**Supplementary Information for**

**Protected area planning to conserve biodiversity in an uncertain world**

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**Appendix S1**. **Worldwide governance indicator definitions from the World Bank (15).**

|  |  |
| --- | --- |
| **Indicator** | **Definition**  Source: World Bank, 2020 (<https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators>) |
| Voice and accountability | “Voice and accountability captures perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.” |
| Political stability and absence of violence | “Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.” |
| Government effectiveness | “Government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.” |
| Regulatory quality | “Regulatory quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.” |
| Rule of law | “Rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.” |
| Control of corruption | “Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.” |
|  |  |

Map

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**Appendix S2. Governance risk (yellow = low, blue= high)**

Map

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**Appendix S3. Land systems risk (yellow = low, blue= high)**

Map

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**Appendix S4. Climate risk (climate velocity) (yellow = low, blue= high)**

**Appendix S5: Supplementary methods**

***Alternative climate risk measure: exposure to extreme events***

Anthropogenic climate change is affecting the frequency and duration of extreme heat events (Diffenbaugh et al. 2017; AghaKouchak et al. 2020). Exposure to these events can adversely affect human populations (Battisti & Naylor 2009; Anderson G. Brooke & Bell Michelle L. 2011; Mitchell et al. 2016) and natural systems (Harris et al. 2018; Maxwell et al. 2019). For species in natural systems, these events can further the decline and extirpation of populations, increasing the chances of extinction (Maron et al. 2015; Maxwell et al. 2019). Extreme heat events and extreme cold events can also promote the formation of novel ecosystems (Harris et al. 2018), generate enhanced selection pressures (Gutschick & BassiriRad 2003; Grant et al. 2017), and change the phenology of life history events (Sorte et al. 2016; Cremonese et al. 2017). There are a number of climate indices that have been used to estimate the occurrence of these events (Smith et al. 2013; Fenner et al. 2019). These indices are often context specific and there is little consensus on the most appropriate technique (McPhillips et al. 2018).

For this alternative measure, we estimated climatic risk based on the estimated trend in the annual proportion of days containing extreme heat events from 1979 to 2019 (La Sorte et al. 2021). Extreme heat events were estimated using hourly air temperature at 2 m above the surface and gridded at a 31 km (0.28125° at the equator) spatial resolution (Hersbach et al. 2018). The temperature data was acquired from the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth generation atmospheric reanalysis of the global climate (ERA5) (Hersbach et al. 2019; Hoffmann et al. 2019 p. 5). The approach first extracted daily minimum and maximum temperature for each grid cell over the 41-year period. To reduce the influence of warming trends, the daily minimum and maximum temperature was then detrended across years for each day and grid cell using empirical mode decomposition (EMD) (Huang et al. 1998; Wu et al. 2007). The occurrence of extreme heat events was estimated using the following approach: The detrended minimum and maximum temperature data was treated as normally distributed across years for each day and grid cell. The probability density function for the detrended minimum and maximum temperature was then estimated using the mean and standard deviation calculated across years for each day and grid cell. Extreme heat events occurred when the probabilities for both minimum and maximum temperature on a given day and grid cell were within the 0.95-1.00 quartile of the probability density function. The trend in the annual proportion of days containing extreme heat events for each year was calculated for each grid cell using beta regression with a logit link function and an identity function in the precision model (Ferrari & Cribari-Neto 2004; Simas et al. 2010) (Appendix S11 – S13). See (La Sorte et al. 2021) for additional details.

**References**

AghaKouchak A, Chiang F, Huning LS, Love CA, Mallakpour I, Mazdiyasni O, Moftakhari H, Papalexiou SM, Ragno E, Sadegh M. 2020. Climate Extremes and Compound Hazards in a Warming World. Annual Review of Earth and Planetary Sciences **48**:519–548.

Anderson G. Brooke, Bell Michelle L. 2011. Heat Waves in the United States: Mortality Risk during Heat Waves and Effect Modification by Heat Wave Characteristics in 43 U.S. Communities. Environmental Health Perspectives **119**:210–218. Environmental Health Perspectives.

Battisti DS, Naylor RL. 2009. Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat. Science **323**:240–244. American Association for the Advancement of Science.

Cremonese E, Filippa G, Galvagno M, Siniscalco C, Oddi L, Morra di Cella U, Migliavacca M. 2017. Heat wave hinders green wave: The impact of climate extreme on the phenology of a mountain grassland. Agricultural and Forest Meteorology **247**:320–330.

Diffenbaugh NS et al. 2017. Quantifying the influence of global warming on unprecedented extreme climate events. Proceedings of the National Academy of Sciences **114**:4881–4886. National Academy of Sciences.

Fenner D, Holtmann A, Krug A, Scherer D. 2019. Heat waves in Berlin and Potsdam, Germany – Long-term trends and comparison of heat wave definitions from 1893 to 2017. International Journal of Climatology **39**:2422–2437.

Ferrari S, Cribari-Neto F. 2004. Beta Regression for Modelling Rates and Proportions. Journal of Applied Statistics **31**:799–815. Taylor & Francis.

Grant PR, Grant BR, Huey RB, Johnson MTJ, Knoll AH, Schmitt J. 2017. Evolution caused by extreme events. Philosophical Transactions of the Royal Society B: Biological Sciences **372**:20160146. Royal Society.

Gutschick VP, BassiriRad H. 2003. Extreme events as shaping physiology, ecology, and evolution of plants: toward a unified definition and evaluation of their consequences. New Phytologist **160**:21–42.

Harris RMB et al. 2018. Biological responses to the press and pulse of climate trends and extreme events. Nature Climate Change **8**:579–587. Nature Publishing Group.

Hersbach H et al. 2018. ERA5 hourly data on single levels from 1979 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). Available from 10.24381/cds.adbb2d47 (accessed October 2, 2020).

Hersbach H et al. 2019. Global reanalysis: goodbye ERA-Interim, hello ERA5.

Hoffmann L et al. 2019. From ERA-Interim to ERA5: the considerable impact of ECMWF’s next-generation reanalysis on Lagrangian transport simulations. Atmospheric Chemistry and Physics **19**:3097–3124. Copernicus GmbH.

Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen N-C, Tung CC, Liu HH. 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences **454**:903–995. Royal Society.

La Sorte FA, Johnston A, Ault TR. 2021. Global trends in the frequency and duration of temperature extremes. Climatic Change **166**:1.

Maron M, McAlpine CA, Watson JEM, Maxwell S, Barnard P. 2015. Climate-induced resource bottlenecks exacerbate species vulnerability: a review. Diversity and Distributions **21**:731–743.

Maxwell SL, Butt N, Maron M, McAlpine CA, Chapman S, Ullmann A, Segan DB, Watson JEM. 2019. Conservation implications of ecological responses to extreme weather and climate events. Diversity and Distributions **25**:613–625.

McPhillips LE et al. 2018. Defining Extreme Events: A Cross-Disciplinary Review. Earth’s Future **6**:441–455.

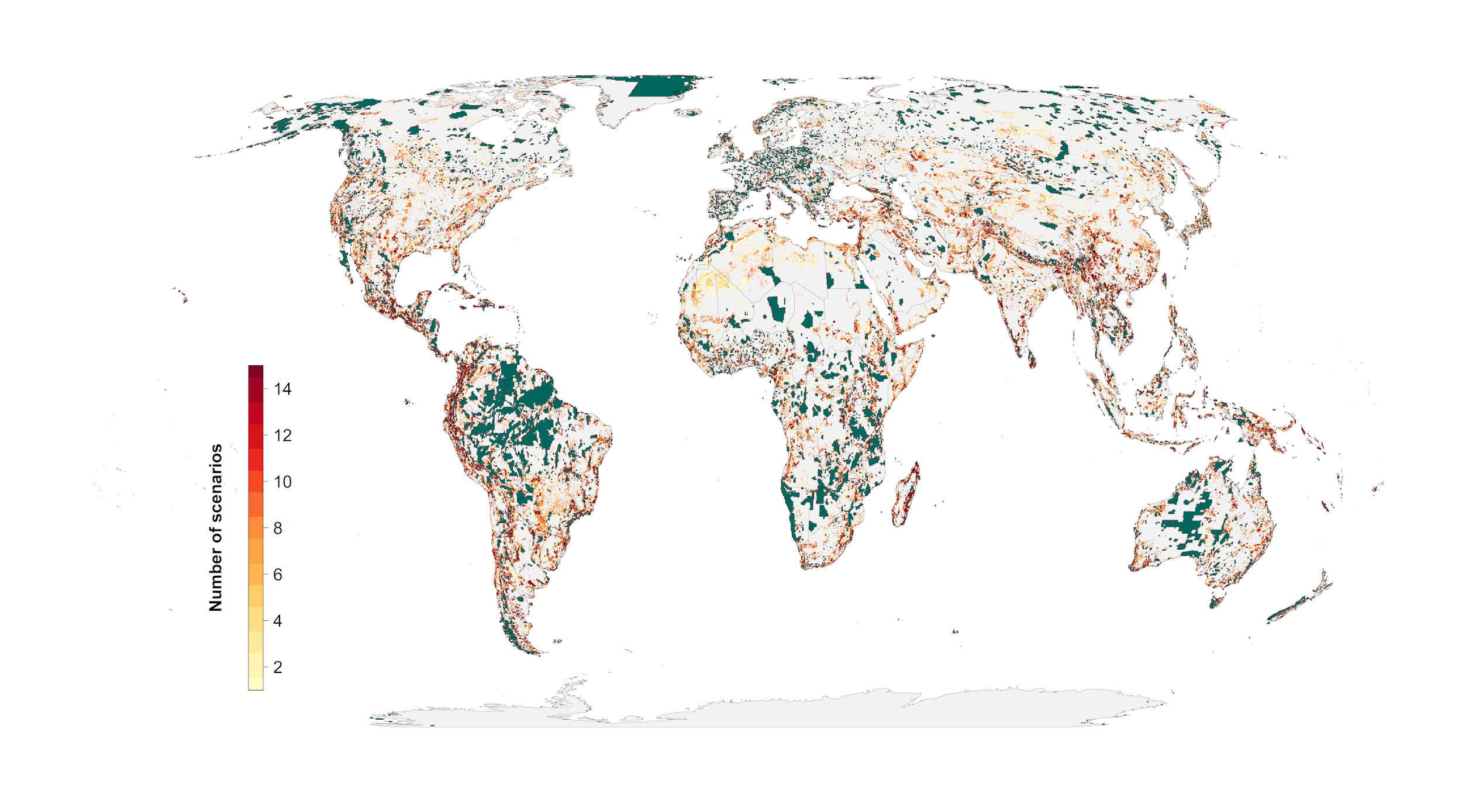
Mitchell D, Heaviside C, Vardoulakis S, Huntingford C, Masato G, Guillod BP, Frumhoff P, Bowery A, Wallom D, Allen M. 2016. Attributing human mortality during extreme heat waves to anthropogenic climate change. Environmental Research Letters **11**:074006. IOP Publishing.

Simas AB, Barreto-Souza W, Rocha AV. 2010. Improved estimators for a general class of beta regression models. Computational Statistics & Data Analysis **54**:348–366.

Smith TT, Zaitchik BF, Gohlke JM. 2013. Heat waves in the United States: definitions, patterns and trends. Climatic Change **118**:811–825.

Sorte FAL, Hochachka WM, Farnsworth A, Dhondt AA, Sheldon D. 2016. The implications of mid-latitude climate extremes for North American migratory bird populations. Ecosphere **7**:e01261.

Wu Z, Huang NE, Long SR, Peng C-K. 2007. On the trend, detrending, and variability of nonlinear and nonstationary time series. Proceedings of the National Academy of Sciences **104**:14889–14894. National Academy of Sciences.



**Appendix S6. Scenario overlap. green = protected areas. Color gradient from yellow (one scenario) to red (15 scenarios) = overlap.**

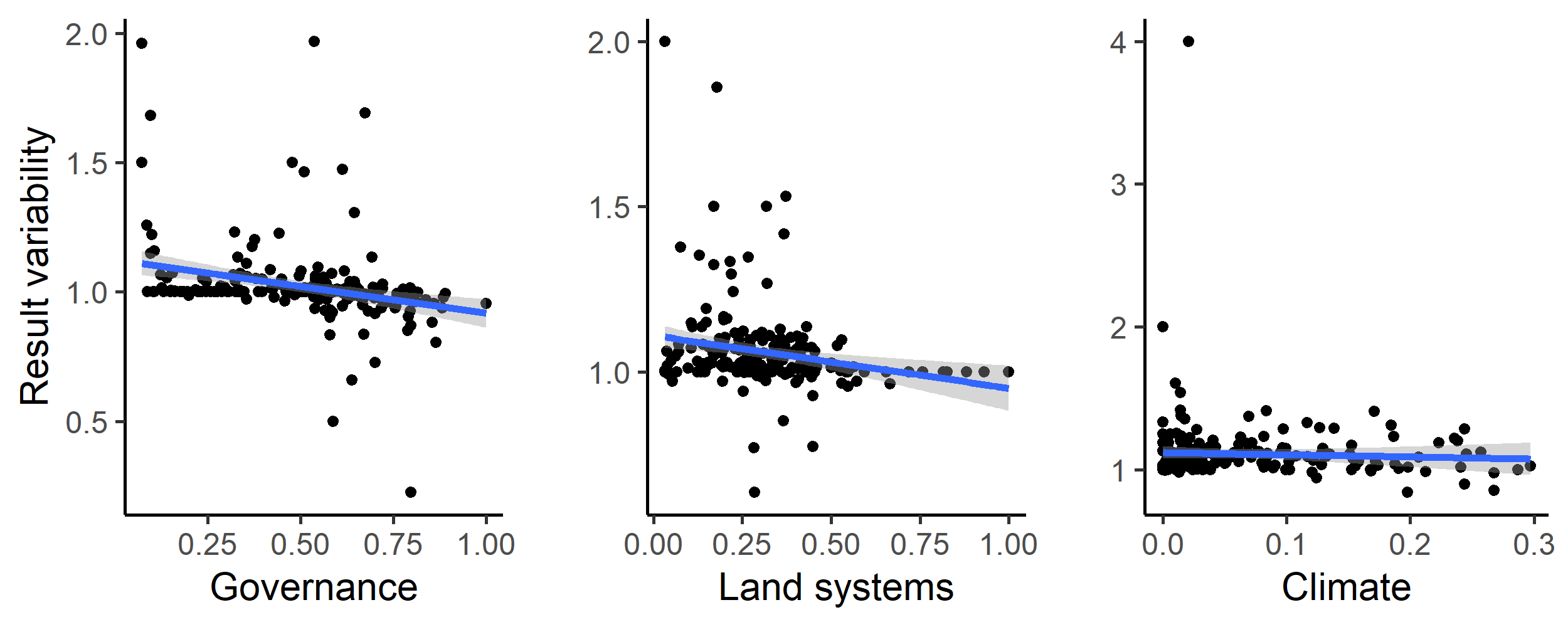
Map

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**Appendix S7. Areas of high scenario overlap (>10 scenarios, green) compared to biodiversity hotspots (*28*) (blue).**

**Appendix S8**. **Country specific results for the 15 scenarios investigated. Numbers represent % of land area of a country selected (including existing protected areas).  
(As an example 5 countries included here, full list in csv. B = baseline, G = governance, L = land use, C = Climate)**   
<https://drive.google.com/file/d/1eD4y4K8XG4nxnRL5fNtiTqzuqfIJ_DfB/view?usp=sharing>

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Afghanistan | Åland | Albania | Algeria |  |
| B | 15.95 | 57.14 | 38.46 | 10.62 |  |
| G | 14.95 | 85.71 | 35.66 | 7.71 |  |
| L | 17.03 | 85.71 | 43.71 | 10.32 |  |
| C | 19.25 | 57.14 | 46.15 | 13.69 |  |
| GL | 15.87 | 85.71 | 37.41 | 8.94 |  |
| LG | 16.55 | 100 | 38.11 | 11.59 |  |
| GC | 19.3 | 57.14 | 46.5 | 13.71 |  |
| CG | 17.89 | 71.43 | 39.16 | 12.74 |  |
| LC | 17.8 | 71.43 | 44.06 | 13.07 |  |
| CL | 19.52 | 57.14 | 40.56 | 13.36 |  |
| GLC | 17.8 | 57.14 | 43.71 | 13.15 |  |
| GCL | 19.44 | 57.14 | 41.96 | 13.38 |  |
| LGC | 17.81 | 57.14 | 44.06 | 13.05 |  |
| LCG | 16.58 | 85.71 | 38.11 | 12.36 |  |
| CGL | 17.52 | 85.71 | 43.36 | 12.4 |  |
| CLG | 19.52 | 57.14 | 40.56 | 13.36 |  |



**Appendix S9. Influence of average country specific risk factors on the optimization outcomes compared between baseline scenario and the scenarios including one of the risk factors. Each data point represents the results for one country. The fitted blue lines and 95% confidence bands are from ordinary least-squares regression.**

**Appendix S10. Governance risk score table (see csv)**

**(As an example Afghanistan – Barbados are included below)**<https://drive.google.com/file/d/1g_LePBfCbphXzTiCOXCzQtNLSSYoV6me/view?usp=sharing>

|  |  |  |  |
| --- | --- | --- | --- |
| Country.Name | Country.Code | MeanIndex | SDIndex |
| Afghanistan | AFG | -1.65038 | 0.16074 |
| Albania | ALB | -0.28043 | 0.219515 |
| Algeria | DZA | -0.86838 | 0.121774 |
| American Samoa | ASM | 0.747997 | 0.127264 |
| Andorra | AND | 1.359029 | 0.04054 |
| Angola | AGO | -1.16429 | 0.217384 |
| Anguilla | AIA | 1.138708 | 0.225908 |
| Antigua and Barbuda | ATG | 0.687351 | 0.143042 |
| Argentina | ARG | -0.19472 | 0.196541 |
| Armenia | ARM | -0.29545 | 0.091655 |
| Aruba | ABW | 1.181311 | 0.090913 |
| Australia | AUS | 1.591282 | 0.033469 |
| Austria | AUT | 1.559385 | 0.080972 |
| Azerbaijan | AZE | -0.84662 | 0.123512 |
| Bahamas, The | BHS | 0.991142 | 0.212122 |
| Bahrain | BHR | 0.067606 | 0.189151 |
| Bangladesh | BGD | -0.8678 | 0.131258 |
| Barbados | BRB | 1.154432 | 0.145899 |

Map

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**Appendix S11. Alternative climate risk metric (extreme heat events) (yellow = low, blue= high)**

Chart, scatter chart

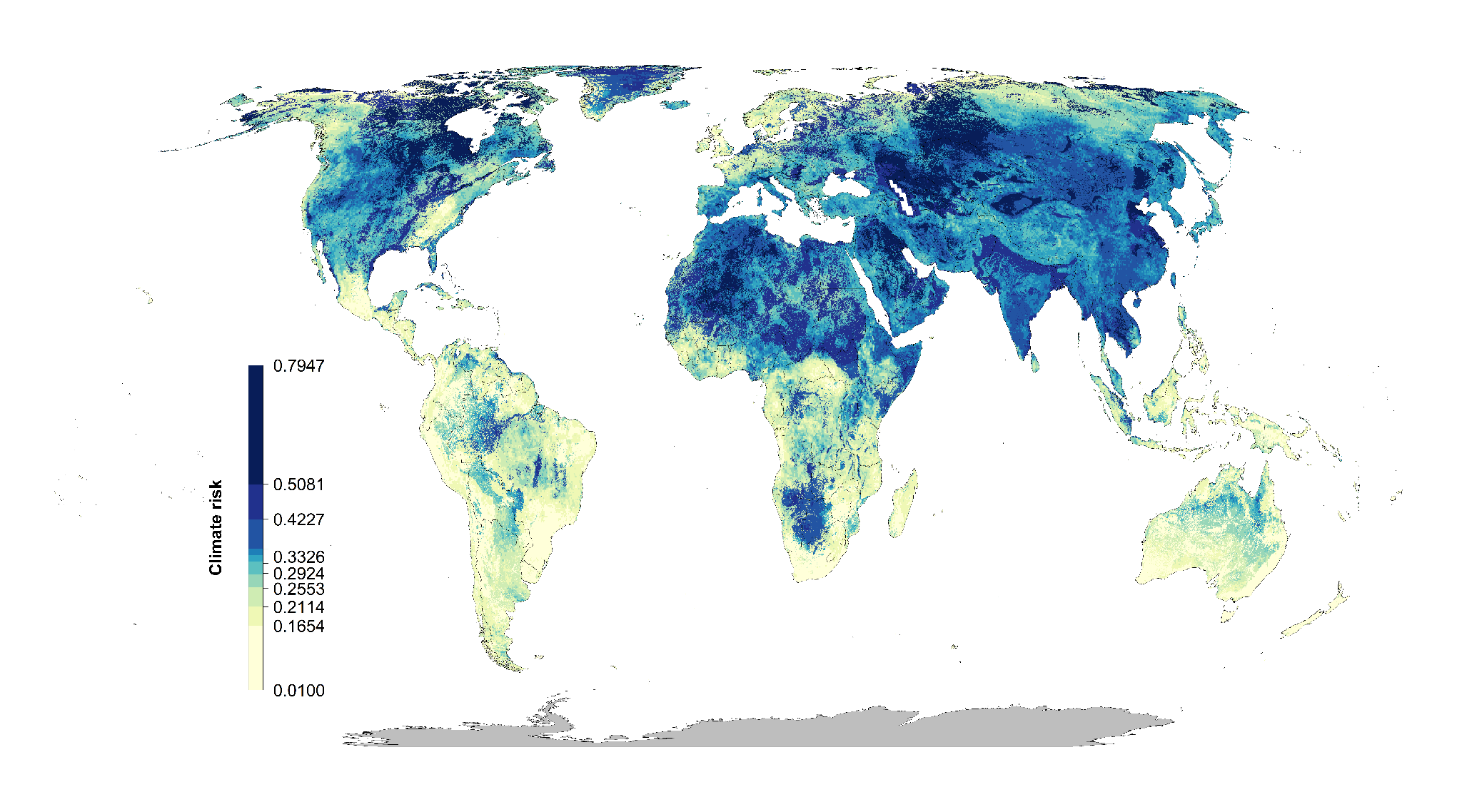
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**Appendix S12 Alternative climate risk scenario “No regrets” areas that were identified as priority habitat for protection regardless of the risks included in our analysis.**

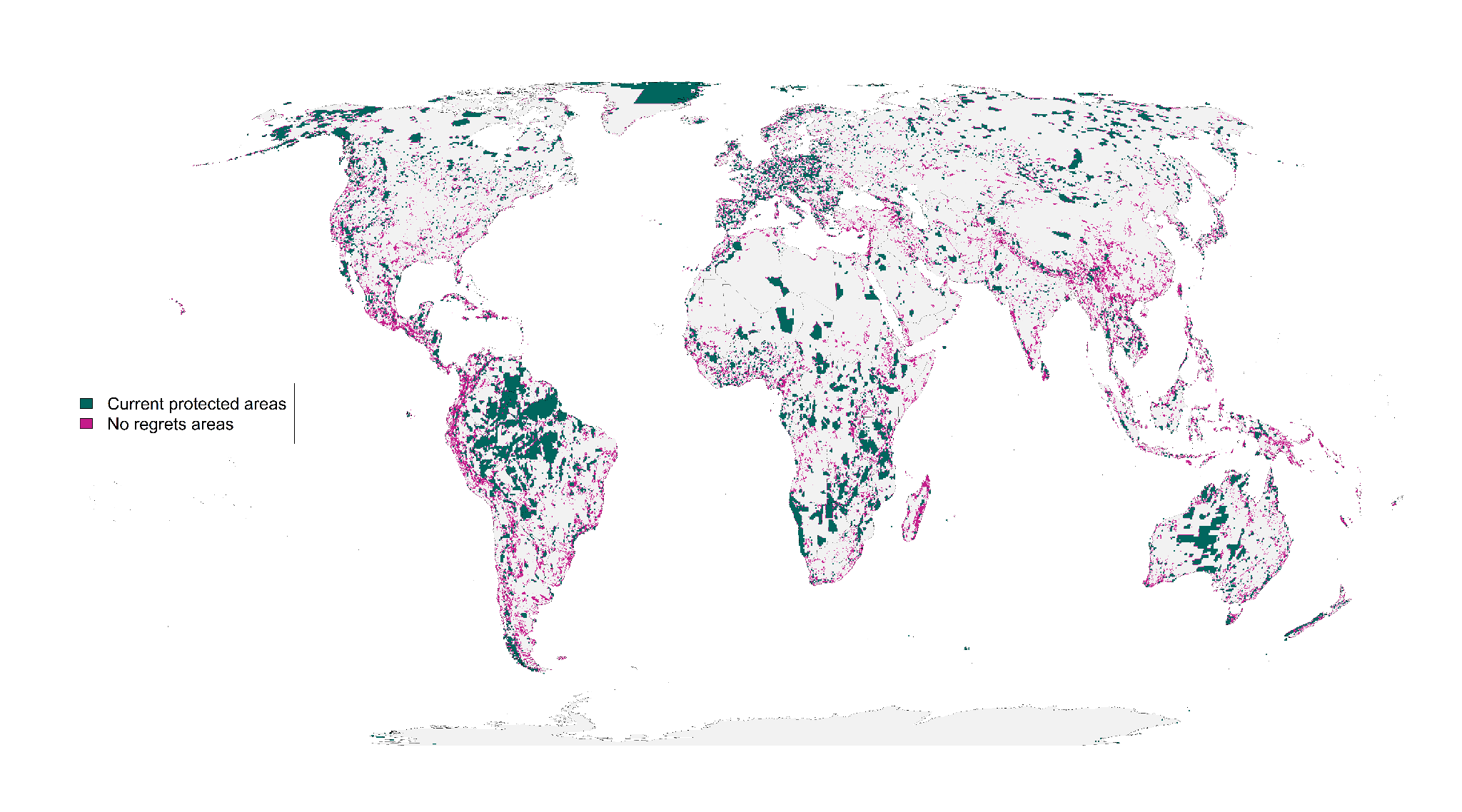
Map

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**Appendix S13. Alternative climate risk scenarios percent country-level variation between the baseline scenario and the 15 scenarios including risk. Countries whose results are consistent across the 15 scenarios (e.g., Brazil) have low variation, while countries whose results are less consistent across the 15 scenarios (e.g., Sweden) have high variation. The kmeans method (*37*) was used to generate class intervals for visualization.**

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**Appendix S14. Combined climate risk metric (climate velocity and extreme heat events combined) (yellow = low, blue= high)**

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**Appendix S15. Combined climate risk scenario “No regrets” areas that were identified as priority habitat for protection regardless of the risks included in our analysis.**

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**Appendix S16. Combined climate risk scenarios percent country-level variation between the baseline scenario and the 15 scenarios including risk. Countries whose results are consistent across the 15 scenarios (e.g., Brazil) have low variation, while countries whose results are less consistent across the 15 scenarios (e.g., Finland) have high variation. The kmeans method (*37*) was used to generate class intervals for visualization.**