicting biodiversity dynamics under climate change scenarios and designing effective conservation strategies (Advani, 2023; Malanoski et al., 2024).

Conservationists typically assess the effects of global warming on species with well-documented geographic distributions (Mancini et al., 2023; Naujokaitis-Lewis et al., 2021; Zhu et al., 2022). However, poorly known species, particularly those with limited occurrence data, are often excluded from climate change research and conservation assessments (Haelewaters et al., 2024). This exclusion is partly justified, as these species not only have limited occurrence data but also often suffer from significant biases and data gaps, such as imprecise localities that lead to geographic uncertainties or their occurrence in undersampled biomes (Hortal et al., 2008; Hughes et al., 2021; Meyer et al., 2016). The Wallacean shortfall, defined as incomplete knowledge of geographic species distribution (Hortal et al., 2015), is particularly challenging because it leads to ignoring their vulnerability (Pacifici et al., 2015). Many poorly known species face extinction risk comparable to those of species with well-documented distributions (Borgelt et al., 2022; Howard and Bickford, 2014; Morais et al., 2013), thereby highlighting the need to explicitly address the Wallacean shortfall in conservation planning (Nori et al., 2023; Urbina-Cardona et al., 2023).

Because of their biological traits and restricted geographic ranges, amphibians are considered among the taxa most vulnerable to climate change (Wake and Vredenburg, 2008). Altered precipitation and temperature patterns may reduce reproductive success, diminish climatically suitable areas, and facilitate the spread of pathogenic fungi (Alves-Ferreira et al., 2022; Luedtke et al., 2023; Ribeiro et al., 2020). Climate change is a major threat to species listed on the IUCN Red List; however, its impacts are often underestimated because they are not explicitly incorporated into most IUCN assessments, which primarily focus on distribution, population size, and habitat trends (Luedtke et al., 2023), particularly for poorly known species (Della Rocca et al., 2019). Biodiversity hotspots (Myers et al., 2000), including the Brazilian Cerrado, warrant special attention in amphibian research because of their exceptionally high endemism (Valdujo et al., 2012) and existing threats, such as agricultural expansion and limited protected area coverage (Pompeu et al., 2024). Projections indicate that the Brazilian Cerrado is set to become increasingly warmer and drier, intensifying the impacts on biodiversity (Hofmann et al., 2021). In addition, the Wallacean shortfall in the Brazilian Cerrado is pronounced due to historical and socioeconomic factors: biodiversity surveys are relatively recent and spatially biased, often concentrated in accessible areas, and reflect patterns of late human occupation (Bini et al., 2006; Guerra et al., 2020; Diniz-Filho et al., 2005). Limited funding for fieldwork and conservation, combined with the rapid conversion of native vegetation prior to the completion of new inventories, further exacerbates these knowledge gaps (Bini et al., 2006; Strassburg et al., 2017). Therefore, the Brazilian Cerrado serves as an desirable biogeographic model for assessing the vulnerability of poorly known anurans to future climate change.

Here, we proposed an integrative approach based on low-cost and

rapid-response techniques to assess the vulnerability of poorly known species in the context of climate change scenarios. Specifically, we integrated common biological traits with niche-modeling predictions (Table 1) to independently quantify the exposure, sensitivity, and adaptive capacity of poorly known anurans from the Brazilian Cerrado by the end of 2070. Together, these dimensions capture a broad range of climate-change-related stresses affecting neglected biological groups facing imminent extinction in a critical biodiversity hotspot, thereby presenting a pressing challenge for conservation biogeography at present.

Methods

Species and climatic data

First, we selected poorly known endemic anuran species based on the official anuran species list for the Brazilian Cerrado (Valdujo et al., 2012). Occurrence records were primarily sourced from the literature and field specialists who documented species occurrences. Additionally, we consulted online databases, such as speciesLink (<http://splink.cria.org.br/>), Global Biodiversity Information Facility (GBIF; <https://www.gbif.org/>), and the *Sistema de Avaliação do Risco de Extinção da Biodiversidade* (SALVE; <https://salve.icmbio.gov.br/>) (Fig. 1 - step 1). The compiled occurrence records cover the period from 1972 to 2013 (Table S1 in the Supplementary Material). All occurrence records were manually reviewed by co-authors who are experts on the anuran fauna of the Brazilian Cerrado. Records were validated based on expert field knowledge of species ecology and known distribution; unreliable records were excluded. Following this validation, we excluded duplicate records within pixels at a 30-s resolution (approximately 1 km). Species with fewer than five unique species records were excluded, leaving seven species with a total of 70 records (Fig. 2, Table 2): *Allobates goianus*, *Allobates brunneus*, *Hylodes otavioi*, *Ischnocnema penaxavantino*, *Leptodactylus tapiti*, *Physalaemus deimaticus*, and *Proceratophrys moratoi*. Most species had limited occurrence records (<10 occurrences, except for *H. otavioi* and *P. moratoi*; refer to Table 2), indicating poor knowledge of their geographic distributions. All data processing and subsequent analyses were performed using R software (R Core Team, 2021).

We obtained 19 bioclimatic variables for the present (1960–1990) and future (2070) climate layers from the WorldClim 1.4 database (<https://www.worldclim.org/>) at 30 seconds spatial resolution (approximately 1 km²) (Fig. 1 - step 1). For future predictions, we used the intermediate RCP6.0 emission scenario, selected to avoid extreme trajectories, under three atmosphere-ocean general circulation models (AOGCMs: CCSM4, HadGEM2-AO, and MIROC ESM). These AOGCMs were selected to preserve the original uncertainties of future climatic predictions (Varela et al., 2015). To reduce collinearity among bioclimatic variables (Fig. 1 - step 1), we applied principal component analysis (PCA) with orthogonal rotation and selected the first six axes, which explained 96.6% of the original variance, as predictors in the niche models. PCA was first performed on the present bioclimatic variables, and the resulting coefficients were subsequently applied to obtain climatic scores for future scenarios. All spatial data, including species occurrences and bioclimatic variables, were projected onto the WGS84 geographic coordinate system.

Niche modeling

The analyses covered the entire Brazilian Cerrado and its neighboring areas (65 ° W, 34 ° W, 35 ° S, 0), considering all accessible areas for the species to develop a niche model (Fig. 2). We employed an ensemble of small models (ESMs) (Breiner et al., 2015, 2018) to model the potential distributions of poorly known anurans under current and future scenarios (Fig. 1 - step 2). ESMs are strongly recommended when occurrence points are few and numerous climatic predictor variables are involved. The ESMs were constructed using bivariate combinations of

Table 1

Variables based on the ecological niche model and biological traits used to quantify and classify poorly known species across the three dimensions of vulnerability: exposure, sensitivity, and adaptive capacity.

| Variables | Variable type | Justification |
|---------------------------------------|------------------------|--|
| Exposure | | |
| Range Shift | Ecological niche model | The geographic distribution of many species is potentially changing due to climate change, which reduces their climate suitability ranges, contributes to increased exposure and increases the risk of extinction (Dubos et al., 2022). |
| Biotic Velocity | Ecological niche model | As habitats with suitable climatic conditions for species survival may change over time in response to climate change, one strategy is to track suitable areas for their survival (Maclean and Wilson, 2011). However, species are often unable to keep pace with these changes, increasing their exposure to climate change (Carroll et al., 2015; Román-Palacios and Wiens, 2020). |
| Representativeness in Protected Areas | Ecological niche model | Tracking by climatically suitable habitats over time may lead species to migrate to areas with more favorable conditions for their survival. Consequently, they may leave protected areas, that were originally delineated based on their current distributions, thereby becoming more exposed. (Chen et al., 2017). |
| Sensitivity | | |
| Climatic Zone | Biological trait | A species that is restricted to a single climatic zone is more sensitive to climate change than a species that occupies multiple zones (Ofori et al., 2017). |
| Climatic Tolerance | Biological trait | Species distribution patterns are related to climatic tolerance limits (Grinnellian niche) that reflect on their establishment and survival. Species with smaller niche breadth are more sensitive to climate change. |
| Range Size | Biological trait | The geographic range size is the best predictor for the extinction risk of some species, where small range sizes increase the risk of extinction (Ripple et al., 2017). With climate change, many species are expected to reduce their range size, becoming more sensitive (Menéndez-Guerrero and Graham, 2013). |
| Reproductive Mode | Biological trait | Amphibians depend on a certain availability of water to reproduce. However, amphibians that need bodies of water for the development of aquatic larvae are more vulnerable than species with direct terrestrial development, as fluctuations in precipitation and temperature patterns can cause evapotranspiration resulting in drying bodies of water (Blaustein et al., 2010). Furthermore, the dependence on two habitats (terrestrial + aquatic) for breeding, makes amphibians with the development of aquatic larvae more sensitive when having to move around in geographic space (Becker et al., 2007). |
| Adaptive capacity | | |
| Dispersal Capacity | Biological trait | The size of the body seems to determine the dispersion capacity in some species (Feijó et al., 2023). Thus, smaller body sizes may be associated with reduced dispersal ability (Feijó et al., 2023; Pabijan et al., 2012), which in turn could lead to lower adaptive capacity (Ofori et al., 2017) in response to new climatic conditions. |

the PCA-derived predictors. Specifically, we examined all possible combinations of the six predictors to construct bivariate models, i.e., with only two predictors, yielding 15 bivariate model combinations. We constructed the ESMs for present conditions and projected them into the future scenario by combining each AOGCM with RCP6.0 and using clamping to limit extrapolation beyond the range of environmental values in the training dataset. We applied five methods based on the presence data: Bioclim (Busby, 1991), Enfa (Hirzel et al., 2002), Gower (Carpenter et al., 1993), MaxEnt (Elith et al., 2011), and SVM (Vapnik, 1995). All algorithms were executed with their default parameter settings. We generated 300 ESMs for each species [15 bivariate model combinations × 5 methods (present scenario) + 15 bivariate model combinations × 5 methods (future scenario) × 3 AOGCMs × 1 RCP6.0]. To calibrate the presence-background methods (MaxEnt and SVM), we generated a set of 10,000 background points that were randomly sampled from the entire study area. The ESM process was performed using the raster (Hijmans, 2023), *dismo* (Hijmans et al., 2023), *adehabitatHS* (Calenge, 2023), *vegan* (Oksanen et al., 2022), and *kernelab* (Karatzoglou et al., 2004) packages. We employed the jackknife leave-one-out method to evaluate the predictive performance of each ESM prior to ensembling, as it is suitable for models with few occurrence points (Pearson et al., 2007) (Fig. 1 – step 2). In this procedure, a model was trained with n-1 points to predict the withheld point. A prediction was considered successful if the suitability score of the point exceeded the 5th percentile threshold derived from the training points. Finally, the D-statistic and its associated p-value were calculated from the complete set of successes and failures using a custom function that implemented the statistical test established by Pearson et al. (2007). We used the mobility-oriented parity (MOP) metric (Owens et al., 2013), as implemented in the *kuenm* package (Cobos et al., 2019), to measure the similarity between climatic combinations and areas of strict extrapolation when projecting from present to future scenarios. We calculated the final ensemble for the present and future ESMs by averaging the models previously weighted according to their D-statistic performance scores, thereby generating climatic suitability maps for each species. The complete R scripts necessary for replicating the entire modeling workflow, including the PCA functions, are available in the GitHub repository (refer to the “Data statement” section).

Scoring and classifying species vulnerability

We evaluated vulnerability by classifying each species according to the three dimensions of climate change vulnerability: exposure, sensitivity, and adaptive capacity (Foden et al., 2013). Exposure, defined as the degree to which species are affected by climate change, was measured using three variables: range shift, biotic velocity, and representativeness in protected areas. Sensitivity, defined as the degree to which species tolerate changing climates (e.g., physiological tolerance), was measured using four variables: climatic zone, climatic tolerance, range size, and reproductive model. Adaptive capacity, defined as the inherent ability of a species to adapt to novel climates, was measured as dispersal capacity (refer to details in Table 1). Species were scored based on each variable as follows (Fig. 1 - step 3):

Exposure

Range shift – We estimated the potential distribution area of each species using a threshold of 0.5% (i.e., each species was distributed within 0.5% of the higher-suitability area). However, predicting the morphoclimatic domains of poorly known anurans often overestimates their geographic distributions and underestimates their exposure to climate change. Therefore, we generated binary maps depicting the geographic distribution of each species under present and future climatic scenarios and analyzed the magnitude of distribution area contraction in the future, calculated using the formula:

$$\text{Range shift} = \text{lost} / (\text{lost} + \text{stable})$$

where ‘lost’ is the currently suitable area that is projected to become unsuitable in the future; and ‘stable’ is the currently suitable area that is expected to remain suitable in the future. The higher the loss of a potential distribution area in the future, the greater the exposure of a species (refer to details below).

Biotic velocity – We calculated the forward biotic velocity (Carroll et al., 2015; Hamann et al., 2015), an indicator of species extinction risk associated with exposure to climate change over time. The forward velocity reflects the minimum distance that a species must disperse to maintain itself under constant climatic conditions (Carroll et al., 2015).

The velocity calculations were based on ensembles of present and future climatic scenarios, measuring the minimum distance a species must disperse from grid cells of the present that are anticipated to lose climatic suitability to those that are expected to become suitable in the future. Subsequently, we calculated the average forward velocity for each species. We assumed that a species is more exposed to climate change if it needs to traverse greater distances to remain within climatically suitable habitats (refer to details below).

Representativeness in protected areas – We evaluated the representativeness of species within the protected areas using the species representativeness index (SRI) method (Alagador et al., 2011). The SRI represents an estimate based on the proportion of the grid cell that is both protected and climatically suitable for a species (Alagador et al., 2011). We mapped all PAs and indigenous lands in the MMA database (available at <http://www.mma.gov.br>) and *Reservas Particulares do Patrimônio Natural* (RPPNs) listed in the ICMBio database (available at <http://www.icmbio.gov.br>). Data on protected areas outside Brazil were sourced from the Protected Planet database (available at <http://www.protectedplanet.net>). Second, we quantified the proportion of grid cells that were protected and estimated the likelihood of species representation within climatically suitable grid cells:

$$SRI_j = \sum_{i=1}^N (s_{ji} * p_i) / \sum_{i=1}^N (p_i)$$

where s_j is the climatic suitability of species j in grid cell i , as determined by the ensemble; p_i indicates the proportion of the grid cell that is protected; and N is the total number of grid cells. We considered that species with reduced representation in protected areas under future climatic scenarios will face increased exposure (refer to details below).

Sensitivity

Climatic zones – We obtained the number of climatic zones occupied by the species using the Köppen climate classification (Alvares et al.,

2013). We analyzed the geographical distribution by overlaying the occurrence points of each species with climatic zones and quantified the number of zones in which each species occurred. If the species was restricted to only one climatic zone, we considered it to be more sensitive than species inhabiting multiple zones (refer to details below).

Climatic tolerance – We estimated climatic tolerance by calculating the difference between the maximum and minimum values of climate predictors (Grinnellian niche) for each species, as determined by the PCA scores in this study. Species with small niche amplitudes were considered more sensitive than those with large niche amplitudes (refer to details below).

Range size – We estimated range sizes by considering the number of occurrence points for each species. We assumed that species with fewer occurrence points exhibited a smaller range; therefore, they were more susceptible to climate change (refer to details below).

Reproductive mode – We classified the species based on their larval development in aquatic and terrestrial environments. Species with aquatic larvae must migrate to aquatic environments for reproduction before returning to terrestrial environments, whereas species that undergo terrestrial development can reproduce without migrating (Becker et al., 2007). Therefore, species with aquatic larval development exhibit greater sensitivity due to their need to migrate across various habitats for reproduction (a requirement absent in terrestrial larvae). Furthermore, changes in precipitation and temperature can impact water availability, thereby challenging water development during drought periods (Blaustein et al., 2010).

Adaptive capacity

Dispersal capacity – We defined dispersal capacity as a function of body size (snout-vent length, SVL) (Ofori et al., 2017). SVL data were derived from original species descriptions, primarily based on holotypes. We assumed that a smaller body size correlated with a reduced dispersal ability to keep up with climate change. In other words, the

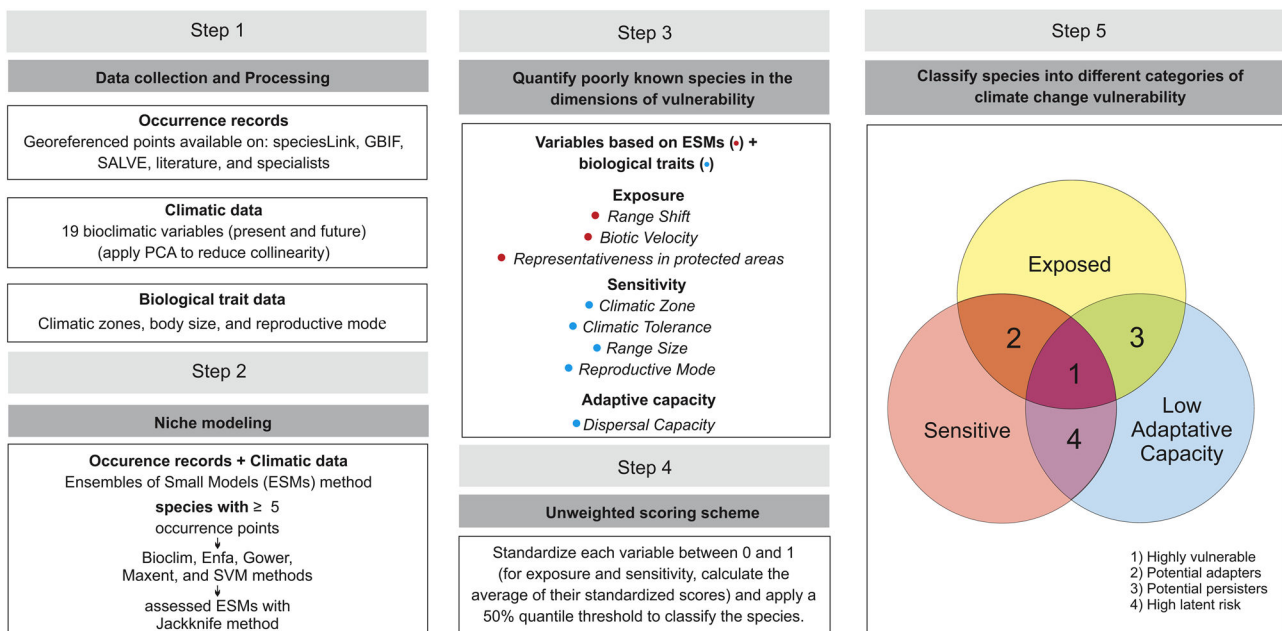


Fig. 1. Methodological procedures used to assess the vulnerability of poorly known species to climate change. The first step corresponds to data collection and preparation (species occurrences, climatic data, and biological traits) (Step 1). With the occurrence records and climatic data, the next step is to model the potential distribution of each species through the current and future scenarios using the ensemble of small models (ESMs) method (Step 2). Next, the three dimensions of vulnerability (exposure, sensitivity, and adaptive capacity) are quantified using various variables based on the ESM results (red dots) and species' biological traits (blue dots) (Step 3). Afterward, the variables are standardized, and a threshold is applied to classify the species in three dimensions of climate change vulnerability (exposure, sensitivity, and adaptive capacity) (Step 4). Finally, based on the combination of these three dimensions, the species are classified into different categories of climate change vulnerability (Step 5). All steps were performed in R software (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

smaller the species, the lower its mobility for dispersal (Ofori et al., 2017). Consequently, these results indicated a reduced capacity to adapt to climate change (refer to details below).

After obtaining all variables, we classified species vulnerability by combining the three dimensions as outlined by Foden et al. (2013). We employed an unweighted scoring scheme to combine the dimensions of vulnerability, assigning equal importance to all variables (Fig. 1 - step 4). Because each variable produced outputs in different units, we initially standardized their scores between zero and one. As exposure and sensitivity encompassed multiple variables, we calculated the mean standardized scores for each of the two dimensions. Consequently, each species was assigned a score for each of the three dimensions, with values ranging from 0 to 1. Additionally, we applied a 50% quantile threshold to classify the most exposed, most sensitive species, and those with the lowest adaptive capacity (Table 2). We assumed equal weights for all variables, although we recognized that some may be more important in assessing the vulnerability of specific species and that the threshold used to classify the species was arbitrary (Foden et al., 2013; Ofori et al., 2017; Pacifici et al., 2015). Our analyses addressed poorly known species with limited available data. As additional information regarding these species emerges, particularly regarding their species traits and climate change impacts, we recommend that variable weights and thresholds be reviewed and updated. Finally, we combined the three dimensions and classified species into four climate change vulnerability categories (Fig. 1 – step 5): highly vulnerable (exposed, sensitive, and low adaptive capacity), potential adapters (exposed and sensitive species), potential persisters (exposed and low adaptive capacity), and high latent risk (sensitive and low adaptive capacity) (Foden et al., 2013).

Results

Niche models (ESMs) effectively predicted species distributions under present and future climate scenarios, demonstrating good predictive performance and transferability (Table S2 and Fig. S1 in the Supplementary Material). Overall, the ESMs also indicated increased current climatic suitability in the southern and southeastern portions of the Brazilian Cerrado, with projected shifts of suitable habitats toward the Atlantic Forest by 2070 (Fig. S2 in the Supplementary Material). The ensemble projections indicated a reduction in the original climatically suitable area for all analyzed species (Table S3 in the Supplementary Material). The magnitude of this loss ranged from 33.2% in *P. deimaticus* to 80.1% in *A. brunneus*.

Five species were identified as vulnerable to climate change by the end of 2070 (Fig. 3 and Table 2); *P. moratoi* (classified as a Least Concern species) and *H. otavioi* (classified as a Vulnerable species) were not considered potentially challenged by climate change (Table 2). Our findings indicated that four species would be highly exposed, four would be highly sensitive, and four would have a low adaptive capacity to climate change by the end of 2070 (Table 2).

Based on the combination of the three dimensions of vulnerability, two species (the Endangered species *A. brunneus* and the Least Concern species *I. penaxavantinho*) were classified as highly vulnerable under climate change scenarios. This classification was based on the highest exposure, sensitivity (narrowest niche breadth), and lowest adaptive capacity (Fig. 3). One species, *L. tapiti* (a Vulnerable species), was classified as a potential adapter because of its high exposure and sensitivity (Fig. 3). One species, *A. goianus* (a Near Threatened species), was classified as a potential persister with low adaptive capacity and high exposure (Fig. 3). One species, *P. deimaticus* (a Least Concern species),

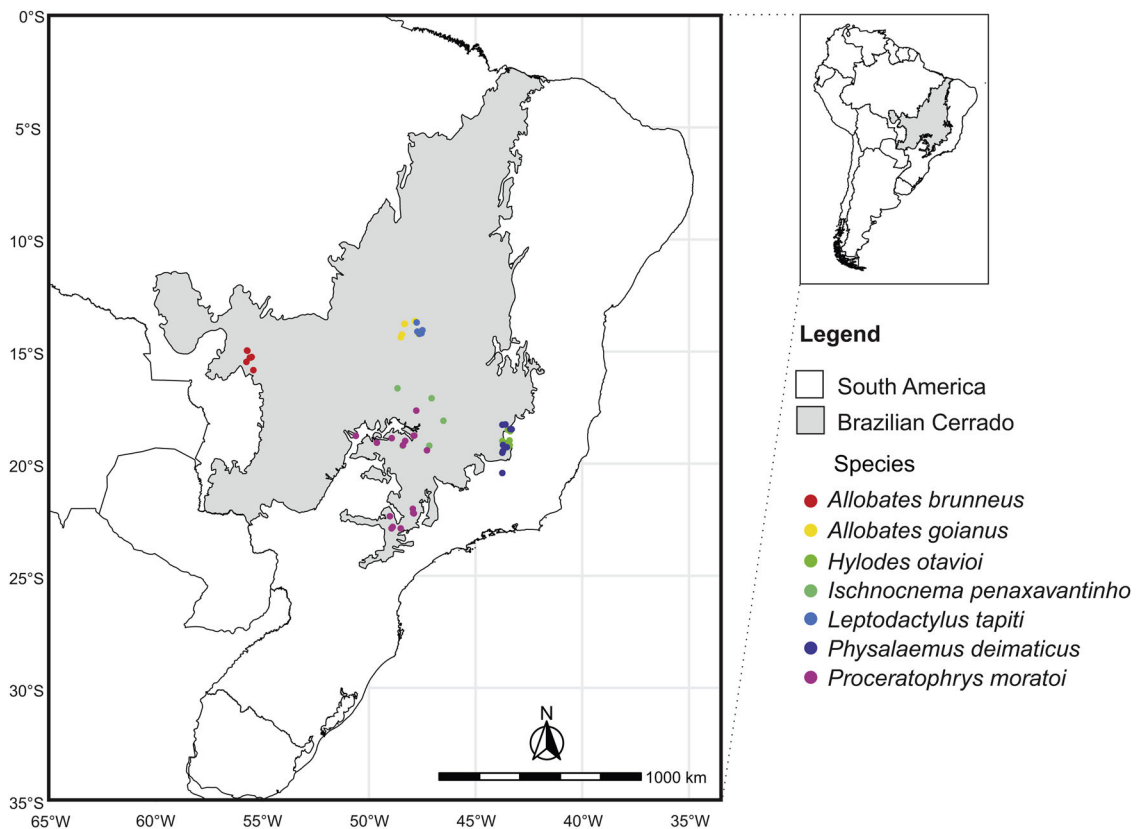


Fig. 2. Study area and spatial distribution of occurrence points for seven poorly known anurans of the Brazilian Cerrado. The main map illustrates the study area, encompassing the entire Brazilian Cerrado (gray area) and neighboring regions used for niche modeling. Different colors indicate occurrence points for each species. The inset map depicts the Brazilian Cerrado (gray area) in South America. Datum: WGS84.

was classified as having high latent risk, low adaptive capacity, and high sensitivity.

Discussion

Our findings explicitly support the possibility of considering poorly known species in the climate change agenda while assessing their vulnerability to ongoing changes. By integrating trait-based and niche modeling approaches, we disentangled the specific dimensions that render species vulnerable to climate change, with distinct implications for conservation prioritization. Our approach revealed that *I. penaxavantinho*, currently classified as a Least Concern anuran, is projected to become as vulnerable as *A. brunneus*, a species classified at one of the highest threat levels (i.e., Endangered) according to the IUCN Red List (IUCN, 2023). This finding indicates that the vulnerability and imminent extinction risk of species categorized as non-threatened may be equivalent to those of conventional target species (most of which are categorized as threats) and should be rigorously considered in conservation planning. Similar patterns have been observed in other climate vulnerability assessments, indicating that non-threatened species also exhibit high vulnerability to climate change (Böhm et al., 2016; Borges et al., 2019). Conservation actions for highly vulnerable species may involve in situ measures, such as the establishment of protected areas and climatic refugia, and in extreme cases, assisted migration. Potential adapters (species that can mitigate the impacts of climate change through dispersion; *L. tapiti*), necessitate rigorous monitoring of their dispersion as a conservation action. In these instances, expanding or reinforcing protected areas and ensuring landscape connectivity may be essential for enhancing their capacity to adapt to future climatic shifts (Böhm et al., 2016). In contrast, conservation efforts for potential persisters (species capable of tolerating climate change in situ; *A. goianus*) and species at latent risk (species not directly exposed to novel climates; *P. deimaticus*) may be less rigorous, emphasizing long-term monitoring and enhancing in situ habitat protection. Our integrated assessment provides insights for strategic conservation planning, research prioritization, and public policy development concerning climate change at the

regional level for poorly known species (Potter et al., 2017; Williams et al., 2008).

The findings demonstrate the interaction of various variables in determining the vulnerability of a species to climate change (Table S4). For example, the high vulnerability of *A. brunneus* results from a combination of high exposure [evidenced by a substantial loss of potential distribution area (range shift) and low representativeness in protected areas] and pronounced biological sensitivity (reflected in its climatic zone, climatic tolerance, and reproductive mode), and low adaptive capacity. In contrast, the risk for *I. penaxavantinho* was accentuated by a distinct set of factors influencing all three dimensions: low representativeness in protected areas (exposure), extremely restricted range size (sensitivity), and very limited dispersal capacity (adaptive capacity). These examples demonstrate that vulnerability arises from the interplay of multiple dimensions rather than a single factor. The true vulnerability of a species is contingent upon the interaction of its specific traits with the spatial patterns of climate change.

Concerns regarding poorly known species have prompted researchers to develop methods for predicting extinction risk or prioritizing these species in conservation plans and research (Bessell et al., 2022; Caetano et al., 2022; Dubos et al., 2022). This approach represents a step forward for a more accurate assessment of the vulnerability of poorly known species. Collectively, these approaches reduce uncertainties and complement current assessments based on red lists (Cazalis et al., 2022; Foden et al., 2013) by providing varied classifications of species vulnerability in the context of climate change. This aids in maximizing and directing conservation efforts toward poorly known species (Hossain et al., 2019).

Nonetheless, we recognize the limitations of using a few potentially inaccurate records in our analyses, particularly concerning niche modeling and potential species distribution estimates (Hernandez et al., 2006; Jeliakov et al., 2022; Yoccoz, 2022). Such limitations, in turn, permeated most of the dimensions we measured here since most of them were based on the dynamics of species distributions. Inaccurate and limited data can result in imprecise and biased estimates of niche breadth, thereby compromising the outcomes of niche models and conservation planning based on these predictions (Erickson and Smith, 2023; Hortal et al., 2008). In these instances, employing an ensemble of small models (Breiner et al., 2018), which conservatively delineate distributional areas via a restrictive threshold, alongside expert support to mitigate bias in the use of occurrence records, enabled us to address most of these limitations. Additionally, we restricted our analysis to species with more than five occurrence records because insufficient records compromise the development and predictive performance of the ESMS.

Despite these potential caveats, our approach presents a means to address the pressing need for identifying conservation targets based on the limited information at hand. We showed that the Wallacean shortfall cannot be seen as an impediment to omit poorly known species from the climate change agenda. Here, we revealed that species with poorly known distributions, classified into different categories by the IUCN Red List, may become increasingly vulnerable to future climate change, thereby displaying varying levels of vulnerability. Our approach offers a method to overcome this challenge and enhance conservation efforts. We encourage researchers to assess the vulnerability of other poorly known taxonomic groups by combining trait-based and niche modeling techniques, such as the newly classified DD species in red lists, which are often neglected in climate change research. Moreover, we recommend that the models should be continually updated as more occurrence records become available in future research. We emphasize that a knowledge shortfall frequently indicates the need for investment in research, including targeted field surveys, citizen science, and monitoring programs, to address taxonomic, functional, and distributional gaps (Baranzelli et al., 2023; Stewart et al., 2021). With the increasing availability of occurrence records from these efforts, more robust modeling methods suited to larger datasets and a wider range of

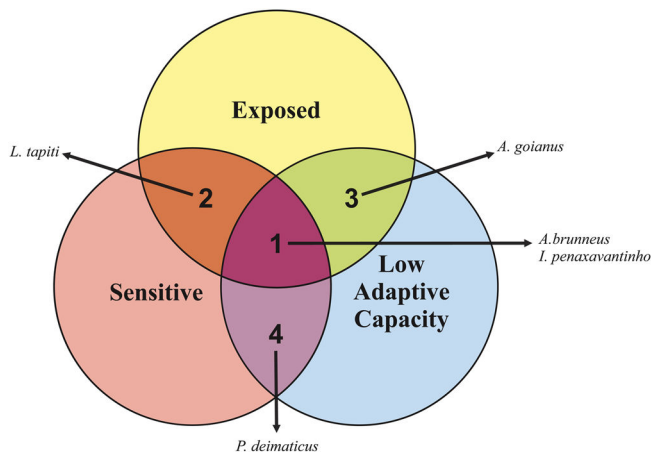


Fig. 3. Classification of poorly known species across the three dimensions of climate change vulnerability (exposure, sensitivity, and adaptive capacity). Exposed: species living in regions where the rate and magnitude of climate change are high across their range; sensitive: species with low climatic tolerance, unable to withstand the exposure to climate change (narrow niche width); low adaptive capacity: species with a low capacity to evolve their climate tolerance and adapt to novel climatic conditions. By overlapping these three dimensions, the species can be classified as follows: (1) highly vulnerable (triple overlap): species that are exposed, sensitive and present low adaptive capacity; (2) potential adapters: exposed and sensitive species but able to adapt to novel climates; (3) potential persisters: exposed species with low adaptive capacity; (4) High latent risk: sensitive species with low adaptive capacity but not exposed.

Table 2

Scores for exposure, sensitivity, and adaptive capacity, with corresponding vulnerability classifications for the poorly known anurans from the Brazilian Cerrado hotspots^a.

| Species | Total Points | Unique Points | Classification IUCN | SCORE | | | CLASSIFICATION | | |
|-----------------------------------|--------------|---------------|---------------------|----------|-------------|-------------------|----------------|-----------|-----------------------|
| | | | | Exposure | Sensitivity | Adaptive capacity | Exposed | Sensitive | Low adaptive capacity |
| <i>Allobates brunneus</i> | 12 | 10 | EN | 1 | 1 | 0.87273 | TRUE | TRUE | TRUE |
| <i>Allobates goianus</i> | 9 | 9 | NT | 0.68056 | 0.64329 | 1 | TRUE | FALSE | TRUE |
| <i>Hylodes otavioi</i> | 13 | 11 | VU | 0.39515 | 0.78576 | 0.13636 | FALSE | FALSE | FALSE |
| <i>Ischnocnema penaxavantinho</i> | 5 | 5 | LC | 0.71382 | 0.82508 | 0.92273 | TRUE | TRUE | TRUE |
| <i>Leptodactylus tapiti</i> | 9 | 8 | VU | 0.63793 | 0.96895 | 0 | TRUE | TRUE | FALSE |
| <i>Physalaemus deimaticus</i> | 12 | 10 | LC | 0.22097 | 0.80696 | 0.5000 | FALSE | TRUE | TRUE |
| <i>Proceratophrys moratoii</i> | 17 | 17 | LC | 0 | 0 | 0 | FALSE | FALSE | FALSE |

^a After using the 50% quantile threshold (exposed ≥ 0.63 , sensitive ≥ 0.80 , and low adaptive capacity ≥ 0.50), we identified the species that fall into any of the three dimensions of vulnerability (indicated by TRUE). The total points represented all sampled occurrence records for each species, while the unique points denoted cleaned occurrence records with a spatial resolution of 30 seconds (approximately 1 km²). IUCN classification: endangered (EN), vulnerable (VU), near-threatened (NT), and least concern (LC).

evaluation metrics can be employed. Despite limitations in financial resources and data availability (Stewart et al., 2021), the application of low-cost and rapid-response techniques allows the identification and prioritization of poorly known species within the climate change conservation agenda. Finally, future research directions could include the integration of land-use change projections with climate scenarios in vulnerability assessments of poorly known species.

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Data statement

The R script for executing the ensembles of small models and vulnerability analyses is available on GitHub (https://github.com/akaro linamoreno/scripts_vulnerability_poorly_known_species/).

[dataset] CRIA (Centro de Referência em Informação Ambiental), speciesLink, CRIA, 2024.

[dataset] GBIF.org, GBIF Home Page, 2024.

[dataset] ICMBio, SALVE (Sistema de Avaliação do Risco de Extinção da Biodiversidade), ICMBio, 2024.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.pecon.2025.11.005>.

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