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A global early warning system for predicting exposure of biodiversity to extreme heat

Author list:

Josep M Serra-Diaz [1,2,3]*, Lauren C Andrews[4], Andreas Schwarz Meyer[5], Ben S. Carlson[2], Brian Maitner[6], Gonzalo E Pinilla-Buitrago [7], Alex L Pigot[8], Christopher H Trisos[5], Adam M. Wilson[9], Mark C. Urban[2,10], Cory Merow[2]

Affiliations:

[1] Botanical Institute of Barcelona, CSIC-CMCNB, Barcelona, 08038, Spain.

[2] Eversource Energy Center & Department of Ecology and Evolution, University of Connecticut, Storrs, CT, USA.

[3] Université de Lorraine, AgroParisTech, INRAE, Silva, Nancy, France.

[4] Global Modeling and Assimilation Office, NASA Goddard Space Flight Center, Greenbelt, MD 20771

[5] Climate Risk Lab, African Climate and Development Initiative, University of Cape Town, Cape Town, South Africa

[6] Department of Integrative Biology, University of South Florida, St. Petersburg, FL, USA

[7] Institute of Ecology, National Autonomous University of Mexico, Merida, 97357, Mexico

[8] Centre for Biodiversity and Environment Research, Department of Genetics, Evolution and Environment, University College London, UK.

[9] Department of Geography, University at Buffalo, Buffalo, NY, USA

[10] Center of Biological Risk, University of Connecticut, Storrs, CT, USA.

*Corresponding author. Email: pep.serra.diaz@csic.es

Abstract

Effective biodiversity conservation during periods of rapid environmental change requires identifying the species and regions at greatest risk. However, most predictions focus on biodiversity shifts several decades ahead, offering limited guidance for immediate conservation action. Here, we develop an early warning system for biodiversity based on 9-month seasonal weather forecasts combined with species-specific historical temperature limits. In May 2024, we predicted that >3,500 vertebrate species (out of 30,585 species), including >1,250 species of conservation concern, would be substantially exposed to extreme temperatures 1-2 months in advance on average. Mexico, sub-Saharan Africa, and the Himalayas were predicted to face the highest threats during this forecast period. Early evidence suggests that exposure in these regions likely negatively impacted some species populations. Such advance notice can enable rapid actions to monitor and mitigate these extreme events for sensitive species and regions.

Main text

As the climate warms, the frequency of extreme weather events has increased[1]. These extremes can affect global biodiversity by initiating range shifts, population declines[2], degrading ecosystems and their benefits to people, and even causing local extirpations and extinctions[3]. Mitigating these losses requires directing resources to the species and ecosystems most at risk. However, current predictions are usually based on climate projections of mean conditions many decades into the future[4,5]. Such predictions, while useful for designing longer-term policy decisions[1], provide little guidance for conservation efforts focused on protecting species from near-term (<1 year) manifestations of climate change such as more frequent and intense heat waves.

Near-term forecasts for biodiversity risks can facilitate emergency monitoring and mitigation for at-risk species but lack of operational examples[6]. For example, actions such as supplying drinking water and watering during heat and droughts[7–10], translocating individuals to safer conditions[11,12], or supplementing feeding to cope with reduced resources[13–15] have successfully mitigated the impacts of extreme weather. Also, near-term forecasting can improve biodiversity models by providing opportunities for continuous and rapid validation of forecasts and impact models[16]. Such forecasting systems enable anticipatory proactive management[6,17] which is already being implemented for climate threats to humans and infrastructure[18] and natural resources[6,19,20], but no such near-term forecasting system exists for global biodiversity. Here, we address this gap by developing an early warning system for forecasting biodiversity exposure to climate extremes up to 9 months in advance. We apply this forecasting system to predict risks on biodiversity for the hottest year on record (2024) to demonstrate the usefulness of the approach.

A near-term biodiversity risk forecast requires continuously updated weather forecasts for months in advance and a flexible, species-centric approach for estimating hazards from the expectations of extreme weather. Advances in subseasonal to seasonal prediction systems can now facilitate a biodiversity risk forecast multiple months into the future, by identifying for each species when the weather conditions at any location (0.5 degree grid cells) exceeds what has been experienced by the species historically across its range. We call this species-specific climate exceedance, *exposure*, a critical component of climate change vulnerability analysis which could indicate the potential for adverse impacts[21,22].

Our seasonal forecasts originate from NASA's GEOS Subseasonal to Seasonal Prediction System, Version 2 (GEOS-S2S), which is an ensemble-based prediction system that utilizes the Goddard Earth Observing System modeling and assimilation framework[22]. The GEOS-S2S system has been demonstrated to skillfully predict atmospheric and oceanic conditions several months in advance, including large-scale teleconnections such as El Niño Southern Oscillation (ENSO)[23], resulting in reasonable predictions of near surface conditions[24,25] including extremes, such as heat waves and droughts[26–30]. However, the skill of these forecasts is spatially and temporally variable (Supplementary Figure 1-7), with a partial dependence on ENSO state (Supplementary Figure 2,4, 8-10, and online methods). GEOS-S2S forecasts are produced monthly in near-real time (see data availability section).

Here, we apply the GEOS-S2S forecast to predict the exposure of 30,585 terrestrial vertebrate species to unprecedented monthly temperatures using the forecasts initialized in May 2024. We specifically focus on the period June 2024 through February 2025, which coincidentally was the warmest period on Earth for more than 100,000 years[31]. The effects of climate change on biodiversity are multidimensional, but we focus here on measuring the extent to which forecasted temperatures exceed the upper and/or lower limits of species thermal history[32]. We concentrate on thermal history limits because high and low temperatures strongly affect most species' survival, metabolism, species interactions, and overall abundance and distribution[33–40], and the GEOS-S2S forecast has the highest forecast skill for temperatures. Although other weather variables (e.g. precipitation) and additional information (e.g. sensitivity and adaptation[21,22,41]) are needed to fully assess an individual species' vulnerability, focusing on temperature exposure provides a tool for rapidly identifying potential risks globally: it can be calculated for many species[32] and has successfully predicted risks from past extreme events such as heatwaves[32,42].

Thermal exposure is identified when predicted temperatures exceed the range of temperatures between the 99th and 1st percentiles of average monthly mean air temperature within each species' range (Fig. 1). We calibrated exposure based on monthly mean air temperatures observed from January 1980- April 2023. We used this period because monthly averages have high predictive skill in GEOS-S2S and reflects current warming rates. Two types of exposure were identified in each location and for each species: *annual exposure* – temperatures that exceeded the 99th (or below 1st) percentile threshold of maximum (or minimum) of monthly temperatures over the year - and *monthly exposure* – temperatures that exceed the 99th (or below 1st) percentile for a specific month, e.g., comparing January temperature only to previous January temperatures. *Annual exposure* identifies temperatures beyond any of the known hottest or coldest monthly records where the species occurs and thus represents extreme temperatures that might be expected to cause acute impacts (e.g. mortality events). *Monthly exposure* informs us about potential sublethal effects on sensitive life stages or phenological mismatches[32] and thus might provide earlier warnings of risk.

We synthesized the short-term biodiversity forecasts for vertebrates hierarchically to demonstrate how such an early warning system can accommodate different management priorities and needs: focusing on species and ecosystems, first, and then the administrative units (e.g., provinces) that would undertake potential mitigation actions.

Where and when species were exposed

Between May 2024 and February 2025, we predicted that 3.2% (N=991) and 11.9% (N=3,626) of vertebrate species would be thermally exposed in more than half of their range, for annual and monthly exposure, respectively. Annual exposure was predicted in at least one location for 21.0% (N=6,483) of species and for 64.5% (N= 19,732) of species for monthly exposure. In contrast, only 22 species in 22 sites were predicted to face an annual cold exposure, and 400 species in 432 sites were expected to be exposed monthly to cold temperatures. We tested the effect the quantile threshold used and only showed minimal differences in of varying the strength and spatial agreement of exposure. We found between 5% and 10% variation in species exposure prevalence depending on the exposure type and month, and spatial correlations >0.65 (Extended Data Figure 1).

Exposure to extreme temperatures was predicted to occur on all continents but was particularly concentrated in the tropical and subtropical areas (Fig. 1), areas also shown to have a high climate change signal-to-noise ratio[43]. The sum of annual exposure events (species exposed at a particular month in a cell, $N_{species\text{-}exposed}$ x month) was concentrated in North America and Mesoamerica, especially in the Yucatan Peninsula, with additional exposure hotspots arising in Sub-Saharan Africa and Northern India and Pakistan (Fig. 1a). Monthly-exposure events were predicted in a substantial proportion of South America as well as in central and Southern Africa, especially in the Congo River regions (Fig 1b). Our measure of annual exposure highlights key areas likely to experience unprecedented temperatures, whereas monthly exposure indicates additional places where temperatures might be seasonally extreme but not extreme on an annual scale, such as an unusually warm winter in 2024 in western and South Australia. Annual exposure hotspots – locations with >200 exposure events – were predicted in the Gulf of Mexico during July and August (Fig 1 a,b), and monthly exposure hotspots concentrated in northeast Bolivia.

Exposure was predicted across all taxonomic groups (Fig. 1 c, d). On average, a higher percentage of species' ranges was exposed for amphibians and reptiles (38%), while birds had lower proportions of their ranges exposed (6 %). This pattern reflects the smaller ranges of amphibians and reptiles relative to bird and mammal ranges (Supplementary Table 1), as well as the smaller thermal breadths found in the Tropics, where the magnitude of warming was also highest (Supplementary Figure 11). Nevertheless, range size, itself, was poorly correlated with exposure overall (Supplementary Table 2), highlighting the need for integrating species-specific range geography and thermal breaths with climate anomalies to identify each species' thermal exposure.

We predicted that most species would be exposed in the first four months of the forecasts: between May 2024 and August 2024, when temperatures were expected to be highest in concert with the lingering effect of the 2023-24 El Niño (Fig 1 c, d). These exposure events combined (e.g. annual and monthly $N_{species\text{-}exposed}$ x month, monthly and annual) were present in both the Northern (56.7%) and Southern Hemispheres (43.3%) and were not just a product of the Northern hemisphere summer. The cumulative exposure of species over time, however, indicated that more than 2,500 new species could become exposed from August until November 2024, especially for monthly exposure (Extended Data Figure2).

FIGURE 1 APPROXIMATELY HERE

Risk to vulnerable species under unprecedented heat

We investigated potential compounding effects of forecasted exposure and species already at risk (IUCN classes: *vulnerable*, *endangered*, or *critically endangered*). Our early warning forecasts predicted widespread monthly and annual exposure (>50% of the species' range) for 24% (N=1,511; Fig. 2) and 6% (N=409) of the species of conservation concern among our study species, respectively. Importantly, exposure was widespread in more than 10% (annual exposure) and 35% (monthly exposure) of data-deficient species - mostly amphibians and reptiles – pointing to important data gaps in species exposed (Fig. 2). Overall, results suggest that preventive or monitoring efforts would have been beneficial for 466 species of conservation concern that were expected to be affected by extreme temperatures.

FIGURE 2 APPROXIMATELY HERE

Ecosystems exposed

A particular advantage of this spatially explicit early warning forecast is the ability to identify concentrations of highly exposed species over regions of similar ecological conditions or ecoregions[44], which could precipitate declines in ecosystem function. In May 2024, widespread exposure was predicted in 5% (N=42) and 23% (N=197) of ecoregions for the next 9 months for annual and monthly types of exposure, respectively (Fig. 3). We define these at-risk ecosystems when more than half of their area or half of their constituent species were predicted to be exposed. Specifically, the early warning forecasts identified seven such ecoregions (e.g. annual exposure, Fig. 3, Extended Data Table 1): the *Sonoran Desert* (Mexico-USA), *Indus Valley Desert* (Pakistan), the *Pantanos de Centla* (Mexico), *Petén-Veracruz moist forests* (Mexico) and the *Tigris-Euphrates alluvial marsh* (Iraq, Iran, Kuwait), *Jamaican moist forest* (Jamaica) and the *Yucatán dry forests* (Mexico). For monthly exposure, twenty-three ecoregions were highly affected (2.7%; Extended Data Table 2).

FIGURE 3 APPROXIMATELY HERE

In addition, ecoregions such as the Brazilian Cerrado, the of the Nile River basin, and the Punjab region of Pakistan were expected to experience a high concentration of annual exposure for species already identified as threatened by IUCN (Extended Data Figure 3). Importantly, these do not coincide with areas of a high concentration of exposed species overall. Other ecoregions with a concentrated monthly exposure for threatened species were the Okavango delta region in Africa, the Aravalli forests in Asia, as well as the Mediterranean woodlands of southeast Australia.

Spatiotemporal monitoring and mitigation needs

Conservation actions and policies are often organized and deployed at the subnational (e.g., states or provinces) spatial scale. These subnational units are often the first responders to biodiversity declines and should be warned ahead of time to deploy counter measures, with rapid indicators that allow identifying the risks over their area and their biodiversity.

We classified administrative units as *vulnerable to exposure* (≥30% of species exposed), *exposed* (≥50% species exposed), and *critically exposed* (≥80% species exposed), following the thresholds defined in the Red List assessments of ecosystems[45], which is based on the extent and severity of abiotic stressors. Here, we adapted them to indicate the exceedance of thermal limits inferred from distributions of both vulnerable species, hence of conservation concern, and widespread species, a proxy for potential effects on ecosystem processes[46,47].

The administrative units most at risk accounted for less than 10% of the total entities analyzed. These units were identified as *critically exposed* (5.3%), *exposed* (0.8%) and *vulnerable* (3.1%), covering an area of 0.86% (1.27 M km^2), 0.31% (0.47 M km^2) and 1.82% (2.68 M km^2) (red gradient of annual exposure, Fig. 4a), respectively, of the world terrestrial surface. Monthly exposure (purple gradient, Fig. 4a) was more widespread than annual exposure and was often adjacent to regions expected to undergo annual exposure (Fig. 4a). However, additional political units were identified with only monthly exposure, in areas of subtropical Africa and Australia (Fig. 4a).

A key aspect for risk preparedness is identifying specific warning times. Knowing the time to respond allows one to prioritize and set feasible and achievable actions, which is a critical feature of successful disaster management[48]. In our May 2024 forecast, most political regions would have been warned of exposure (e.g. time to the onset of maximum duration exposure event) between three and five months (32.3%, Fig. 4b) in advance of potential events. Shorter warning times, less than three months, were predicted in 25.8% of the political units. 35.7% of the units would have been warned during the same month of the prediction (although many of these likely would have been identified earlier for a forecast made before May 2024). For ecoregions, the warning time was on average 2.3 and 2.9 months for annual and monthly exposures, respectively. These exact estimates are expected to vary depending on the month and year that the forecast is made, as well as initial conditions in the atmosphere and the ocean. For instance, largescale teleconnections – like ENSO – can result in an increased T2M forecast skill over longer lead times (see online methods for this particular system). However, we still expect exposure to occur due to global warming, and such early warning forecasts could continuously and increasingly report exposure for many species as the climate continues to warm.

As forecasts update and new data come in to validate them, our pipeline is positioned to update parameters to improve forecasts to potentially extend the lead time associated with our early warnings.

Periods of long exposure might accumulate impacts on a species' physiology, demography, and fitness[42,49]. The average duration of predicted exposure within each political unit was 1.8 months, (Extended Data Figure 4), and in 85.9% of the cases, this duration was below 3 months. Such durations for the May 2024 forecast are in line with the timing of the boreal summer, but exceptions apply. For instance, the warning time for Southeast Papuan rain forest was in September at the end of the dry season (Fig 5c and Extended Data Figure 4).

FIGURE 4 APPROXIMATELY HERE

Regional prioritization for monitoring and mitigation

We next performed an ensemble ranking to integrate multiple exposure metrics in a single prioritization scheme to predict risk at the province/state level (or appropriate political units just below the country level). Our prioritization gave equal weight to each of the 34 variables which include information on species threat risk, area exposed, and the number of species exposed, after accounting for correlations among variables and information content (see online Methods and Supplementary Table 3). Such ranking may help prioritize monitoring and mitigation efforts internationally or within a country and help mobilize data or downscale exposure to relevant scales for local managers. This ranking procedure recommended preparing for potential heat impacts in the Caribbean, the Himalayas, and the Pacific Southeast Asian islands (Fig. 5). The countries that would have been prioritized (>5 regions in the top 100 exposure ranking, e.g. ca. 3% percentile) were Mexico, Jamaica, the Bahamas, the Philippines, Trinidad and Tobago and Puerto Rico. The top three regions most expected to be exposed were Uttar Pradesh in India, and Tabasco and Campeche in Mexico. However, other regions of Northern Africa especially in Mali, regions in Brazil, and western Australia as well as Japan and Russia were included in this monitoring prioritization baseline (Fig. 5). We analyzed alternative scenarios based on four different visions of prioritizing the monitoring of exposure, which made largely similar predictions.

We explored three additional schemes in which (i) only annual exposure is considered, to focus on the highest potential impact through extreme monthly heat, (ii) only vulnerable species are considered, to focus on safeguarding biodiversity at risk, and (iii) only variables related to widespread species exposure are incorporated, to focus on potential large-scale impacts on ecosystems (Extended Data Figure 5). These alternative approaches were largely similar in predictions, except for the species conservation approach focused on vulnerable species. In that approach, a higher priority is given to South America in regions like the Mato Grosso and Rondônia (Brazil) and Beni (Bolivia).

FIGURE 5 APPROXIMATELY HERE

Discussion

Early warning systems have proven valuable in other environmental fields including for predicting wildfires[50] and pollution[51]. Moreover, predictions and subsequent validation would allow for continuous refinement of models not only to improve the early warning system but also to aid decision making[6,16]. In this study we used a single forecasting system (NASA’s GEOS-S2S) but future efforts could apply other S2S systems or leverage multimodel ensembles, such as the such as the North American Multi-Model Ensemble[52], the Climate System Historical Forecast Project[53] and the World Meteorological Organization[54] could improve the accuracy of these forecasts[55] and support efforts to predict to predict risks and limit biodiversity loss[56].

An iterative early warning forecast would prioritize where to deploy costly monitoring and mitigation efforts with a few months' notice and could be tied to event-driven mitigation plans and emergency funds[6,17]. Once notified, land managers, conservation groups, and citizens could mobilize efforts to collect baseline data such as population abundances or health metrics and then monitor weather for anomalies[56]. Mitigation strategies, such as supplying refugia or resources, could also be pre-deployed. If extreme heat occurs as predicted, then regions and species could be monitored for deleterious effects and emergency mitigation strategies be readied for implementation. Although such emergency response efforts might not be well-developed now, part of the reason might be the absence of early warning systems. By providing an early warning system, we seek to provide an opportunity as well as an incentive to implement actions to protect biodiversity proactively, rather than always responding retroactively to the last disaster.

Although it is too soon for most published scientific reports to determine ecological responses to exposure predictions, some reports support our predictions. For example, die-offs of Mexican mantled howler Monkeys (*Alouatta palliata*, *A.pigra*) in Southern Mexico were consistent with predictions for this region[57]. These reports quantified up to 31% die-off attributed to heat-stroke in Chontalpa, Tabasco, and other die-offs in Chiapas and Veracruz states, regions areas we predicted to be critically exposed to extreme temperatures in May and June (Fig. 1a; Extended Data Figure 6). Additionally, news reports (without specific data mentioned) documented die-off of bats and birds in San Luis Potosí, (Mexico), as well as deaths of wild bats, birds and monkeys in India and Pakistan between May and June. In January, birds were dying in Western Australia where temperatures exceeded 40°C. All incidents were aligned with our predictions (Extended Data Figure 7), showing the need for a more-detailed emergency monitoring prior to the onset of potentially harmful conditions for biodiversity. On a cautionary note, although compelling, we acknowledge that formal connection between exposure and impacts will require controlled comparisons of predictions of exposure and non-exposure, or simply the use of advanced impact models for species with enough data. Using long-term and high-quality abundance and distribution data will be needed, which is unfortunately also usually lacking, especially for many of the predicted regions at risk. However, exposure provides a baseline to which managers could establish hypothesis about potential impacts.

The exposure metric implemented, based on upper and lower thermal limits inferred from species ranges, provides a proxy for risk that can be applied across all species globally with range data[35,58]. However, we do not know when these observed limits also correspond to the multiple processes that affect fitness, including food availability, biotic interactions, physiology, fitness, etc.[59–61]. Crucially, exposure to high temperatures based on thermal history does not necessarily result in mortality[62] but more often in chronic direct (physiological) and indirect (ecological) responses. As the Earth continues to warm, the exposure thresholds should be updated. Ideally, species exposure thresholds should be based on observations of decreased fitness at levels that trigger important mitigation actions. In the most likely situation that these data are not available, we recommend thresholds to be updated every 5 years with concomitant updates in species ranges to account for potential range contractions or shifts. This ensures capturing ENSO events and provides a higher frequency than decadal climate forecasts.

Although we focus on heat, any relevant weather variables could be incorporated in the same way and weighted depending on their proposed effects on species. For example, our thermal exposure approach could be underestimating species adapted to warm temperatures that are experiencing abnormal precipitation anomalies. Incorporating future precipitation forecasts would enable us to identify exposure to extreme droughts, extreme precipitation events, and storms. Ultimately, a multidimensional climate extreme index would be justified that accounts for all the potential for extreme events. Additionally, future work should incorporate additional mechanisms underlying responses to extreme weather such as food resources, movement, adaptation, and biotic interactions[63,64], including the effects of microclimate variation[65] and improving the biological realism of the forecasting models used. However, these models require information on important species-specific parameters, which are often missing for most species a problem that is most acute in understudied regions such as the tropics that are also often under the greatest threat of extreme temperatures[66]. Applying parameter and trait imputations, using model taxa, or applying simpler versions of mechanistic models could rapidly expand the application of risk assessments globally. For now, our exposure estimates can be used to translate forecasted short-term temperature anomalies to a more biologically relevant proxy.

Amidst the global climate and biodiversity emergency[67], society needs to mobilize available weather forecasts and biodiversity models to better predict potential risks and mitigate impacts of biodiversity loss. A global monitoring system, coupled with a rapid assessment prior to the onset of climatic events is needed to improve our forecasting ability[68]. Making such forecasts synthetic across species, ecosystems, and administrative units would provide the information needed so that every community can mobilize and prioritize their available resources to conserve biodiversity in the face of the accelerating onslaught of extreme weather events.

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Author Contributions Statement

JMSD, LCA, CM, MU, AMW conceptualized the work, the methodology was developed by JMSD, LCA, CM, ASM. Funding acquisition to develop this study was acquired by CM, MU, JMSD. JMSD, LCA wrote the original draft with subsequent review and edits from all coauthors.

Competing Interests Statement

The authors declare no competing interests

Figure Captions

Fig 1. Species exposure was predicted globally and over the forecasting period using subseasonal to seasonal forecasts of (A) species annual-exposure events ($N_{species\text{-}exposed}$ x month, beyond the recorded species thermal limit in the historical period of 1980-present for any month) and (B) monthly-exposure events ($N_{species\text{-}exposed}$ x month, beyond historical thermal limit of the target forecasted month). In C-D, we depict the number of species exposed to annual (C) and monthly exposure (D) by taxonomic group. Species exposure events are most concentrated in the Tropics, monthly exposure events are more widespread, taxonomic groups do not differ in exposure, and most exposure occurred in the Northern Hemisphere's summer months.

Fig 2. Total number of threatened species forecasted to experience increased risk from elevated temperatures by IUCN vulnerability category or monthly and annual exposure. Species at risk, defined when exposure was predicted to cover more than half of the species range for IUCN vulnerable and data-deficient species.

Fig 3. Ecoregions are affected by monthly and annual exposure. Category colors correspond to combinations of extreme and monthly exposure levels for regions where more than 50% of the Area is exposed (A) more than 50% of the species are exposed (S) and when both species and area are exposed (A+S). Ecoregions without exposure (N) are in gray.

Fig 4. The early warning system identifies regions with high levels of species-specific thermal exposure (a). Classes indicate vulnerable regions (≥30% of species exposed), exposed regions (≥50% of species exposed), and critically exposed regions (≥80% of species exposed). These categories are adapted from the Red List assessment of Ecosystems (43). Percentages indicate species within an administrative unit under consideration (GADM level 2). Insets indicate key forecasted regional hotspots of thermal exposure for vertebrates (b), and (c) shows the time in months before the onset of the exposure event or warning time from the forecast initialization (May 2024).

Fig 5. Regions prioritized for biodiversity risk mitigation. Monitoring priority ranking is based on multiple exposure criteria (34 exposure metrics) and calculated at the administrative level 1 – first administrative level below countries. Alternative rankings based on different sets of criteria are shown in fig S5, here we show the top 400 regions – 0.5 percent of all regions with at least one exposure event – employing all criteria selected balancing weights to avoid criteria redundancy.

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Online Methods

Subseasonal-to-seasonal climate forecasting products

We used National Aeronautics and Space Administration (NASA) Global Modeling and Assimilation Office (GMAO) seasonal forecasts produced with the Goddard Earth Observing System (GEOS) Atmosphere-Ocean General Circulation Model and Data Assimilation System Version 2[23] (GEOS-S2S hereafter). The GEOS-S2S provides the current month (partial) plus a forecast for the next 9 months, updated every month at a half-degree spatial resolution. Here, we use May 2024 retrospective forecasts to calibrate species exposure models and May 2024 forecasts to identify species exposure to hot and cold temperatures.

GEOS-S2S system is composed of the GEOS Atmosphere-Ocean General Circulation model (AOGCM) and Atmosphere-Ocean Data Assimilation System (AODAS), which serves to initialize GEOS-S2S forecasts[23,69] . The current system, GEOS-S2S Version 2 has been used to produce a series of retrospective forecasts (1981-2016) and near real time forecasts (2016-present). The retrospective forecast ensemble is produced from four fixed dates each month with no atmospheric or oceanic perturbations (4-member lagged ensemble). Near-real time forecast ensembles are produced using a lag-burst technique[23] with four lagged, unperturbed ensemble members and six perturbed members initialized on the last forecast start date of a given month[23].

The GEOS-S2S system is experimental, not operational; however, results from the AODAS and the GEOS-S2S forecasts are contributed to the North American Multimodel Ensemble (NMME[70]) and a suite of end users. The GEOS-S2S system has continued to improve its prediction of and has been valuable at predicting the El Niño-Southern Oscillation[23]. The S2S sea surface temperature (SST) forecasts generally demonstrate a strong correlation with observed Niño indices between forecast lead months 1-3, with forecasts initialized during boreal summer displaying strong correlations for several months longer[23]. How SST and other ocean and atmospheric characteristics impact forecasts of temperature and precipitation can be regionally and temporally dependent[71]. Previous work demonstrates that the current GEOS-S2S system reasonably predicts near surface air temperature in North America[72] and globally[73]. However, it should be noted that, in general, the skill of a multimodel ensemble is equal to or greater than that of an individual model[72] because such ensembles provide minimization of random errors and increased parameterization diversity, which can improve the representation of uncertainty[74,75]. Despite this, we choose to use the GEOS-S2S system for this demonstration to take advantage of the higher resolution than the NMME (0.5° vs 1°), while acknowledging that the framework of species exposure presented here is easily adaptable to any probabilistic S2S system.

The GEOS-S2S system demonstrates reasonable skill at predicting large-scale teleconnections up to 6 months in advance between May and August[23]. Therefore, to provide the best balance between GEOS-S2S forecast skill and boreal summer species exposure, we use GEOS-S2S forecasts initialized in May 2024. To evaluate the ability of the GEOS-S2S system to produce deviations from the climatological mean, we calculate the anomaly correlation, which is simply the correlation between the ensemble mean forecast anomaly and the observed anomaly (in this case ERA-5) and the root mean squared error (RMSE), which is square root of the squared differences between the ensemble mean forecast anomaly and the observed anomaly (again, ERA-5) for the 36-year retrospective period. We also examined the likelihood that each ensemble member of the retrospective forecast suite accurately reproduces monthly mean 2-m air temperature anomaly in three climatologically equiprobable categories (below normal, normal, and above normal) relative to ERA-5.

S2S systems can derive increased predictability in 2-m air temperatures and other atmospheric variables when forecasts are initialized during warm ENSO (or El Niño) events[76,77]. In order to characterize the impact of warm ENSO events on GEOS-S2S forecast skill, we evaluated the anomaly correlation, anomaly RMSE, and ensemble distribution for three categories of the retrospective forecasts: (1) the full retrospective time period, (2) retrospective forecasts initialized when the May sea surface temperature (SST) anomaly in the Niño 3.4 region was below 0.5°C (neutral or cold ENSO conditions; 1981, 1984-1986, 1988-1991, 1994-1996, 1999-2014, 2016), and (3) retrospective forecasts initialized when the May SST anomaly in the Niño 3.4 region was at or above 0.5°C (El Niño events; 1982, 1983, 1987, 1992, 1993, 1997, 1998, 2015). This index was calculated using the HADISST 1.1 SST dataset[78] and is closely followed by the GEOS-S2S initial conditions due to SST and sea surface salinity assimilation[79].

GEOS-S2S captures the near surface temperature anomaly over the land surface and declines with lead time, with limited skill in the Northern Hemisphere beyond lead month 3 in the retrospective period for the full suite of retrospective forecasts (Supplementary Figure 1) and for retrospective forecasts initialized during neutral or cold ENSO conditions (Supplementary Figure 8). However, retrospective forecasts initiated during warm ENSO conditions show higher overall anomaly correlations that tend to persist, particularly in North America, for at least an additional month though there are some limitations on statistical significance due to the small sample size (8 retrospective forecasts; Supplementary Figure 9). The presence of warm ENSO conditions during forecast initialization has less impact on the anomaly RMSE (Supplementary Figure 2, shown out to lead month 3 due to the limited differences). North America exhibits an improvement in anomaly RMSE of ~0.4°C at lead month 1 between the forecasts initialized during neutral or cold ENSO (Supplementary Figure 2d) conditions and warm ENSO conditions (Supplementary Figure 2g); however, this improvement dissipates by lead month 2. Globally, the anomaly RMSE is similar across the three retrospective groupings.

The GEOS-S2S retrospective forecast ensemble contains four members. This small ensemble size limits the utility of spread/skill analysis[80]; however, to provide an assessment of forecast confidence, we assess the mean number of ensemble members that appropriately forecast the 2-m air temperature as below normal, normal, and above normal relative to ERA-5. Overall, forecast confidence is strongest in the tropics (Supplementary Figure 3), which corresponds to regions of strong anomaly correlation (Supplementary Figure 1), though this ensemble agreement wanes beyond lead month 3 for both the full retrospective forecast period and for forecasts initialized during neutral or cold ENSO conditions (Supplementary Figure 4). In forecasts initialized during warm ENSO, there is greater agreement in the forecast ensemble, including in regions of North America and Western Asia, out to lead month 4 (Supplementary Figure 10). However, this increased agreement is spatially variable, likely in part due to the small number of El Niño initialized forecasts.

GEOS-S2S has additional skill in predicting 2-m air temperatures when warm ENSO conditions are present in the initial conditions. However, it should be noted that there is evidence that changing patterns in the location of maximum SST anomaly[77] and tropical convection[81] can impact the atmospheric response and hence S2S predictability associated with warm ENSO conditions. Further, while there was a strong El Niño during the 2023/24 boreal winter, this warm SST anomaly faded and El Niño conditions were not present in May 2024 (anomaly of 0.41)[78] when the forecasts used in this analysis were initialized.

In order to assess the skillfulness of the May initialized near real time GEOS-S2S forecasts, we again use the anomaly correlation, and we use the de-biased rank probability skill score (RPSS), which provides an evaluation of the probabilistic forecasts relative to the observed values and introduces a measure of skill relative to the forecast climatology[82,82]. Here we choose the de-biased RPSS to minimize the intrinsic unreliability of small ensemble sizes and reduce inconsistencies in the RPSS formulation[83]. Because GEOS-S2S has a 4-member retrospective forecast suite and a 10 member near real time forecast suite, we use the formulation for the ensemble correction presented in Weigel et al.[83]. To calculate RPSSd, we evaluated all probabilistic forecasts of monthly mean 2-m air temperature for three climatologically equiprobable categories (below normal, normal, and above normal) based on the retrospective forecast period. In all cases, we evaluated the RPSSd based on the forecast lead month to account for the seasonal temperature cycle. For reference, RPSSd scores of 1 indicate perfect skill relative to the climatology and a RPSSd of zero indicates no skill. Negative RPSSd values indicate a misleading forecast less accurate than climatology.

GEOS-S2S captures the near surface temperature anomaly over the land surface declines with lead time, with limited skill in the Northern Hemisphere beyond lead month 3 in the forecast period (Supplementary Figure 8). However, we find that the GEOS-S2S system shows reasonable skill at predicting monthly mean 2-m air temperatures below, at or above normal, with 60°N to 60°S RPSSd averages between 0.4 and 0.25. However, there are several features of note. Despite the strongest anomaly correlation for June and July forecasts (lead 1-2, Supplementary Figure 8), there are several regions which show a negative RPSSd (Supplementary Figure 9). These regions generally show negative anomaly correlations and are associated with an increased probability of below normal temperatures for June and below or normal temperatures for July. This suggests that, in some regions, are under performing relative to the forecast climatology due to a potential cold bias in near real time forecasts. Such an issue could affect the utility of species exposure forecasts for such regions. The issue is generally resolved by lead month 3 and all regions show a decline in RPSSd as lead time increases.

To specifically address the skill of the 2024 forecasts used for species exposure herein, we evaluated the anomaly root mean squared error (RMSE) against ERA-5 for all forecast lead times for a range of latitude zones (Supplementary Figure 10), with anomalies relative to the period 1981-2016. The tropics and Southern Hemisphere mid-latitudes show a consistently low RMSE relative to 2024 ERA-5 temperature anomalies (between 1.3°C and 2.2°C). The Northern Hemisphere midlatitudes exhibit anomaly RMSE values between 1.8°C and 2.2°C for the first three forecasted months (June-August), followed by an increase in anomaly RMSE values for the remainder of the forecast months.

In combination, these analyses of the GEOS-S2S forecasts initialized in May, suggest that GEOS-S2S forecasts can provide skillful 2-m air temperature up to 3 months in advance for midlatitudes and potentially longer in the tropics when neutral or cool ENSO conditions are present in the initial conditions and potentially longer when warm ENSO conditions are present. However, that care should be taken because near real time forecasts can produce ensemble forecasts with a higher probability of colder than average or average temperatures, relative to the forecast climatology, during this period.

Species temperature exposure

We targeted four major vertebrate groups to analyze exposure: reptiles, amphibians, mammals, and birds. These major groups have been used before to identify key disruptions in ecosystems[58,84]. We restricted our analyses to 30,585 terrestrial species and native ranges among these groups, and in the case of birds, we focused on breeding and resident ranges of extant species. We obtained species ranges from the International Union for Nature Conservation[85] and BirdLife International[86]. Species ranges were transformed to raster in R using the terra package v.1.7 [87] to adapt to the same grid resolution as the GEOS-S2S forecasting grid. In each species range raster, the percentage of area occupied by the species in each grid cell was recorded and subsequently used as weight to calculate species specific thresholds (see below). Due to the coarse grain of the GEOS-S2S forecasts, species with cells located only on very small islands or the coast were not retained for analysis, as the temperatures forecasted may only reflect sea conditions.

For each species range, we extracted the 2-meter temperature monthly averages (T2M) from the GEOS-S2S ensemble member hindcasts for each lead time. That is, every species range has 10 monthly temperature time series from January 1980 until April 2024 corresponding to the 0 to 9-month forecast. By calculating a unique threshold for each lead time, we ensure forecasting biases and uncertainties – that increase as lead time increases – are accounted for in the threshold estimation.

For each lead time monthly time-series, the 1st and 99th percentile of T2M were calculated using the "Type 7" quantile weighted by species occupancy in the grid implemented in the cNORM R package[88]. Weighting prevents over-emphasizing cells that only have minimal species occupancy, avoiding the estimation of temperature thresholds stemming from local adaptation processes, microenvironments not accounted for at coarse resolution, or imprecisions in the delineation of expert range boundaries. For each lead time time-series, we estimated monthly thermal limits, those corresponding to the percentiles 99 and 1 for a specific month (used in monthly exposure), and an extreme threshold (used in annual exposure), corresponding to the maximum or minimum value among all months in the hindcast period (e.g. the maximum or minimum threshold computed).

We forecasted exposure from May 2024 to Feb 2025 at monthly intervals. Monthly exposure was determined for a given species and grid cell when the temperature was above or below the species thermal limit within species range in the target forecast month. For example, in the case of the June 2024 forecast (lead time 1), species thermal limits were calculated using the hindcast time series for lead time 1 and for the specific month of June. We acknowledge that the May exposure forecast (lead time 0) is based on <30 days due to initialization time, but we decided to report exposure for consistency. To determine annual exposure, we used the same lead time time-series (e.g. 1), but we selected the thermal limit corresponding to the maximum or minimum threshold irrespective of the month.

Recent analysis has shown low sensitivity of the choice of quantile (e.g. 90^{th}, 95^{th}, 99^{th} quantile) on exposure estimates[89]. We additionally evaluated the sensitivity of our exposure forecast to the thresholds used in this study. We evaluated alternative quantile thresholds: the paired 95th-5th percentile and the paired 90^{th} -10^{th} percentile. We evaluated changes in species exposure prevalence as a function of percentile exposure thresholds. We additionally computed the spatial agreement between maps of exposure events with different threshold combinations. We focused on two metrics: Spearman rank correlation and Kendall's tau correlation. Spearman correlation assesses the congruence in the spatial pattern, while Kendall's tau is focused on the ordering of the pixels and therefore the agreement in ranked exposure (and the hotspots) using different percentiles. We observed minimal variation in exposure prevalence as a function of the quantile used: between 5 and 7% averaged prevalence for annual exposure, and between 5 and 10% averaged prevalence for monthly exposure across species exposed. There was an overall high agreement in both metrics ranging from 0.76 to 0.95 in their spatial consistency, and 0.64 to 0.85 in their spatial ranking similarity, on average across all forecasted months. All correlations are >0.5, and there is no apparent temporal pattern in the correlation.

We computed several exposure attributes for each species and grid cell within species range. We determined the number of events – months with exposure within the forecasting period, the maximum duration of consecutive months under exposure, and the warning time – or months prior to the onset of the maximum duration of exposure.

Comparison with historical products and within GEOS-S2S uncertainty

The use of May forecast allows the comparison of exposure and thermal limits between GEOS-S2S forecasts and recent reanalysis products that depict other month's forecasts. We compared May 2024, June 2024, and July 2024 GEOS-S2S exposure forecasts with predictions using ERA5 historical monthly reanalysis[90] downloaded from the Copernicus Center in August 2024, coarsened to match the grid size and extent of the S2S climate forecasts. Here, we focused on the congruence and the level of agreement between forecasting an exposure event (from GEOS-S2S) or identifying it *a posteriori* (from ERA5).

We performed two types of comparisons: (1) based on the species thermal threshold estimation and (2) based on the exposure prediction. For the first analysis, we identified the magnitude of exposure. - that is, the difference between the observed and predicted temperature and the associated species thermal threshold at a given location, averaged across locations. Then we computed the average deviation in species thermal limits between S2S and ERA5. We further analyzed the differences in exposure quantile estimation for both S2S and ERA5[90] datasets. Differences between GEOS-S2S and ERA5 in thermal limit estimation for species were -0.054 C on average (Supplementary Fig. 12).

For the exposure comparison, we computed, for every species and forecasted month, the confusion matrix between GEOS-S2S and ERA5 exposure projections and assess their accuracy (proportion of the predictions of S2S that are the same as in ERA5, computed using the Metrics R package v 0.1.4[91] . Overall accuracy of the exposure remained high (>0.9) but the sensitivity – e.g. the spatial distribution of exposed pixels for ERA5 vs GEOS-S2S varied among species (Supplementary Fig. 13-14), with values of exposed pixels agreement between 45% to 75% on average among all species, which reflects the inherent uncertainty between the S2S forecast and the ERA5 reanalysis. A probabilistic evaluation of the forecasts demonstrated accurate probabilistic forecasts (Brier Scores <0.2 in 88% of the species x months) relative to the exposure estimated by ERA5 reanalysis (Supplementary Figure 15a). The forecasting system also showed a positive skill against the baseline prediction based on quantiles (e.g. baseline prediction of 0.02 based on 99th and 1st quantile thresholds), with Brier Skill Scores > 0 in 70% of species x months (Supplementary Figure 15b). Annual exposure predictions showed generally higher degrees of accuracy than monthly exposure (Supplementary Figure 15).

We further assessed the sensitivity of the GEOS-S2S ensemble members on exposure estimates. GEOS-S2S produces 10 ensemble members, typically performed to measure climate prediction uncertainty. For the May 2024 forecast such perturbations on the initial conditions did not substantially affect our results. The spread within S2S exposure predictions was low, with 90% agreement for each species among ensemble mean and each of the GEOS-S2S perturbed forecasts, and ~0.1 C standard deviation in species thermal margins (Supplementary Figure 16). This ensured a high consistency of exposure forecasts from the GEOS-S2S weather forecasts.

Biodiversity exposure categorization and monitoring prioritization

We synthesized pixel level exposure forecasts within ecoregions to determine which regions at high exposure that would call for imminent monitoring and/or mitigation. We identify exposure within ecoregions[44] and administrative levels because these are often the levels at which conservation decisions are made. Specifically, we used the global administrative data (version 4.1, available at gadm.org) level 1 (GID 1, corresponding to large regions or states or provinces) and level 2 (GID2, corresponding to counties or parishes). These ecological and administrative units were coarsened to match the resolution of the GEOS-S2S forecast. Consequently, 66 small islands or mountain top ecoregions were not analyzed due to their minimal area with respect to GEOS-S2S cell size.

In each unit, we computed several variables related to important approaches to conservation and mitigation: the magnitude of the impact (e.g. annual exposure), the threat status of species exposed (per species categorized as IUCN vulnerable or above, as well as data deficient species), the pervasiveness of the species defining ecosystem processes (widespread species – defined as those covering >50% of the target administrative unit), and the total number of species affected (number of exposure events affecting any species). Specifically, we initially used 16 variables for each month and annual exposure (thus 34 in total): (1) the total area with at least one species exposed, (2) the percentage of area exposed, (3) the percentage of area where widespread species were exposed, (4) the number of widespread species exposed, (5) the percentage of widespread species exposed, (6) the percentage of area exposed by vulnerable species, (7) the percentage of vulnerable species exposed, (8) the number of vulnerable species exposed, (9) the percentage of vulnerable species exposed in more than half of their range, (10) the number of vulnerable species exposed in more than half of their range, (11) the average number of events (species x months averaged across cells), (12) the sum of exposure events (incidence) in the administrative unit, (13) the first date of exposure, (14) the last date of exposure, (15) the number of consecutive months of exposure, (16) the peak date or date where the maximum number of exposure events is achieved, and (17) the maximum length in months of exposure duration. For dates, earlier dates imply higher prioritization for monitoring.

We classified key regions at risk using three categories of exposure inspired by the Red List of Ecosystems of the IUCN[45]: critically exposed, exposed, and vulnerable. The IUCN system uses severity and extent of the impact to identify such risk categories with thresholds of >80%, >50% and >30% in each of them. We adapted such a framework to use two dimensions as well: vulnerable species (critically endangered, endangered, and vulnerable) and the widespread species. The first dimension covers species conservation through the lens of unique species at risk, the second variable aims at quantifying the effect over widespread species in the area that may affect key ecosystem processes. This was performed for both monthly exposure and annual exposure estimates. These two categories are not mutually exclusive.

Finally, we ranked level-1 administrative units to determine key hotspots for vertebrate biodiversity mitigation in our 9-month forecast based on the 34 variables detailed above Here we choose Level-1, instead of level 2 as in the regionalized exposure in Figure 5, because it is these regions have more comparable areas to one another, in contrast to countries, whose areas vary considerably.

We used a multicriteria assessment to recommend the top areas for biodiversity surveillance. Multicriteria assessment is widely used for decision making for ranking different alternatives and may vary according to the weights (e.g. importance) of the variables considered as well as the algorithm employed for ranking. A meta-ranking was obtained by averaging the rankings produced by four different algorithms for each administrative unit. We used (1) the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS[92]) (2) VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR[93]) (3) the Multi-Objective Optimization by Ratio Analysis in its multiplicative form (MOORA[94]) , and (4) the Weighted Aggregated Sum Product ASsessment (WASPAS[95]). These algorithms are implemented in MCDM R package v.1.2 [96].

Multicriteria analysis involves the choice of agreed criteria (variables) and specific weights (e.g. importance) for each criterion under consideration. Different agencies or experts could choose different variables and apply different weights according to their conservation approach and objectives (fine-grain vs. coarse-grain conservation viewpoint[97]). To allow for different focus and opinions – even among authors– about which variables should be considered for ranking we implemented four alternative scenarios: (i) All-in , (ii) Extreme first, (iii) Species-at-risk (fine grain approach), (iv) Ecosystems at risk (coarse-grain approach). For the *All-in* scenario all exposure indices are considered, for the Extreme-first scenario only variables related to annual exposure are considered, because it focuses on the highest thermal threshold that could potentially lead to greater impacts. In the case of the *Species-at-risk* scenario, we only consider exposure in species categorized as vulnerable, endangered, critically endangered or data deficient by IUCN; whereas for the Ecosystem-at-risk scenario only variables related to widespread species that contribute most to ecosystem function (covering >50% of the administrative unit) are selected. To minimize variable correlation and avoid over-emphasizing certain criteria we removed strongly correlated variables (r>0.7). Among the resulting criteria, we employed an "objective" weighting system. We used an entropy-weights (algorithm-based weights as opposed to subjective weights) method that assigns weights based on variable information content (dispersion and degree of differentiation[98]). It is thus transparent and has the added benefit of minimizing the effect of the remaining correlation among variables. That is, correlated or redundant criteria will have low cross-entropy and thus will be down-weighted. While this solution is not perfect under high zero inflation and variables involving ranking[99], our case study is not prone to this issue. All scenarios, variables considered, and their entropy-weights are available in Supplementary Table 3.

Data Availability

Species expert range maps from IUCN are available at https://www.iucnredlist.org/resources/spatial-data-download. The GEOS-S2S-V2 data are available on the Discover server of NCCS at https://www.nccs.nasa.gov/systems/ data-portal, and GEOS-S2S-V2 forecasts output data are presently available at https://gmao.gsfc.nasa.gov/gmaoftp/gmaofcst/. Historical climate reanalysis data from ERA5 are available at https://cds.climate.copernicus.eu/ ERA5. Administrative units available at gadm.org v. 4.1. Climate exposure results are synthesized by large groups (e.g. mammals, birds, amphibians, reptiles) to respect species expert ranges licensing and protect vulnerable species. These and resulting data are available at a dedicated code release in[100] https://doi.org/10.5281/zenodo.19253736

Code Availability

Code used to compute exposure can be found in the repository[100] https://doi.org/10.5281/zenodo.19253736

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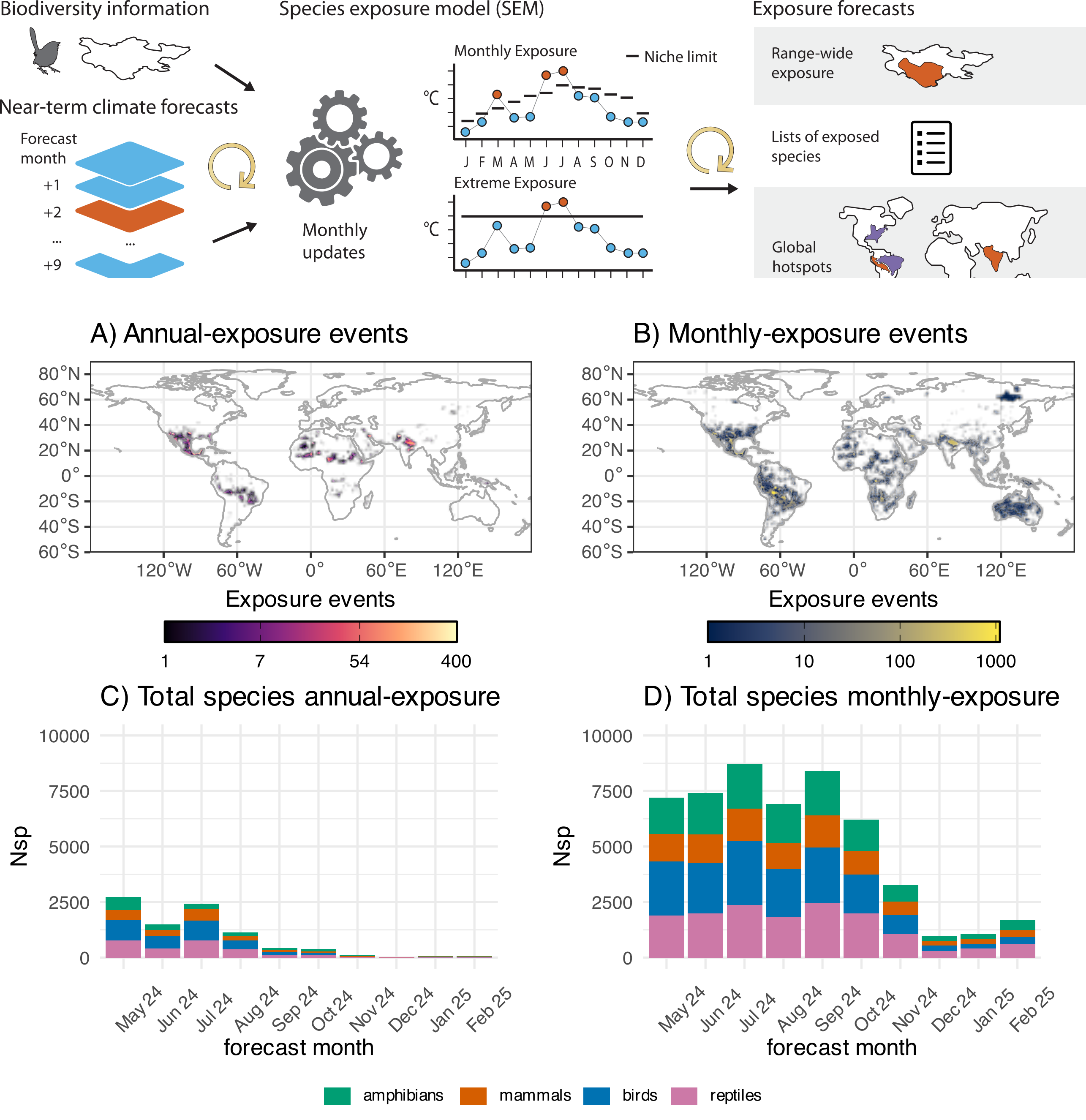
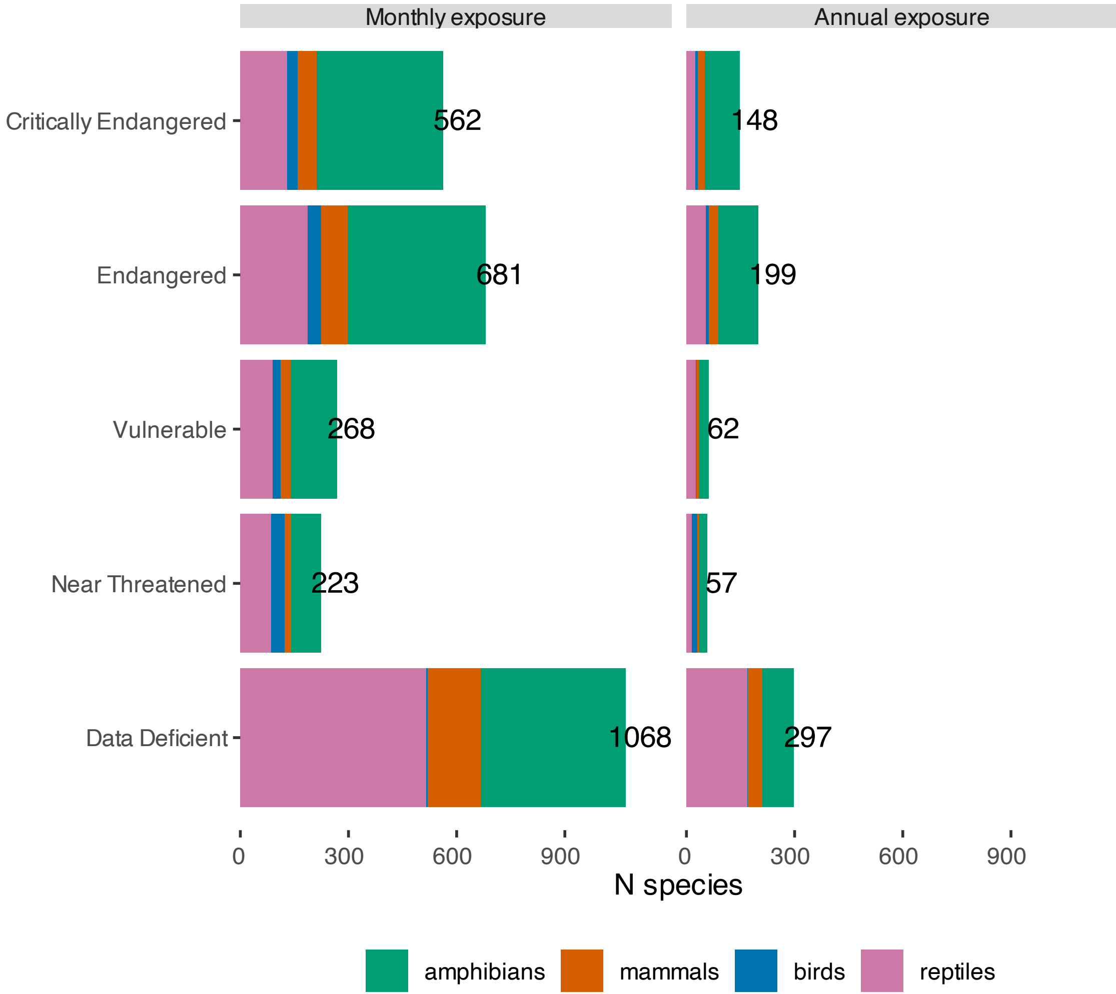
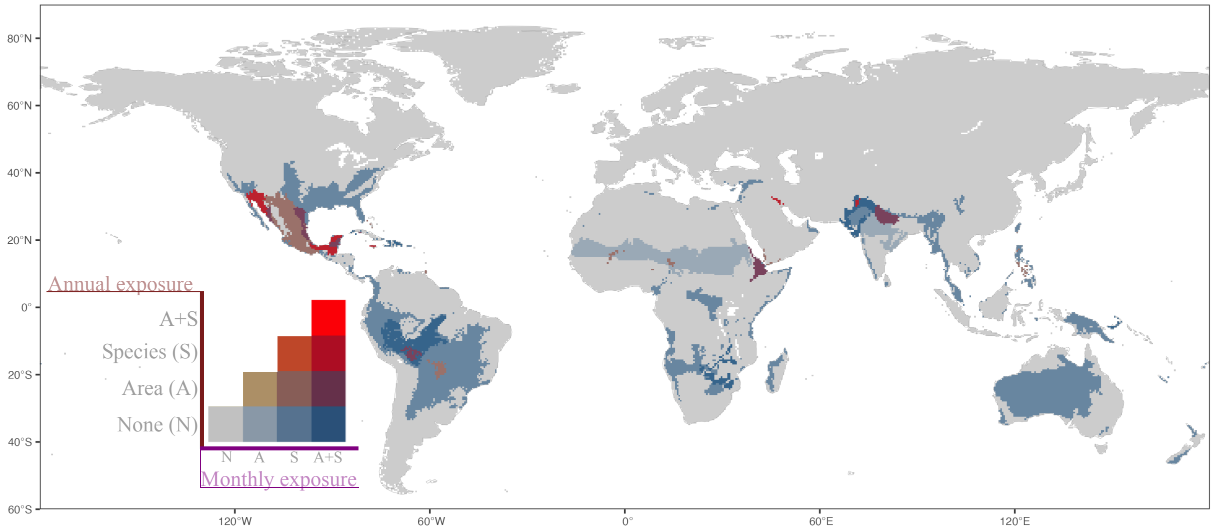


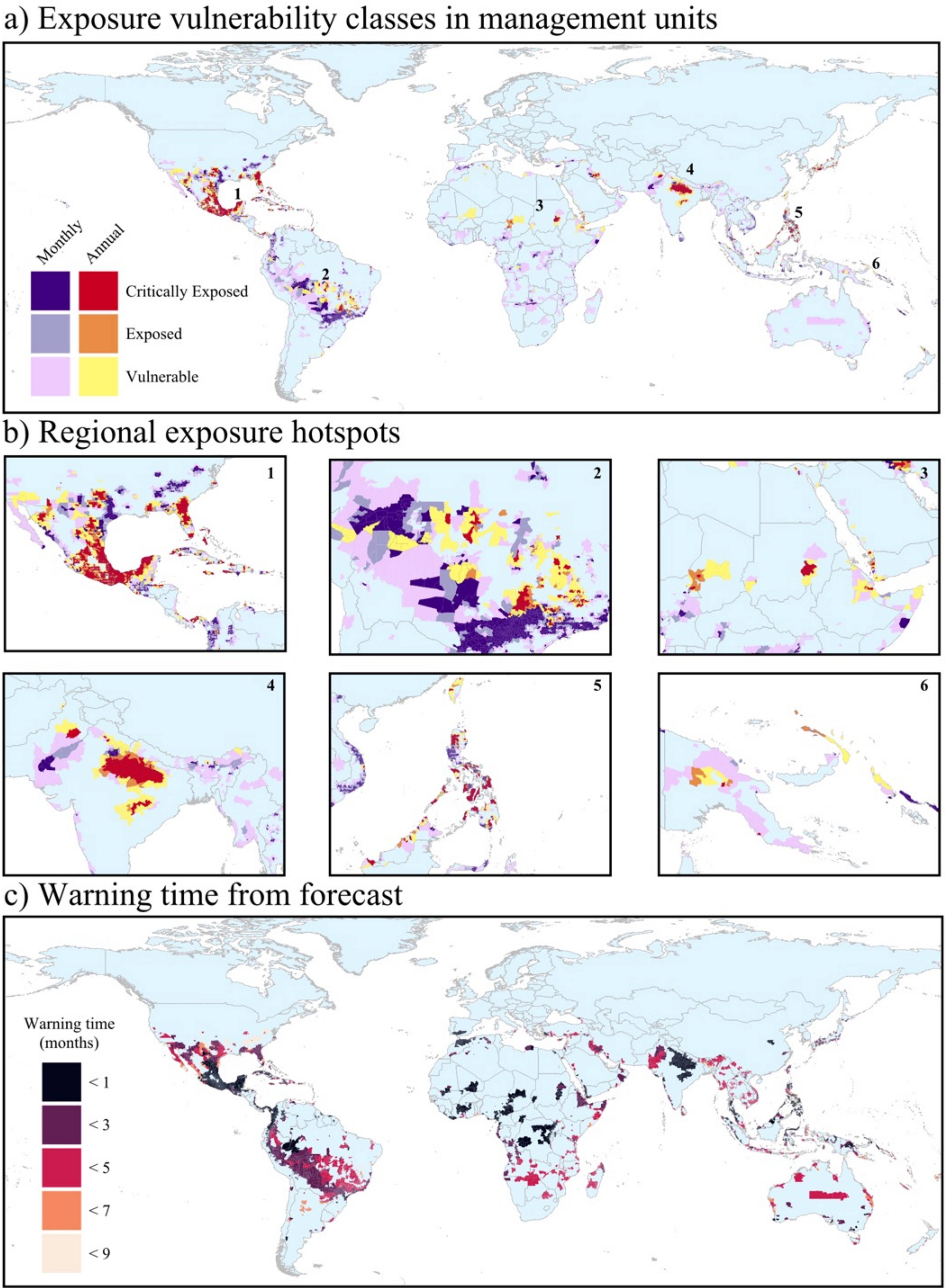
Biodiversity information
Species exposure model (SEM)
Exposure forecasts
Near-term climate forecasts
Forecast month
+1
+2
...
+9
Monthly updates
Monthly Exposure
Niche limit
°C
J F M A M J J A S O N D
Extreme Exposure
°C
Range-wide exposure
Lists of exposed species
Global hotspots
A) Annual-exposure events
80°N
60°N
40°N
20°N
0°
20°S
40°S
60°S
120°W
60°W
0°
60°E
120°E
Exposure events
1
7
54
400
B) Monthly-exposure events
Exposure events
1
10
100
1000
C) Total species annual-exposure
Nsp
10000
7500
5000
2500
0
May 24
Jun 24
Jul 24
Aug 24
Sep 24
Oct 24
Nov 24
Dec 24
Jan 25
Feb 25
forecast month
D) Total species monthly-exposure
Nsp
forecast month
amphibians
mammals
birds
reptiles

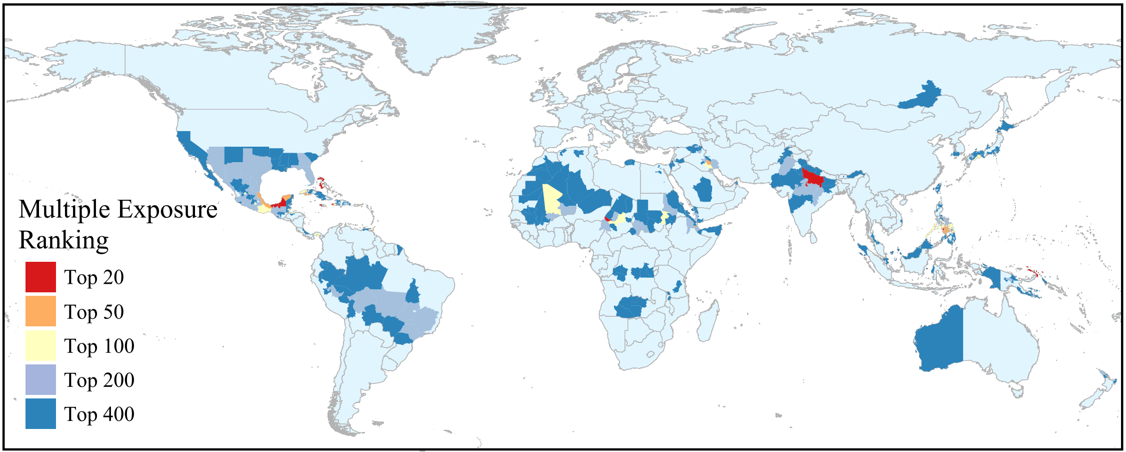


Monthly exposure
Annual exposure
Critically Endangered
Endangered
Vulnerable
Near Threatened
Data Deficient
562
681
268
223
1068
148
199
62
57
297
0
300
600
900
0
300
600
900
N species
amphibians
mammals
birds
reptiles

Ecoregions exposed




a) Exposure vulnerability classes in management units
Monthly
Annual
Critically Exposed
Exposed
Vulnerable
1
2
3
4
5
6
b) Regional exposure hotspots
1
2
3
4
5
6
c) Warning time from forecast
Warning time (months)
< 1
< 3
< 5
< 7
< 9


Multiple Exposure Ranking
Top 20
Top 50
Top 100
Top 200
Top 400