Biological Conservation 309 (2025) 111313

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

# The spatial distribution of tests of conservation interventions does not align with global conservation needs

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ARTICLE INFO

Dataset link: Data and code associated with manuscript: "The spatial distribution of tests of conservation interventions does not align with global conservation needs" (Original data)

*Keywords:*
Evidence
Evidence-based conservation
Interventions
Conservation
Prioritisation
Funding
Threats
Biodiversity loss

ABSTRACT

Aligning research effort to address major threats to biodiversity is key to bending the curve of biodiversity loss with limited resources. Recent global threat mapping for terrestrial amphibians, birds, and mammals enabled us to assess whether there was alignment between the spatial distributions of key threats (logging, hunting, agriculture, pollution, Invasive Non-Native Species, and climate change) and published tests of conservation interventions addressing these threats (1025 English and 147 non-English language studies from 15 languages collated in the Conservation Evidence database). We ran Generalised Linear Models (GLMs) to determine the key predictors (including socio-economic factors) of the number of studies that test interventions on amphibians, birds, and mammals per country. We found poor spatial alignment between studies and the impact probabilities of threats for each taxon. Studies were distributed across 92 countries with 64 % of all studies conducted in the United States, United Kingdom, Canada, and Germany. Most studies focused on interventions against agricultural threats (60 %, 79 %, and 58 % for amphibians, birds, and mammals, respectively) – next most common were interventions tackling climate change (18 % of bird studies), hunting/trapping (29 % of mammal studies), and logging (20 % of amphibian studies). Countries with the highest threat levels typically had few or no studies, although several countries had both high threat levels and numbers of studies, including: Germany for amphibian interventions against agriculture, New Zealand for bird interventions against invasive species, and Brazil for mammal interventions against hunting. However, our modelling suggested that certain socio-economic factors, not levels of conservation risk posed by threats, were associated with more studies testing interventions. These factors included countries with higher levels of Gross Domestic Product (GDP) (amphibians and birds) and greater levels of government effectiveness (mammals). We call for rapid action to remove barriers to (and incentivise) reporting tests of interventions, such as through specific funding to test conservation actions and a global reporting database in both English and non-English languages to fill evidence gaps in underrepresented regions. Building 'testing partnerships' to link Global North and Global South institutions through networks of funders, local community, governmental, non-governmental and research organisations would also help to better coordinate testing of interventions to address conservation needs. This will require international coordination to build capacity for testing interventions and reporting their effects, whilst avoiding parachute science.

## 1. Introduction

Our planet's natural ecosystems are being degraded at an unprecedented rate and there is an urgent need to bend the curve of biodiversity loss (Leclère et al., 2020). Conservation science is a mission-driven discipline that seeks to tackle this biodiversity crisis through developing an understanding of what threatens species and which actions and policies work best to protect them (Soulé, 1985; Di Marco et al., 2017). In the face of insufficient funding (Dirzo et al., 2014), conservation actions must also seek to be as efficient and effective as possible. However, whilst we know that conservation generally seems to be reducing the risk of species extinctions, the outcomes of different

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https://doi.org/10.1016/j.biocon.2025.111313
Received 22 November 2024; Received in revised form 12 June 2025; Accepted 14 June 2025
Available online 21 June 2025

conservation actions can still be highly variable from being beneficial to harmful or having no effect (Senior et al., 2024, Langhammer et al., 2024, Simkins et al., 2025). Sharing reliable and relevant evidence on the likely effects of conservation actions is therefore key to tackling the biodiversity crisis effectively (Sutherland et al., 2004).

To enable more effective practice, the ideal evidence base for conservation actions would contain multiple tests of interventions covering a wide range of conservation outcomes for different taxa and geographies (encompassing different habitats, climate, cultures, governance, legal, and regulatory structures). This would ensure that enough relevant and reliable evidence would be available to inform decision-makers with tailored, specific management recommendations (Christie et al., 2020; Nuñez et al., 2019; Christie et al., 2020). To do this, we need to know what gaps and biases exist in this subset of the conservation literature to prioritise knowledge gaps and fill them efficiently, particularly given that field studies can be costly in a discipline that typically lacks sufficient funding (Martin et al., 2012; Aranda et al., 2011). For example, we know that geographic biases (Bladon et al., 2025; Christie et al., 2020, 2021; Junker et al., 2020; Hordern et al., 2024; Speight et al., 2025) and language biases (Amano et al., 2021) limit the global distribution of evidence on conservation interventions for different taxa. Specifically, many studies on interventions to conserve biodiversity are conducted in the Global North, particularly in the UK, USA, and Australia – for example, 64 % and 63 % of studies for amphibians and birds, respectively, occur in these countries (Christie et al., 2021). Amano et al. (2021) showed that incorporating non-English-language studies can expand the geographical coverage of the evidence base by 12–25 %, especially in biodiverse regions such as the tropics where the threats to biodiversity are often greatest too (Willig et al., 2003; Myers et al., 2000; Laurance et al., 2014). Speight et al. (2025) suggested that the key driver influencing where studies on reptile interventions were conducted was Gross Domestic Product (GDP) (as well as species richness and the proportion of threatened species to lesser extents), whilst Hordern et al. (2024) did not find a relationship between the number of studies on interventions and the species richness of marine ecoregions for marine mammals. However, for amphibians, birds, and terrestrial mammals, we still lack an understanding of which factors are the most influential drivers of the spatial distribution of evidence on interventions, as well as whether this distribution aligns with the level of risk posed by key threats to these taxa.

In our paper, we focus on studies that have tested conservation interventions targeting terrestrial amphibians, birds, and mammals, and on the six major threats to biodiversity – agriculture and aquaculture, pollution, climate change, logging, invasive species, and hunting and trapping covered by Harfoot et al. (2021). Conservation interventions are defined as any "actions that have been or could be used to conserve biodiversity" (Sutherland et al., 2019). We analyse the major predictors of the spatial distribution of studies by country, including the conservation risk posed by these threats and/or socio-economic factors including: GDP, National Biodiversity Index, Government Effectiveness, Environmental Performance Index, and adult literacy rates. We chose these five factors because: i) GDP is known to positively correlate with the production of research (Jack et al., 2021; Hefler et al., 1999; Thompson, 1999); ii) conservation research should ideally be prioritised to areas of higher biodiversity and areas where biodiversity is most at risk; iii) good governance enables and encourages research (Wen et al., 2021); iv) EPI measures the environmental performance of different countries (EPI, 2024) which should be correlated with ecological research output; and v) adult literacy rates should lead to greater levels of research production (Jiang et al., 2023). This study will therefore generate new insights on what drives the spatial distribution of studies on conservation interventions for amphibians, birds, and mammals and how we might best prioritise future tests of interventions to maximise the usefulness of the evidence base to tackle key threats to biodiversity.

## 2. Methods

### 2.1. Conservation Evidence database

For our analysis, we acquired data on 2861 English language studies testing conservation interventions from the Conservation Evidence database (https://www.conservationevidence.com/). The Conservation Evidence project gathers, organizes, and summarizes studies that have quantitatively tested the effect of conservation interventions, as defined earlier (Sutherland et al., 2019). Systematic manual searches of the available conservation literature, as well as 'grey literature' such as government reports and conference proceedings, are used to find studies for the database using Subject-Wide Evidence Synthesis (SWES; Sutherland et al., 2019). Relevant studies are grouped into synopses that contain the interventions that could be used to conserve a particular species group or habitat. We analysed the evidence available for amphibians, birds, and terrestrial mammals based on Conservation Evidence synopses compiled with systematic searches of core conservation and specialist taxa-specific journals up until 2014 for amphibians (Smith and Sutherland, 2014), 2012 for birds (Williams et al., 2012), and 2020 for terrestrial mammals (Littlewood et al., 2020), respectively. We used metadata extracted from each study that contained the latitude and longitude of the site(s) of the study, and what threat(s) the study addressed.

We also considered an additional 231 non-English-language studies from the Conservation Evidence database testing the effectiveness of conservation interventions in our analysis to reduce language publication bias. These studies were derived from Amano et al. (2021), who conducted a literature search of 326 journals published across 16 languages to identify relevant studies for inclusion in the Conservation Evidence database. We extracted the threat(s) that each study addressed based on the abstracts in the Amano et al. (2021) dataset to align with the English language studies.

### 2.2. Global threat maps

We looked at six major threats to amphibians, birds, and mammals - agriculture, climate change, pollution, Invasive Non-Native Species, logging, and hunting and trapping. We obtained information on the global spatial distribution of these threats from previous work conducted by Harfoot et al. (2021). Harfoot et al. used expert-derived information from the International Union for Conservation of Nature (IUCN) Red List of Threatened Species in a probabilistic framework to map the global distribution of the threats to terrestrial amphibians, birds, and mammals (23,271 species). The IUCN Red List only contains information on whether a given species is affected by a certain threat anywhere within its range. To account for this, the methods used by Harfoot et al. explicitly incorporated the spatial uncertainty inherent in the Red List to produce threat maps. The produced threat maps at a 50 $\times$ 50 km resolution contain threat intensity as impact probability, or the "probability that a randomly selected species occurring in a given grid cell is impacted in that cell by a particular threat, while accounting for the spatial uncertainty inherent in the Red List data" (Harfoot et al., 2021).

The shapefile utilised in our analysis contained these impact probabilities for amphibians, birds, and mammals and each of the six threats, along with the species richness for each taxon per 50 $\times$ 50 km cell. We only included cells containing $>$10 species to ensure our analysis was robust.

### 2.3. Analysis

Of the 2861 English language studies on amphibians, birds, and mammals, we retained 1025 that focused on the six major threats we analysed. Similarly, of 231 non-English language studies on these three taxa, we retained 147 for the same reason. Therefore, the dataset we analysed was made up of a total of 1172 studies.

For each of the various threat and taxon combinations, we aggregated the Conservation Evidence dataset by country to find the total number of studies testing conservation interventions per country. Studies were grouped by country according to the site of the field study. A single field study based in more than one country was counted separately for each of countries it was based in. The list of countries and their borders was obtained from the 'wrld_simpl' object in the R package maptools (Bivand and Lewin-Koh, 2023). We did not include laboratory studies, reviews, and meta-analyses in our analysis. Similarly, for each of the 18 threat and taxon combinations, we used the threats dataset (at a 50 × 50 km resolution) to obtain impact probabilities for each country. The average impact probability for each country was evaluated by overlaying the 'wrld_simpl' object with the shapefile containing threats data, and calculating the mean impact probability from all the 50 × 50 km grid cells falling within each country's borders.

To identify areas of conservation priority, the spatial distribution of biodiversity richness must be incorporated along with probabilities of threat impact. To do this, we multiplied impact probability with species richness for each 50 × 50 km grid cell in the threats dataset to get a measure of 'conservation risk', or the estimated number of species that would be impacted in each grid cell (Harfoot et al., 2021):

$$\text{Conservation risk}_{\text{per grid cell}} = \text{Impact probability}_{\text{per grid cell}} \text{ x Species richness}_{\text{per grid cell}}$$

We then calculated the mean conservation risk for each country by overlaying the 'wrld_simpl' object, and calculating the mean conservation risk from all the 50 × 50 km grid cells falling within each country's borders. We used this to create another set of bivariate maps, showing the relationship between conservation risk per country and the number of studies per country.

We used Generalised Linear Models (GLMs) to explore which factors predict the variation in the number of studies per country testing conservation interventions. As there was limited and variable geographic distribution of studies testing interventions for different threats for each taxon (amphibians, birds, and mammals), we chose to model each taxon separately and restricted our dataset to only threats for which there were studies distributed across at least 10 countries. For amphibians, this meant we included conservation risk for agriculture (27 countries) and pollution (11 countries); for birds, we included agriculture (31 countries), pollution (14 countries), invasives (13 countries), and logging (11 countries); and for mammals, we included agriculture (56 countries), pollution (18 countries), hunting (56 countries), and logging (28 countries). For an additional quality filter, we also excluded countries that had <10 % data coverage for conservation risk of a given threat – i.e., if the area covered by grid cells with data was <10 % of the country's land area.

We ran Poisson GLMs (with a log link function) using the package lme4 (Bates et al., 2015) for amphibians and birds as there was no substantial overdispersion or zero inflation detected using QQ plots, comparing residuals and predicted values and other tests with the DHARMa package (Hartig, 2022) (i.e., no significant dispersion, outliers, or deviation of residuals (Kolmogorov–Smirnov test); $p > 0.05$). However, for mammals, we instead ran negative binomial GLMs using the package *glmmTMB* (Brooks et al., 2017) because when testing Poisson and quasi-Poisson GLMs we found significant overdispersion, outliers, and deviation of residuals using the DHARMa package ($p < 0.05$; Hartig, 2022). A negative binomial error structure specifically accounts for zero inflation and overdispersion (Brooks et al., 2017).

Using these GLMs, we looked at the relationship between the number of studies per country and: i) GDP (in US dollars), ii) NBI (National Biodiversity Index), iii) government effectiveness (from the World Governance Indicators), iv) EPI (Environmental Performance Index), v) adult literacy rates, and vii) threat pressure as conservation risk (as this was a composite of impact probability and species richness that combined conservation priorities, as described above). We obtained data on GDP and government effectiveness from the World Bank (2024a, 2024b), literacy rates from the World Population Review (Worldwide Governance Indicators, 2024), The National Biodiversity Index from the Convention on Biological Diversity's Global Biodiversity Outlook 1 (CBD, 2024), and Environmental Performance Index from Yale University's EPI website (EPI, 2024).

We centred and scaled all continuous explanatory variables so that they had a mean of 0 and SD of 0.5 (i.e., subtracting mean and dividing by 2 SD) following recommendations by Gelman (2008) and Grueber et al. (2011). Note that this means any z scores for explanatory variables are technically half-Z scores (Grueber et al., 2011). To generate a set of candidate models, we first specified a global GLM for each taxon: Amphibians: (nstudies ~ Agriculture Risk + Pollution Risk + EPI + GDP + NBI + Government Effectiveness + Literacy); Birds: (nstudies ~ Agriculture Risk + Pollution Risk + Logging Risk + Invasives Risk + EPI + GDP + NBI + Government Effectiveness + Literacy); Mammals: (nstudies ~ Agriculture Risk + Pollution Risk + Logging Risk + Hunting Risk + EPI + GDP + NBI + Government Effectiveness + Literacy).

We used an information theoretic approach via the Dredge function to select from the full set of models (including a null model), resulting in a total model set of 128 for amphibians, 512 for birds, and 512 for mammals, respectively (Table S3-S5). As multiple models were of similar weights and Akaike Information Criterion (Corrected for small sample sizes (AICc)) values, we used a ΔAICc threshold of 2 units to select a final set of top models for each taxon. We used the zero method to conduct model averaging across the top models. This is where a parameter estimate (and error) of zero is substituted into those models where the given parameter is absent - the parameter estimate is obtained by averaging over all models in the top model set (Anderson and Burnham, 2002). We used the zero method because we wanted to determine which explanatory variables have the strongest effect on the response variable (as recommended by Nakagawa and Freckleton, 2011; Grueber et al., 2011).

Relative variable importance (Akaike weights or SW) was also calculated, which is equal to the sum of the weights for the models in which a given variable appears. This estimates the probability that a particular explanatory variable is kept in the best model(s) – i.e., a value of 1 indicates it is present, a value of 0 indicates it is not (Giam and Olden, 2016; Anderson and Burnham, 2002). Variable with relative importance values closer to 1 suggests they are present in more models with larger weights and thus represents the overall support for each variable across all models in the final set of top models.

We tested for multicollinearity between explanatory variables in the global GLMs using the performance R package (Lüdecke et al., 2021) and found the Variance Inflation Factor (VIF) for both amphibians and birds were less than or equal to five (low-moderate correlation). For mammals, VIF values were all less or equal to five except for agriculture and logging conservation risk. We found that the relative importance of agriculture was lower than for logging (0.13 vs 0.61) in the final model set and so removed agriculture from the global GLM and reran the Dredge function (now from a total model set of 256 models). This modelling process resulted in seven top models for amphibians, eight top models for birds, and six top models for mammals (Table S2). Other thresholds for selecting top models resulted in excessively large numbers of models (Amphibians: 21 models using $<4$ ΔAICc, 25 models using 95 % Confidence; Birds: 44 models using $<4$ ΔAICc, 163 models using 95 % Confidence; Mammals: 17 models using $<4$ ΔAICc, 82 models using 95 % Confidence).

We checked the robustness of our model selection procedure using traditional backward stepwise model selection and comparing the minimum adequate model found (Table S6) to the final model set found using the Dredge function (Tables S3–5). All modelling, mapping, and spatial analyses were conducted using R version 4.4.0 (R Core Team, 2024).

## 3. Results

We considered a total of 1172 studies that considered the six threats we focused on, spanning a range of 15 languages. 1025 of these studies were English-language studies from the Conservation Evidence database, and 147 were non-English language studies (in Arabic, French, German, Hungarian, Italian, Japanese, Korean, Polish, Portuguese, Russian, Simplified and Traditional Chinese, Spanish, and Ukrainian) obtained from Amano et al. (2021). There were 49 studies that were based in more than one country, 30 studies that tested interventions on more than one of the three taxa considered, and 185 studies that addressed more than one of the six threats.

Agriculture was the most studied threat (total of 762 studies; Figs. 1 and 2), followed by hunting/trapping (200 studies), logging (172 studies), pollution (131 studies), Invasive Non-Native Species (48 studies), and climate change (44 studies). The percentage of studies on different threats was similar between English and non-English languages (Table 1), although there were no studies on interventions tackling climate change in the non-English language data. The percentage of studies on different threats varied somewhat more between taxa (Table 1). For example, a relatively high percentage of studies tackled agricultural threats and climate change for birds, hunting for mammals, and climate change for amphibians, whilst there was a relatively low percentage of amphibian and bird studies on hunting/trapping and mammal studies on Invasive Non-Native Species (Table 1).

Studies were distributed across 92 countries. Showing a clear geographic bias, 64 % of all (English and non-English) studies were conducted in four countries – the United States, the United Kingdom, Canada, and Germany (Fig. 1 and Fig. 2). We found 29.4 % of all studies were based in the United States, while 55 % of countries had five or fewer studies based in them. For the non-English language studies, 22 % of studies were from Germany, followed by Japan (12 %), Argentina (10 %), China (9 %) France (9 %), Italy (7 %), Russia (7 %), Republic of Korea (6 %), Poland (6 %), and Hungary (5 %).

A strong geographic bias was also apparent when mapping out the distribution of studies and levels of conservation risk posed by each threat (Figs. 3–5). Many countries appear to have few or no studies for each taxon (coloured grey to deep red, bottom row of colour key; Figs. 3–5) and most countries either have: a.) high mean conservation risk and few or no studies (light to deep red), or b.) many studies but relatively lower conservation risk (light to deep turquoise; Figs. 3–5). Few countries had both high mean conservation risk (or impact probability) and many studies tackling that threat, although these included: Germany for amphibian interventions against agricultural threats (Fig. 3); New Zealand for bird interventions against invasive species (Fig. 4); as well as Brazil and several sub-Saharan African and Southeast Asian countries for mammal interventions against hunting (Fig. 5).

When analysing possible predictors of the distribution of studies for amphibians, our model selection process generated seven top models with Delta AICc $<2$ – for a list of all amphibian models, please see Table S2. Model-averaged results suggest that the most important predictors based on relative importance were GDP and EPI (further supported by their presence in all seven models; Table 2). GDP and EPI both had a significant positive effect (GDP: $z = 6.22$, $p < 0.0001$; EPI: $z = 2.81$, $p = 0.005$) on the number of studies (95 % CIs both greater than zero; Table S1), although EPI had a relatively stronger effect size (approximately three times greater) than GDP and other predictors (Table S1). 95 % Confidence Intervals for all other variables overlapped with zero, indicating there was little evidence that they affected the number of studies per country (Table S1) – their relative importance was also noticeably lower, with the next most important predictor being NBI at 73 % (in 5 models) and agriculture conservation risk 49 % (in 4 models) relative importance to GDP and EPI (Table 2). Literacy rate was not present in the seven top models and so was probably not a useful predictor (Table 2).

For birds, our model selection process generated eight top models with Delta AICc $<2$ – Table S3 presents all bird models. Model-averaged results suggest that the most important predictors based on relative importance were GDP and NBI (present in all top models). GDP had a significant positive effect on the number of studies (GDP: $z = 5.83$, $p < 0.0001$), whilst NBI had a significant negative effect ($z = 2.15$, $p = 0.0316$) on the number of studies (95 % CIs both greater than zero; Table S1). Nevertheless, their effect sizes were relatively moderate compared to other predictors (Table S1). Pollution conservation risk (present in 7 models) and government effectiveness (present in 6 models) had 91 % and 70 % relative importance, respectively, to GDP and NBI (Table 2; Table S1). However, 95 % Confidence Intervals for all variables, except GDP and NBI, overlapped with zero and thus there was little evidence that they affected the number of studies per country (Table S1). The conservation risk of logging and agriculture were not present in the eight top models and unlikely to be useful predictors (Table 2).

For mammals, our model selection process generated six top models (Delta AICc $<2$; Table S4 presents all mammal models). Model-averaged results suggest that the most important predictors were GDP, pollution conservation risk, and government effectiveness. Government effectiveness had significant positive effect on the number of studies ($z = 3.13$, $p = 0.0017$; 95 % CIs both greater than zero; Table S1) whilst pollution had a significant negative effect ($z = 2.51$, $p = 0.0120$; 95 % CIs both less than zero; Table S1). Both variables had relatively larger standardised effect sizes compared to the other predictors, except GDP (Table S1). 95 % Confidence Intervals for all variables (except for pollution and government effectiveness) overlapped with zero, indicating there was little evidence they affected the number of studies per country (Table S1). Other predictors relative importance was also somewhat lower – logging and hunting were the next most important predictors at 70 % and 42 % relative importance (Table 2). Literacy rate was not present in the six top models and so was probably not a useful predictor (Table 2).

For a robustness check, where we used traditional backward stepwise model selection, we found that the minimum adequate model was identical to the model with the lowest AICc in the final model sets for amphibians, birds, and mammals (Tables S2–4). This indicated that our results were robust to alternative model selection procedures.

## 4. Discussion

Across amphibians, birds, and mammals, our analyses suggest that there is poor alignment between where studies test interventions and where the threats they tackle represent the greatest conservation risk. Countries with higher EPI and GDP tended to have more amphibian studies, whilst countries with higher GDP and lower NBI tended to have more bird studies, and countries with greater GDP and government effectiveness had more mammal studies. The level of conservation risk from logging, hunting, invasive species, pollution, and agriculture did not appear to significantly affect the number of studies per country for any taxonomic group (and there insufficient data to analyse climate change for any group). These results suggest that socioeconomic factors,

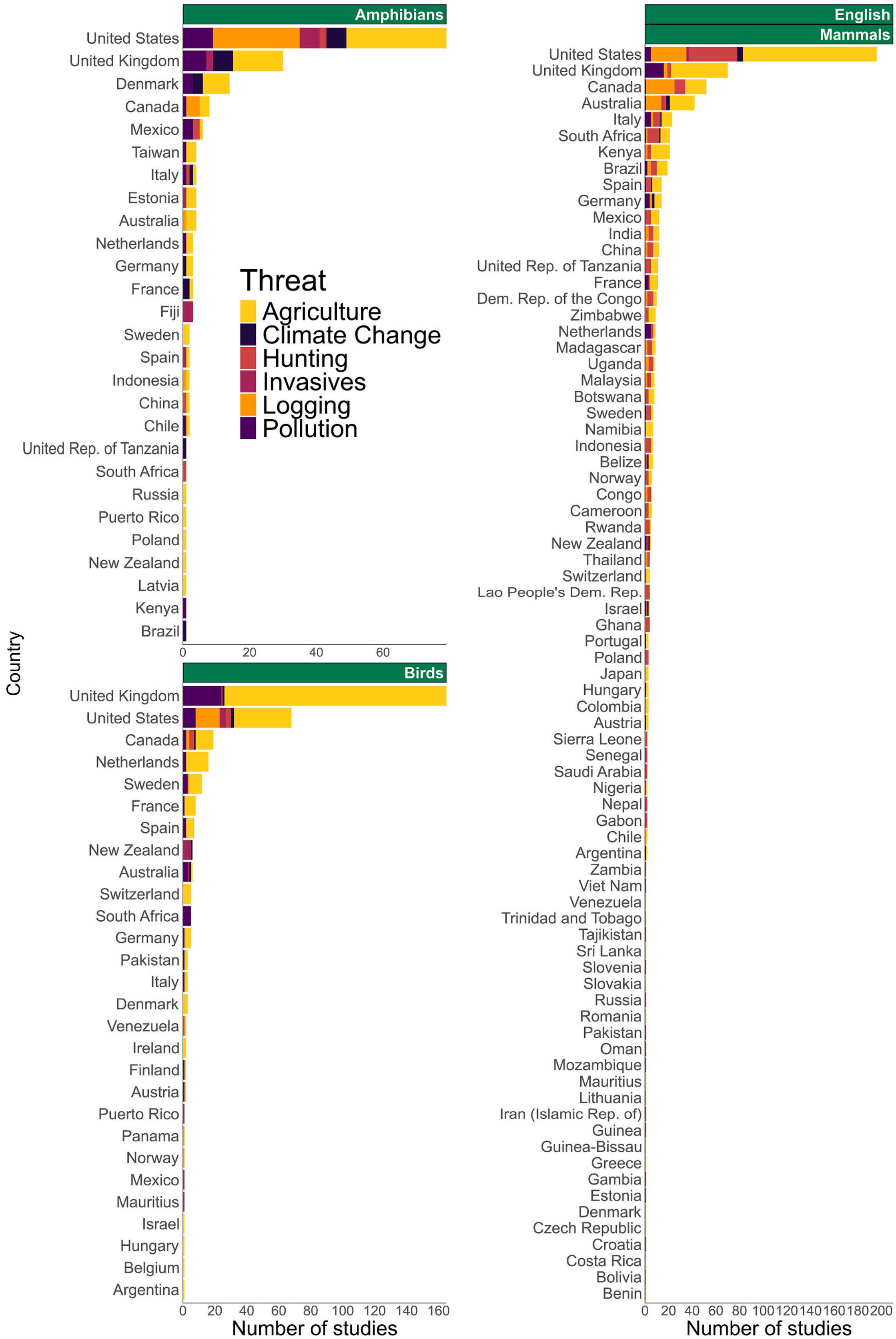


**Fig. 1.** Number of English language studies testing conservation interventions to tackle a particular threat within each country. Only studies testing conservation interventions on amphibians ($n = 147$), birds ($n = 297$), or mammals ($n = 589$), threatened by agriculture, pollution, climate change, invasive species, logging, or hunting are considered here. No studies were found to be based within countries absent from the graph.

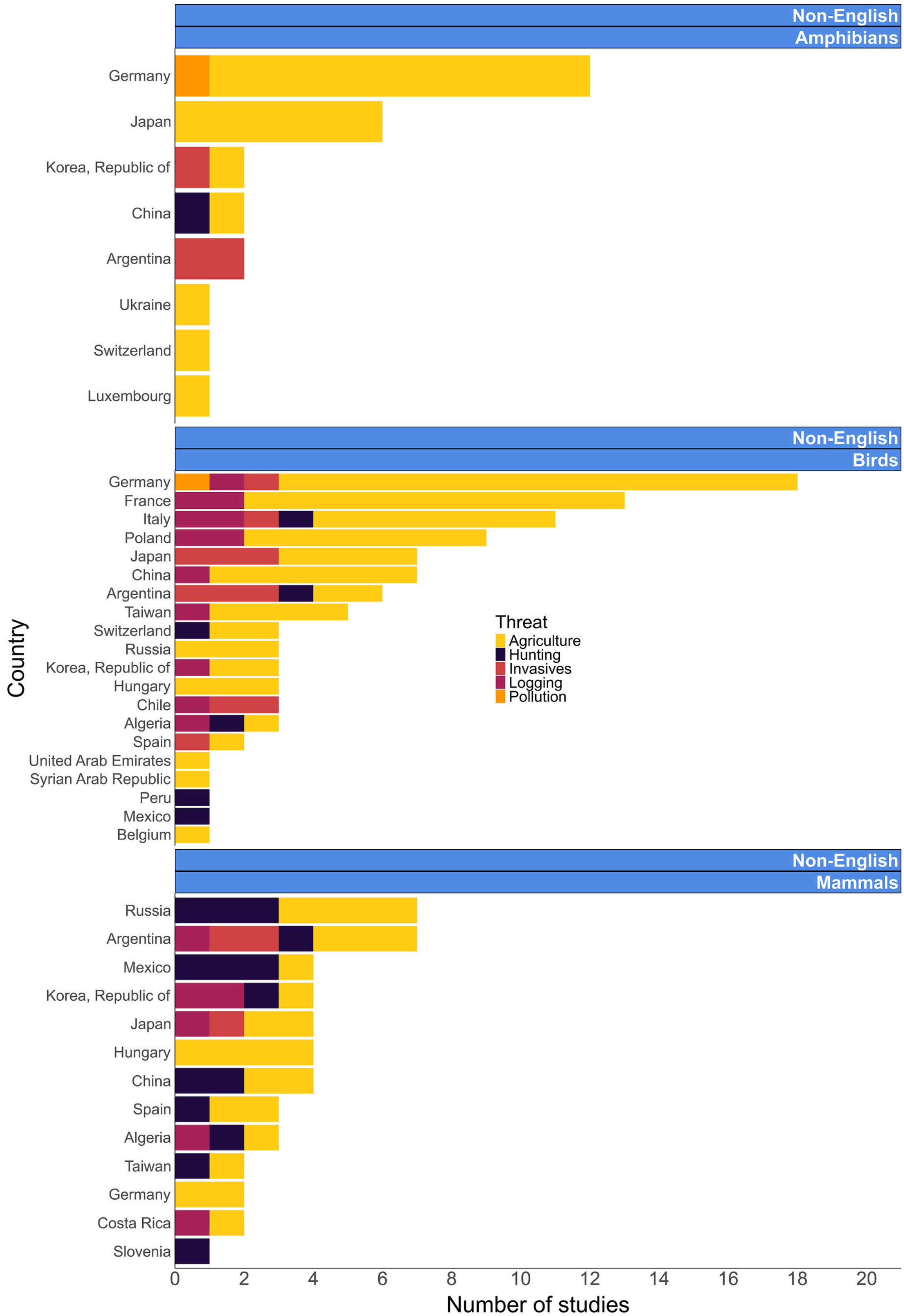


**Fig. 2.** Number of Non-English language studies testing conservation interventions to tackle a particular threat within each country. Only studies testing conservation interventions on amphibians ($n = 26$), birds ($n = 95$), or mammals ($n = 41$), threatened by agriculture, pollution, climate change, invasive species, logging, or hunting are considered here. No studies were found to be based within countries absent from the graph.

**Table 1**
Percentages of English language ($n$ = 1025 studies) and non-English language ($n$ = 147) studies that studied interventions addressing different threats. N.B. Percentages may add up to >100 % due to the presence of studies on multiple threats and taxa.

| Threat | English language | Non-English language | Amphibians | Birds | Mammals | Total |
|---|---|---|---|---|---|---|
| Agriculture | 63.8 | 73.5 | 59.5 | 78.6 | 58.1 | 65.4 |
| Climate change | 4.29 | 0 | 12.7 | 17.9 | 2.70 | 3.78 |
| Hunting/trapping | 17.7 | 12.9 | 5.78 | 3.32 | 29.2 | 17.2 |
| Invasives | 3.41 | 8.84 | 10.4 | 6.89 | 1.90 | 4.12 |
| Logging | 15.0 | 12.2 | 19.7 | 8.16 | 17.9 | 14.8 |
| Pollution | 12.6 | 13.6 | 17.3 | 13.8 | 7.78 | 11.2 |

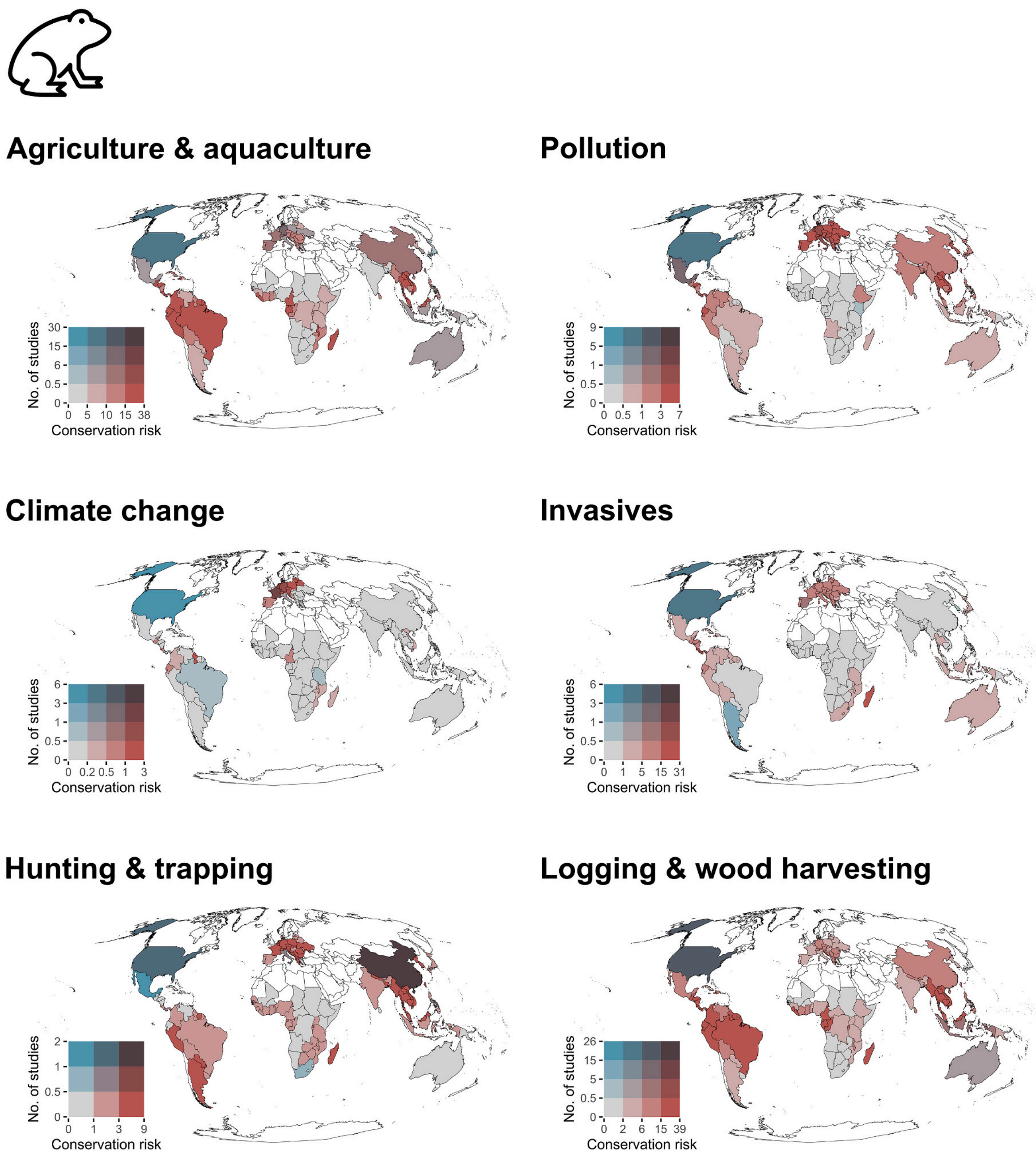


**Fig. 3.** Conservation risk and number of studies testing conservation interventions on amphibians threatened by agriculture, pollution, climate change, invasive species, hunting, and logging. Conservation risk for each country is the product of impact probability and species richness per 50 × 50 km grid cell, averaged across all the grid cells that fall within the borders of the country. Darker colors indicate countries with high conservation risks, as well as a relatively large number of studies testing conservation interventions. The bottom row of the colour key, grey to deep red, indicates countries with no studies. Regions in white either have no data on threats or were excluded for quality control in the analysis due to cells containing fewer than 10 species. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

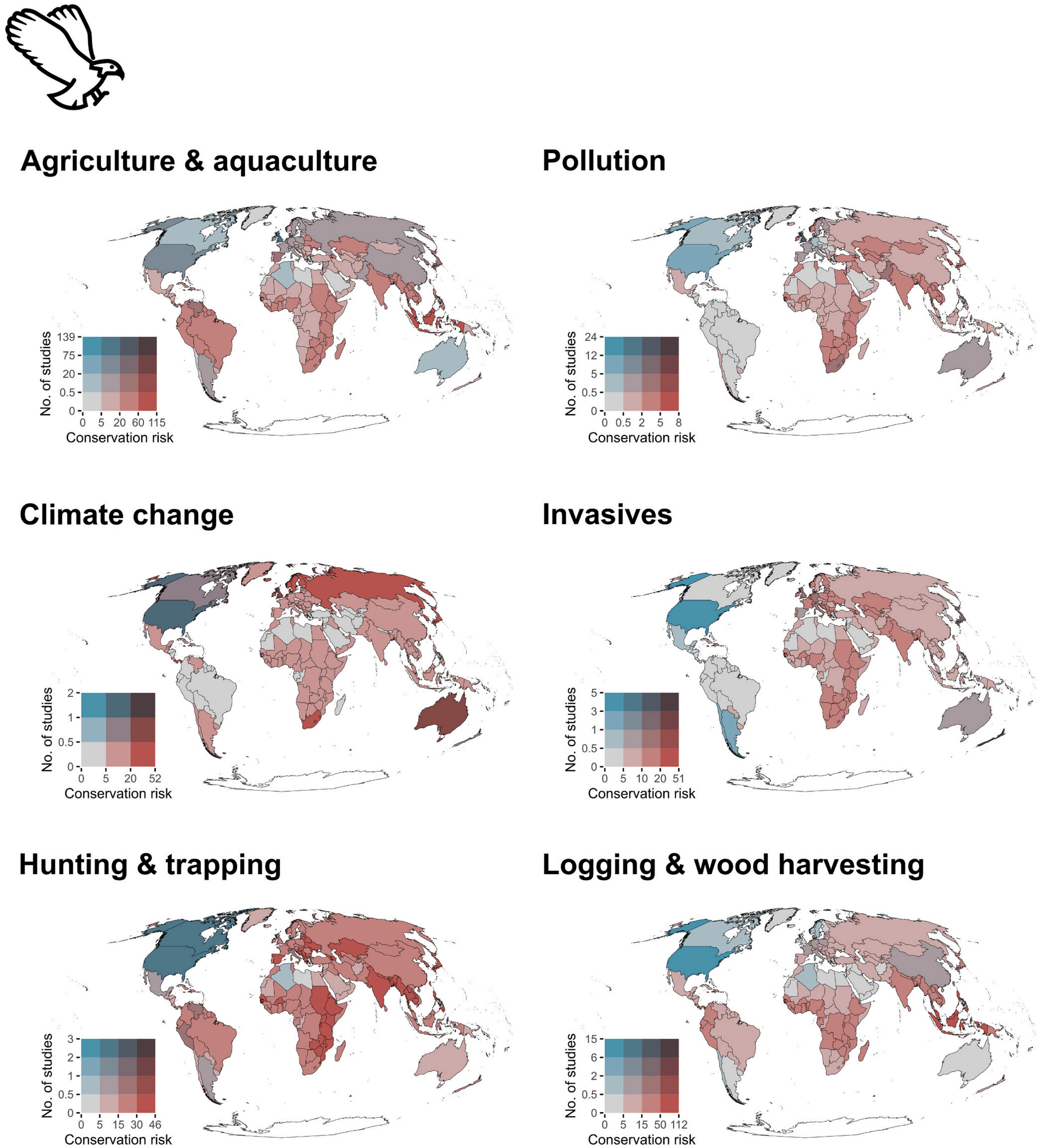


**Fig. 4.** Conservation risk and number of studies testing conservation interventions on birds threatened by A) agriculture, B) pollution, C) climate change, D) invasive species, E) hunting, and F) logging. Conservation risk for each country is the product of impact probability and species richness per 50 × 50 km grid cell, averaged across all the grid cells that fall within the borders of the country. Darker colors indicate countries with high conservation risks, as well as a relatively large number of studies testing conservation interventions. The bottom row of the colour key, grey to deep red, indicates countries with no studies. Regions in white either have no data on threats or were excluded for quality control in the analysis due to cells containing fewer than 10 species. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

GDP in particular, are more important drivers of the spatial distribution studies testing conservation interventions.

Whilst the strong geographic bias towards North America and Western Europe is known in ecology and conservation literature (Martin et al., 2012; Hickisch et al., 2019; Di Marco et al., 2017; Nuñez et al., 2019; Christie et al., 2021), our finding of a lack of alignment between the numbers of studies testing interventions and the conservation risk of threats they tackle is novel to our knowledge. However, we acknowledge that the conservation risk data we used may overestimate threats in regions where data on threats are lacking, which might partially explain

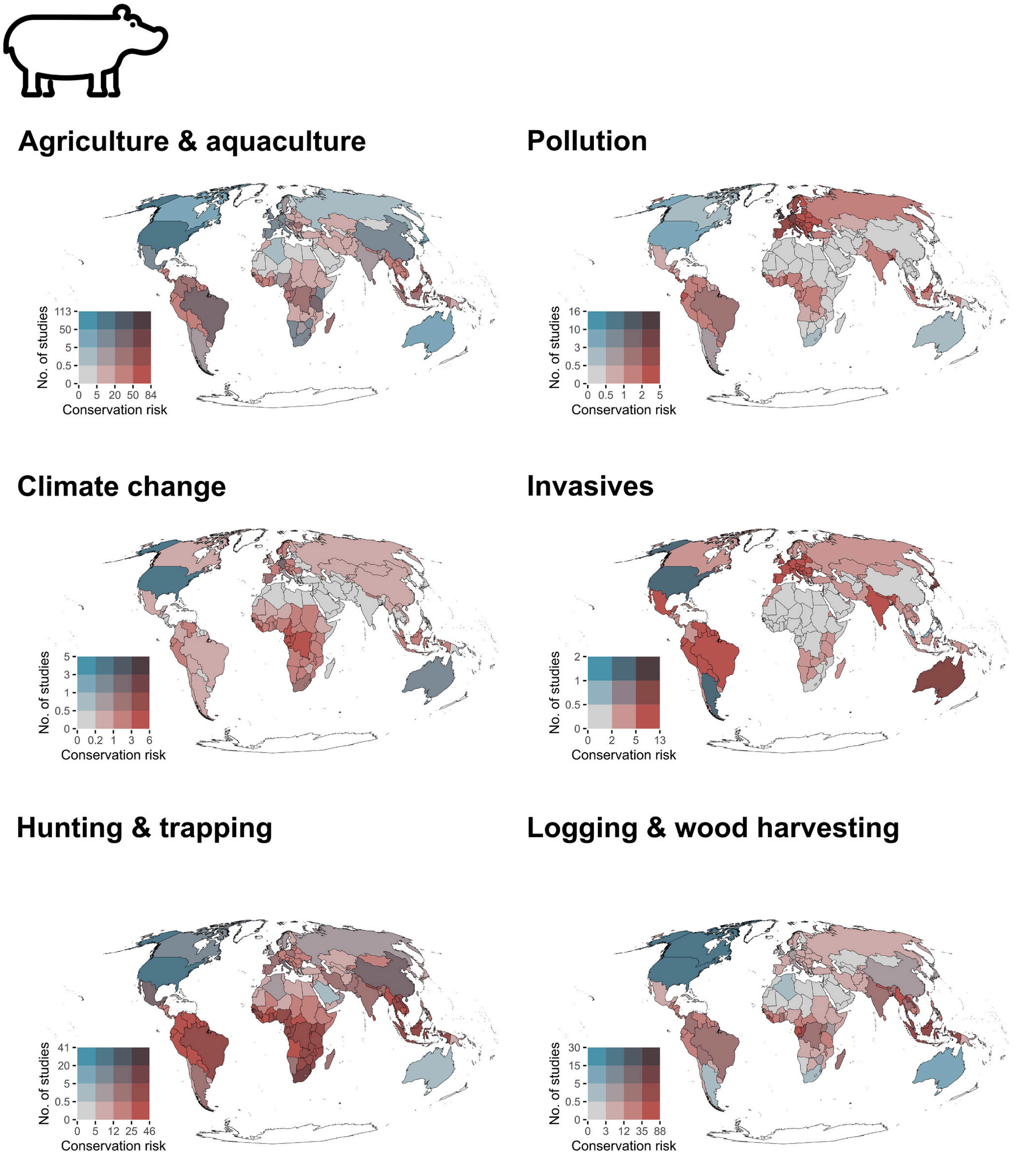


**Fig. 5.** Conservation risk and number of studies testing conservation interventions on mammals threatened by A) agriculture, B) pollution, C) climate change, D) invasive species, E) hunting, and F) logging. Conservation risk for each country is the product of impact probability and species richness per 50 × 50 km grid cell, averaged across all the grid cells that fall within the borders of the country. Darker colors indicate countries with high conservation risks, as well as a relatively large number of studies testing conservation interventions. The bottom row of the colour key, grey to deep red, indicates countries with no studies. Regions in white either have no data on threats or were excluded for quality control in the analysis due to cells containing fewer than 10 species. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the mismatch between studies and threats – although the IUCN Red List process is explicitly structured to avoid bias and give estimates grounded in scientific, vetted evidence (Harfoot et al., 2021).

Our other finding that there was alignment between number of studies testing interventions and GDP for amphibians, birds, and mammals concurs with results from the wider ecological literature. For example, Nuñez et al. (2019) found that GDP had a significant influence on the geographic variation in submission rates to *Journal of Applied*

**Table 2**
Summary of relative importance and *p*-values of variables for each final averaged model for amphibians, birds, and mammals (EPI = Environmental Performance Index, GDP = Gross Domestic Product, NBI = National Biodiversity Index). Estimates were obtained by model averaging using zero method and full model results are presented in Table S2. We only included conservation risk for threats where studies addressing a threat were distributed across at least 10 countries. X indicates where the variable was not included in the final averaged model, whilst # indicates where threats were excluded for not having studies from at least 10 countries. ‖ indicates where a variable was removed due to multicollinearity. Cells with (+) indicate explanatory variables with a statistically significant positive effect ($p < 0.05$, 95 % CIs >0) and cells with (-) signify explanatory variables with a statistically significant negative effect ($p < 0.05$, 95 % CIs <0).

| Model term | Amphibian | Birds | Mammals |
|---|---|---|---|
| Agriculture Risk | 0.49 | X | ‖ |
| Hunting Risk | # | # | 0.42 |
| Invasives Risk | # | 0.42 | # |
| Logging Risk | # | X | 0.70 |
| Pollution Risk | 0.09 | 0.91 | 1.00 |
| EPI | 1.00(+) | 0.08 | 0.11 |
| GDP | 1.00(+) | 1.00(+) | 1.00(+) |
| Government Effectiveness | 0.22 | 0.70 | 1.00(+) |
| Literacy | X | 0.48 | X |
| NBI | 0.73 | 1.00(-) | 0.34 |

*Ecology*, whilst Martin et al. (2012) found approximately 90 % of ecological field studies in their sample were conducted in countries that fell within the 70-100th percentiles of Gross National Income (GNI). Although Wilson et al. (2016) found no correlation between GDP and the number of conservation studies conducted in a country, they did find a positive correlation between the number of publications and a country's expenditure on research as a proportion of its GDP.

Furthermore, whilst GDP was consistently a significant predictor of the number of studies per country across taxa, there were also differences between taxa. Amphibians were the only group for which countries with higher EPI had significantly more studies. This might be because a relatively high proportion of studies addressed pollution and logging, typically related to creating habitat or translocating amphibians in line with legislative and regulatory requirements as part of mitigation strategies for new infrastructure development (Christie et al., 2021; Smith and Sutherland, 2014). The focus on these types of interventions may provide some link with a country's EPI as this is meant to gauge how close countries are to meeting certain environmental policy targets (EPI, 2024). For mammals, we saw that countries with higher government effectiveness had significantly more studies. A relatively high proportion of studies were focused on addressing hunting/trapping and logging (e.g., through habitat protection and management interventions; Littlewood et al., 2020) and so testing might be more associated with levels of government effectiveness where such interventions (e.g., protected areas) are easier to put in place and monitor. For birds, we found an unexpected pattern that countries with higher NBI – i.e., more endemic species – had fewer studies. This is probably largely associated with the geographic bias towards North America and Europe where countries tend to have lower species richness and endemism – therefore, greater testing of interventions in countries with fewer species is likely to be driven by other factors such as patterns in research capacity or legislation linked to key protected species (Christie et al., 2020, 2021). However, whilst there may be arguments for why EPI and government effectiveness might be significant predictors for amphibians and mammals, respectively, it is unclear why these two factors and NBI were not significant predictors across taxa. We must acknowledge though that comparisons between taxonomic models, particularly in terms of relative variable importance, must be treated with caution due to the relative nature of Akaike weights and separate scaling of predictor variables.

An important issue to discuss relating to GDP as a consistent cross-taxon predictor of the distribution of evidence is its relationship to the 'publication filter' problem (Di Marco et al., 2017). This problem refers to how conservation research in certain regions may have occurred but remains unpublished (either offline or in the grey literature, where it is hard to find) due to accessibility, language barriers, and lack of funding – ultimately driven by levels of GDP. For example, Amano et al. (2016) found that almost 36 % of conservation articles published in 2014 were in languages other than English. Language and literature biases are therefore important limitations to consider in any literature synthesis. In our study, we were able to analyse both the English and non-English language studies testing conservation actions thanks to efforts by Amano et al. (2021) to add non-English studies to the Conservation Evidence database (Sutherland et al., 2019). The ratio of 1:3.6 of non-English language studies (1234) found by Amano et al. (2021) compared to the English language studies (4412) found in the Conservation Evidence database at the time (using the same inclusion criteria) is broadly similar to our dataset focusing on amphibians, birds, and mammals (1:4.4 non-English:English). Furthermore, grey literature reports and documents from major conservation organisations and repositories are routinely searched by the Conservation Evidence project (Sutherland et al., 2019), further helping to limit the impact of the publication filter problem for our analysis. Therefore, it is unlikely that the publication filter problem can fully explain our overall findings. Nevertheless, incorporating more non-English language studies could help to address the poor alignment between tests of conservation actions and conservation threats (Amano et al., 2021). This is particularly the case for Global South countries that have some of the higher impact probabilities and levels of conservation risk for several threats and are often extremely rich in biodiversity (Cincotta et al., 2000; Nuñez et al., 2019; Chowdhury et al., 2022).

We also acknowledge that our analysis is limited by the different date ranges searched for studies between taxa and languages (see Methods), which limits our ability to make comparison and understand more recent changes in the distribution of studies. Temporal differences between data sources are another limitation of our analyses – for example, data on conservation risk or government effectiveness were not necessarily from the same year as a study was published. This might explain why some of the explanatory variables in our analysis do not show statistically significant relationships with the number of studies. However, whilst the values of some explanatory variables may have changed over time, we believe there are unlikely to have been relative between-country changes that would substantially affect our findings. Future research could conduct updated searches of studies and investigate the changes in the distribution of studies and its predictors over time, whilst also incorporating recent threat data on reptiles (Farooq et al., 2024). The correlation between the distribution of published studies testing actions and the actual implementation of actions could also be investigated – whilst the latter may be difficult to obtain data on from conservation organisations, this would highlight where the publication filter problem is particularly acute. Some may question whether a lack of such a correlation matters, but we would argue that without sharing tests of conservation interventions, we miss important opportunities to share evidence on the effects of actions across different contexts and thus improve conservation practice.

Overall, our results and previous findings from the wider literature suggest that levels of funding and research infrastructure are likely to be driving the distribution of studies that test conservation interventions. This is because existing infrastructure supported by initial funding can reduce the costs of further research, therefore driving even further investment in the same areas (Ahrends et al., 2011). To address gaps and biases in this global evidence base and improve alignment with the levels of conservation risk posed by threats, there are several potential solutions. First, we need more top-down strategies to mobilise evidence on underrepresented locations and actions, in line with several calls for funding agencies and conservation organisations to focus more funding on testing actions strategically (Tinsley-Marshall et al., 2022; O'Connell et al., 2024). This could be supported by a globally coordinated prioritisation strategy that operates across the conservation community (particularly within and across funders), to encourage greater research effort on testing actions where the threats they tackle pose the greatest conservation risk (Craigie et al., 2015). This would involve prioritising a list of countries, regions, and actions that funders could use to decide where an evaluation of an intervention would be the most useful, alongside requiring that funded projects appropriately evaluate and report their findings so that they can be shared with the wider conservation community. There are now many journals that offer simple formats for publishing tests of interventions, such as Conservation Science and Practice, Conservation Evidence, and Ecological Solutions and Evidence for little or no fee (fees could be costed into funding). There are also increasing efforts to develop simple reporting tools that could build living, verified databases of tests of conservation actions, as demonstrated by the Mangrove Restoration Tracker Tool (Gatt et al., 2024) – an equivalent database is also being developed to collate tests of interventions to control Invasive Non-Native Species (Taylor, 2024).

To implement these prioritisation and mobilisation of evidence strategies, we suggest that an international Conservation Action Testing Unit could help to provide assistance to funders and conservation practitioners to build tests of interventions into their practice. This testing unit would include a globally diverse network of universities and research organisations to provide technical assistance on designing and implementing evaluations at local scales, as well as facilitating the publishing of their findings. Capacity building through strengthening links between Global North and Global South institutions, in ways that avoid parachute science (Miller et al., 2023), would be crucial to support these targeted evaluations. Imagine if such a testing unit could encourage even a small proportion of conservation projects globally to embed a single evaluation into their practice each year and report its findings. The cumulative effect of this knowledge dissemination on the effects of conservation actions could be incredibly powerful, in line with the theory of marginal gains and Kaizen Conservation (Sutherland, 2019). Ultimately, doing so would help inform the conservation community on the most promising actions to effectively and efficiently bend the curve of biodiversity loss in different locations for different taxa and ecosystems.

## CRediT authorship contribution statement

**Anindita Anjan:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jonas Geldmann:** Writing – review & editing, Resources, Methodology, Conceptualization. **Mike Harfoot:** Writing – review & editing, Resources, Methodology, Conceptualization. **Alec P. Christie:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare no conflicts of interest.

## Acknowledgements

Anindita Anjan was funded by the managers of the J. Arthur Ramsay Trust Fund. Alec Christie received financial support from Imperial College London through an Imperial College Research Fellowship grant, as well as a Henslow Fellowship funded by the Cambridge Philosophical Society. Jonas Geldmann received financial support from the Danish Independent Research Council (grant 0165-00018B).

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2025.111313.

## Data availability

I have shared the link to my data/code in the attach file step.

Data and code associated with manuscript: "The spatial distribution of tests of conservation interventions does not align with global conservation needs" (Original data) (Zenodo)

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