Testing the climate niche framework for amphibian extinction risk

Claus Sarnighausen [1,2], Maximilian Kotz [2], Sanam Vardag [1]

[1] Institute of Environmental Physics, University of Heidelberg, Germany

[2] Department of Complexity Science, Potsdam Institute for Climate Impact Research, Germany

Motivation

Measuring the influence of climate change on species' extinction risk remains complex and lacks the appropriate tools (Cazalis et al., 2022). We test the suitability of the **climate niche** for predicting the risk status of 6,288 amphibian species, using the IUCN **Red List Category** as a proxy.

Main Question

- Do climate-niche measures improve the prediction of Red List Categories

Climate Impact Measures

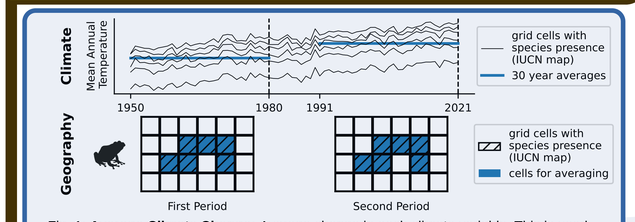

Fig. 1: **Average Climate Change:** Average change in each climate variable. This is used e.g. in Lucas et al. (2024)

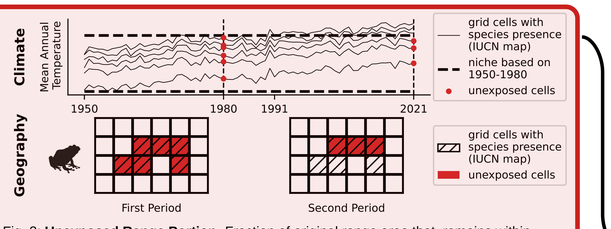

Fig. 2: **Unexposed Range Portion:** Fraction of original range area that remains within the limits of historical climate conditions. This is used e.g. in Pigot et al. (2023)

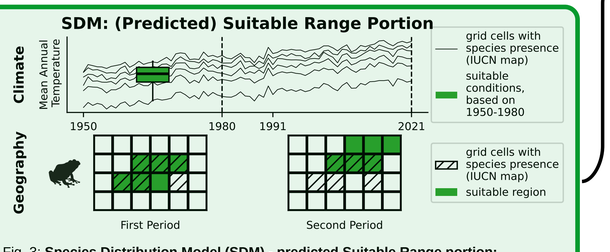

Fig. 3: **Species Distribution Model (SDM) - predicted Suitable Range portion:** Fraction of original range area that is predicted as suitable in the second period by an ensemble of SDMs. This is used e.g. in Velasco et al. (2021)

Based on Climate Niche

Results

Average Change (Avg)

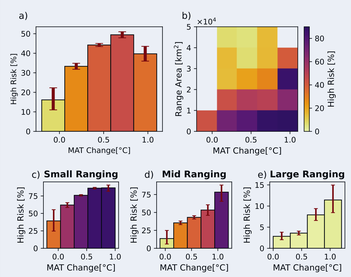

Fig. 4: Mean Annual Temperature Change (1980 – 2021) correlates with increased extinction risk in the 6,288 amphibians. Bottom: small ranging species (< 10.000 km², n = 2848), middle ranging species (10.000 - 30.000 km² , n = 902) and large ranging Species (≥ 30.000 km² , n = 2556)

Exposure-Based (Exp)

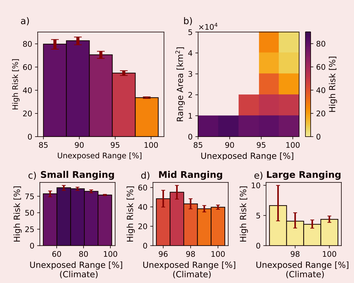

Fig. 5: Unexposed Range (1980 – 2021) shows correlation with increased extinction risk in the 6,288 amphibians, but is also strongly correlated with range area.

Species Distribution Model -Based (SDM)

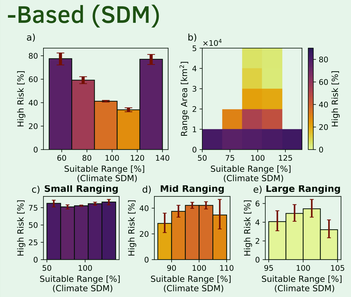

Fig. 6: Predicted suitable range (1980 – 2021) shows no correlation with extinction risk in the 6,288 amphibians, once range area is controlled for.

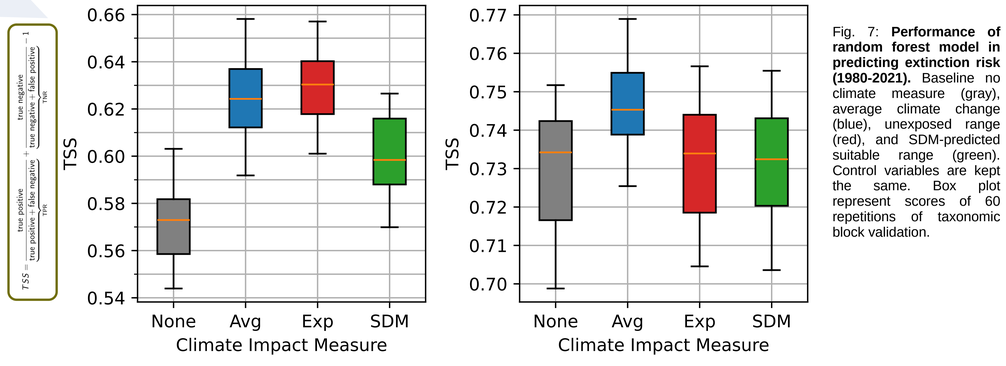

Fig. 7: **Performance of random forest model in predicting extinction risk (1980-2021).** Baseline no climate measure (gray), average climate change (blue), unexposed range (red), and SDM-predicted suitable range (green). Control variables are kept the same. Box plot represent scores of 60 repetitions of taxonomic block validation.

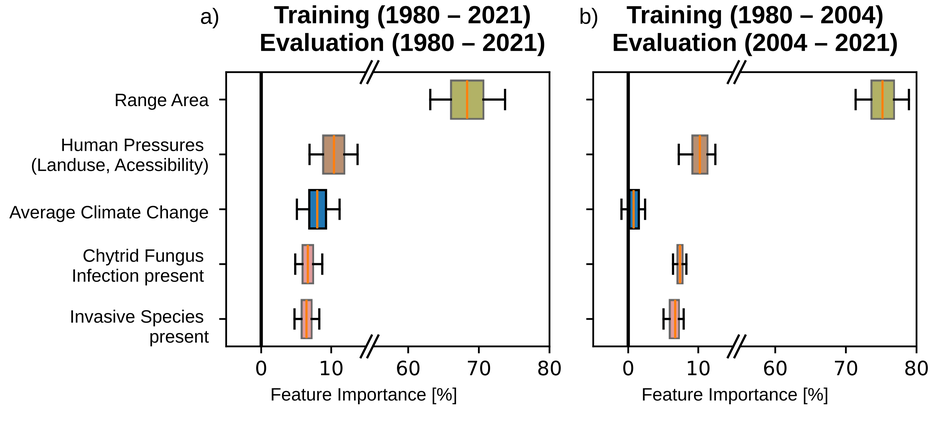

Fig. 8: **Grouped feature importance for forward-in-time prediction.** Average climate change loses predictive power while other variables remain predictive. Area is the largest predictor.

Predicting Past Red List Changes

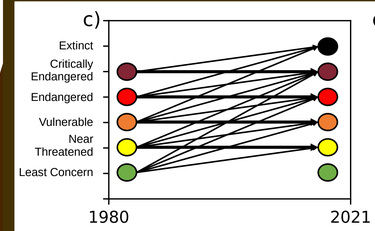

Fig. 9: **Definition of the prediction target:** "High risk" changes in Red List category.

Fig. 10: **Number of Red List category changes** between 1980 and 2021, among amphibian species in the dataset.

A **random forest model** is trained on predicting transitions from the following **Data:**

- **ERA5 climate data**

  5 Bioclimatic variables and fractions of range within historical niche, derived from Temperature, Precipitation

  [1940 – today, monthly; 0.25° x 0.25° global] (Hersbach et al., 2023)

- **Human Pressure variables**

  Cropland*, Rangeland, Pasture*, Urban areas*, Human population density*, Mean Human accessibility†

  [1980, 2004, 2021; 0.5° x 0.5° global] (Goldewijk et al., 2017)

  †[2000, 2015; 0°00'30" x 0°00'30" global] (Nelson et al., 2019)*

Key Points

1. Climate Niche measures have **no significant predictive power** for extinction risk beyond their correlation with range area.

2. Highly predictive measures of climate impact **do not necessarily extrapolate** for future predictions

3. Climate niche models can be are very useful for individual, well studied species. For a large number of species, they have to be **applied with great caution**.

Contact
claus.sarnighausen@iup.uni-heidelberg.de
Im Neuenheimer Feld 229, 69120 Heidelberg
Room 306

Sharing is encouraged

Abstract Information

References

1. Cazalis, V., Di Marco, M. et al. Bridging the research-implementation gap in IUCN Red List assessments. Trends in Ecology & Evolution (2022). https://doi.org/10.1016/j.tree.2021.12.002
2. Hersbach, H. et al., (2023): ERA5 monthly averaged data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/cds.f17050d7
3. Klein Goldewijk, K., Beusen, A., Doelman, J., and Stehfest, E. Anthropogenic land use estimates for the Holocene – HYDE 3.2, Earth Syst. Sci. Data 9, 927–953 (2017).
4. Lucas, Pablo Miguel et al. (2024). "Using Comparative Extinction Risk Analysis to Prioritize the IUCN Red List Reassessments of Amphibians". In: Conservation Biology n/a.n/a, e14316. doi: 10.1111/cobi.14316.
5. Nelson, A., Weiss, D.J., van Etten, J. et al. A suite of global accessibility indicators. Sci Data 6, 266 (2019). https://doi.org/10.1038/s41597-019-0265-5
6. Pigot, Alex L. et al. (2023). "Abrupt Expansion of Climate Change Risks for Species Globally". In: Nat Ecol Evol 7.7, pp. 1060–1071. doi: 10.1038/s41559-023-02070-4.
7. Velasco, Julián A. et al. (2021). "Synergistic Impacts of Global Warming and Thermohaline Circulation Collapse on Amphibians". In: Commun Biol 4.1, pp. 1–7. doi: 10.1038/s42003- 021- 01665- 6.
8. This work used Resources from the Foote High Performance Cluster at the Potsdam Institute for Climate Impact Research