Supplementary Information for

Protected area planning to conserve biodiversity in an uncertain world

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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). 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) (Supplementary Figures 7 – 9). See (La Sorte et al. 2021) for additional details.

Multi-objective optimization of risk reduction

In systematic conservation planning, conservation features describe the biodiversity units (e.g., species, communities, habitat types) that are used to inform protected area establishment. Planning units describe the candidate areas for protected area establishment (e.g., cadastral units). Each planning unit contains an amount of each feature (e.g., presence/absence, number of individuals). A prioritization describes a candidate set of planning units selected for protected establishment. Each feature has a representation target indicating the minimum amount of each feature that ideally should be held in the prioritization (e.g., 50 presences, 200 individuals). To minimize risk, we have a set of datasets describing the relative risk associated with selecting each planning unit for protected area establishment. Thus, we wish to identify a prioritization that meets the representation targets for all of the conservation features, with minimal risk.

Let I denote the set of conservation features (indexed by i), and J denote the set of planning units (indexed by j). To describe existing conservation efforts, let p_j indicate (i.e., using zeros and ones) if each planning unit $j \in J$ is already part of the global protected area system. To describe the spatial distribution of the features, let A_{ij} denote (i.e., using zeros and ones) if each feature is present or absent from each planning unit. To ensure the features are adequately represented by the solution, let t_i denote the conservation target for each feature $i \in I$. Next, let D denote the set of risk datasets (indexed by d). To describe the relative risk associated with each planning unit, let R_{dj} denote the risk for planning units $j \in J$ according to risk datasets $d \in D$.

The problem contains the binary decision variables x_j for planning units $j \in J$.

$$x_j = \begin{cases} 1, & \text{if } j \text{ selected for prioritisation,} \\ 0, & \text{else} \end{cases} \qquad \text{(eqn 1a)}$$

The reserve selection problem is formulated following:

$$\begin{aligned}
&\text{lexmin } f_1(x), f_2(x), \ldots f_D(x) && && \text{(eqn 2a)} \\
&\text{subject to } f_d(x) = \sum_{j \in J} R_{dj} x_j && \forall d \in D && \text{(eqn 2b)} \\
&\sum_{j \in J} A_{ij} \geq t_i && \forall i \in I && \text{(eqn 2c)} \\
&x_j \geq p_j && \forall j \in J && \text{(eqn2d)} \\
&x_j \in \{0, 1\} && \forall j \in J && \text{(eqn 2e)}
\end{aligned}$$

The objective function (eqn 2a) is to hierarchically (lexicographically) minimize multiple functions. Constraints (eqn 2b) define each of these functions as the total risk encompassed by selected planning units given each risk dataset. Constraints (eqn 2c) ensure that the representation targets (t_i) are met for all features. Constraints (eqn 2d) ensure that the existing protected areas are selected in the solution. Finally, constraints (eqns 2e) ensure that the decision variables x_j contain zeros or ones.

References

AghaKouchak, A., Chiang, F., Huning, L.S., Love, C.A., Mallakpour, I., Mazdiyasni, O., Moftakhari, H., Papalexiou, S.M., 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.

Battisti, D.S. & Naylor, R.L. (2009). Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat. *Science*, 323, 240–244.

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, N.S., Singh, D., Mankin, J.S., Horton, D.E., Swain, D.L., Touma, D., Charland, A., Liu, Y., Haugen, M., Tsiang, M. & Rajaratnam, B. (2017). Quantifying the influence of global warming on unprecedented extreme climate events. *PNAS*, 114, 4881–4886.

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.

Grant, P.R., Grant, B.R., Huey, R.B., Johnson, M.T.J., Knoll, A.H. & Schmitt, J. (2017). Evolution caused by extreme events. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 372, 20160146.

Gutschick, V.P. & 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, R.M.B., Beaumont, L.J., Vance, T.R., Tozer, C.R., Remenyi, T.A., Perkins-Kirkpatrick, S.E., Mitchell, P.J., Nicotra, A.B., McGregor, S., Andrew, N.R., Letnic, M., Kearney, M.R., Wernberg, T., Hutley, L.B., Chambers, L.E., Fletcher, M.-S., Keatley, M.R., Woodward, C.A., Williamson, G., Duke, N.C. & Bowman, D.M.J.S. (2018). Biological responses to the press and pulse of climate trends and extreme events. *Nature Climate Change*, 8, 579–587.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Sabater, J.M., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D. & Thépaut, J.-N. (2018). ERA5 hourly data on single levels from 1979 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS).

Hersbach, H., Bell, W., Berrisford, P., Horányi, A., J., M.-S., Nicolas, J., Radu, R., Schepers, D., Simmons, A., Soci, C., Dee, D. & Dee, D. (2019). Global reanalysis: goodbye ERA-Interim, hello ERA5 [WWW Document].

Hoffmann, L., Günther, G., Li, D., Stein, O., Wu, X., Griessbach, S., Heng, Y., Konopka, P., Müller, R., Vogel, B. & Wright, J.S. (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.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.-C., Tung, C.C. & Liu, H.H. (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.

La Sorte, F.A., Johnston, A. & Ault, T.R. (2021). Global trends in the frequency and duration of temperature extremes. *Climatic Change*, 166, 1.

Maron, M., McAlpine, C.A., Watson, J.E.M., Maxwell, S. & Barnard, P. (2015). Climate-induced resource bottlenecks exacerbate species vulnerability: a review. *Diversity and Distributions*, 21, 731–743.

Maxwell, S.L., Butt, N., Maron, M., McAlpine, C.A., Chapman, S., Ullmann, A., Segan, D.B. & Watson, J.E.M. (2019). Conservation implications of ecological responses to extreme weather and climate events. *Diversity and Distributions*, 25, 613–625.

McPhillips, L.E., Chang, H., Chester, M.V., Depietri, Y., Friedman, E., Grimm, N.B., Kominoski, J.S., McPhearson, T., Méndez-Lázaro, P., Rosi, E.J. & Shiva, J.S. (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, B.P., Frumhoff, P., Bowery, A., Wallom, D. & Allen, M. (2016). Attributing human mortality during extreme heat waves to anthropogenic climate change. *Environ. Res. Lett.*, 11, 074006.

Simas, A.B., Barreto-Souza, W. & Rocha, A.V. (2010). Improved estimators for a general class of beta regression models. *Computational Statistics & Data Analysis*, 54, 348–366.

Smith, T.T., Zaitchik, B.F. & Gohlke, J.M. (2013). Heat waves in the United States: definitions, patterns and trends. *Climatic Change*, 118, 811–825.

Sorte, F.A.L., Hochachka, W.M., Farnsworth, A., Dhondt, A.A. & Sheldon, D. (2016). The implications of mid-latitude climate extremes for North American migratory bird populations. *Ecosphere*, 7, e01261.

Wu, Z., Huang, N.E., Long, S.R. & Peng, C.-K. (2007). On the trend, detrending, and variability of nonlinear and nonstationary time series. *PNAS*, 104, 14889–14894.

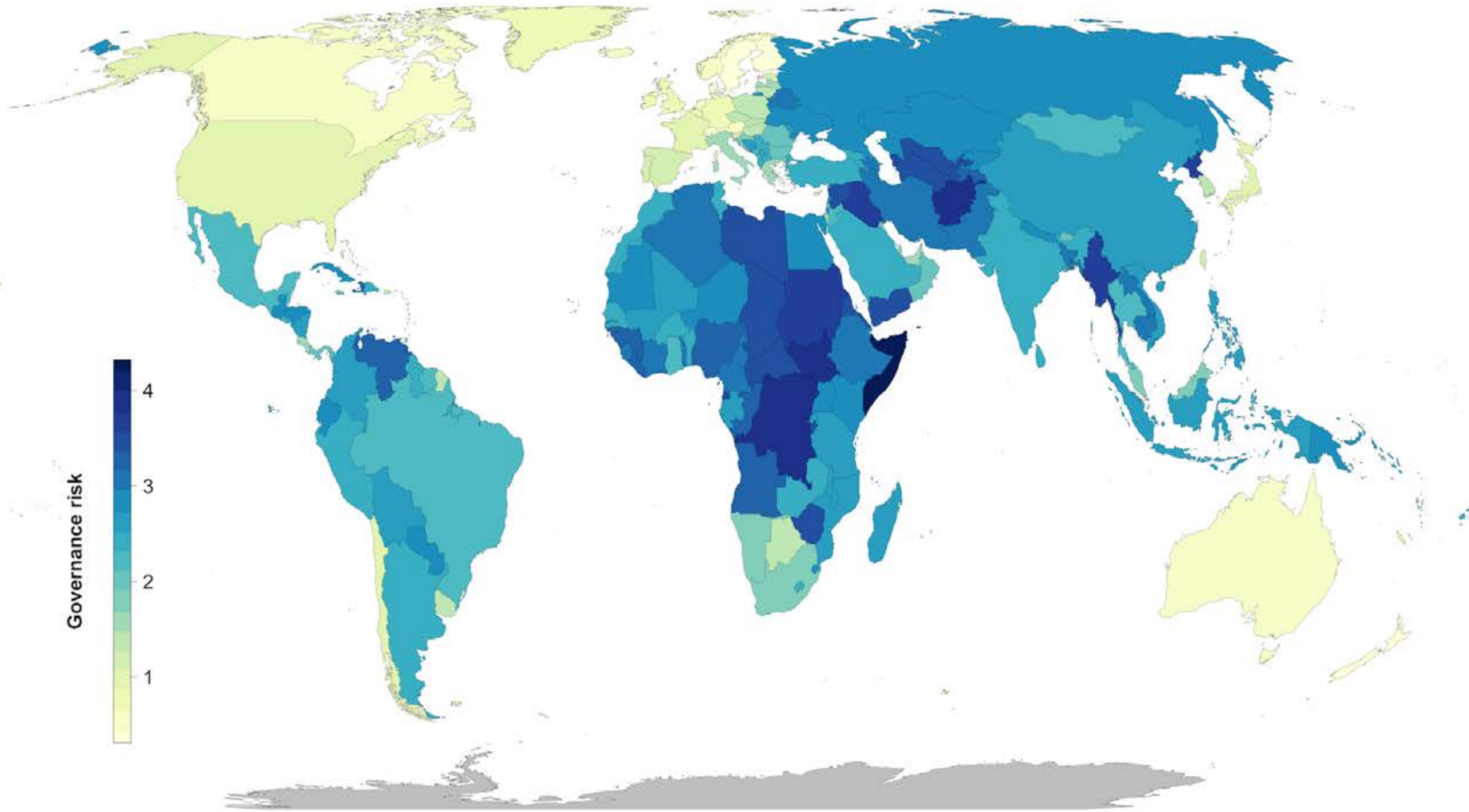

Figure S1. Governance risk (yellow = low, blue= high)

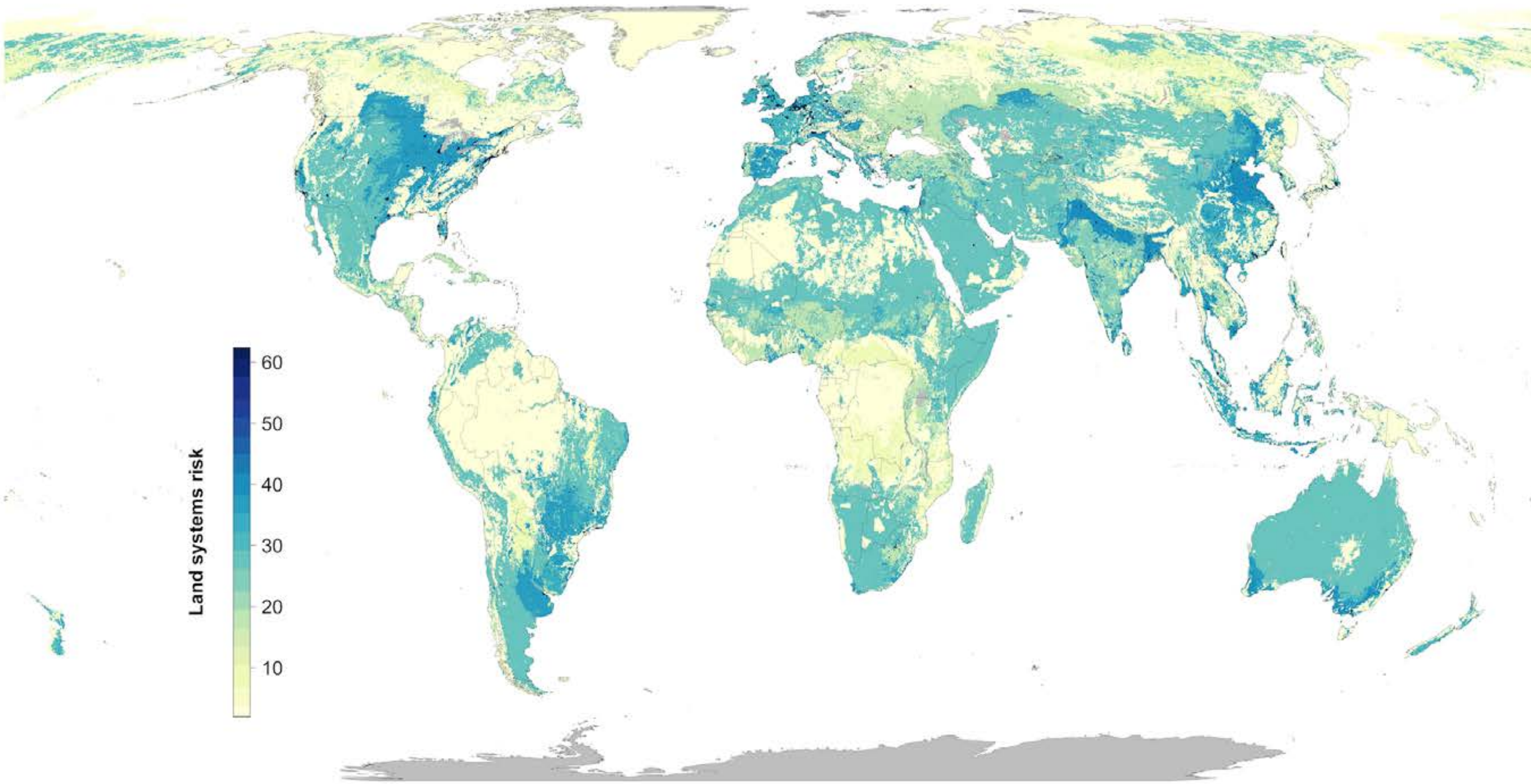

Figure S2. Land systems risk (yellow = low, blue= high)

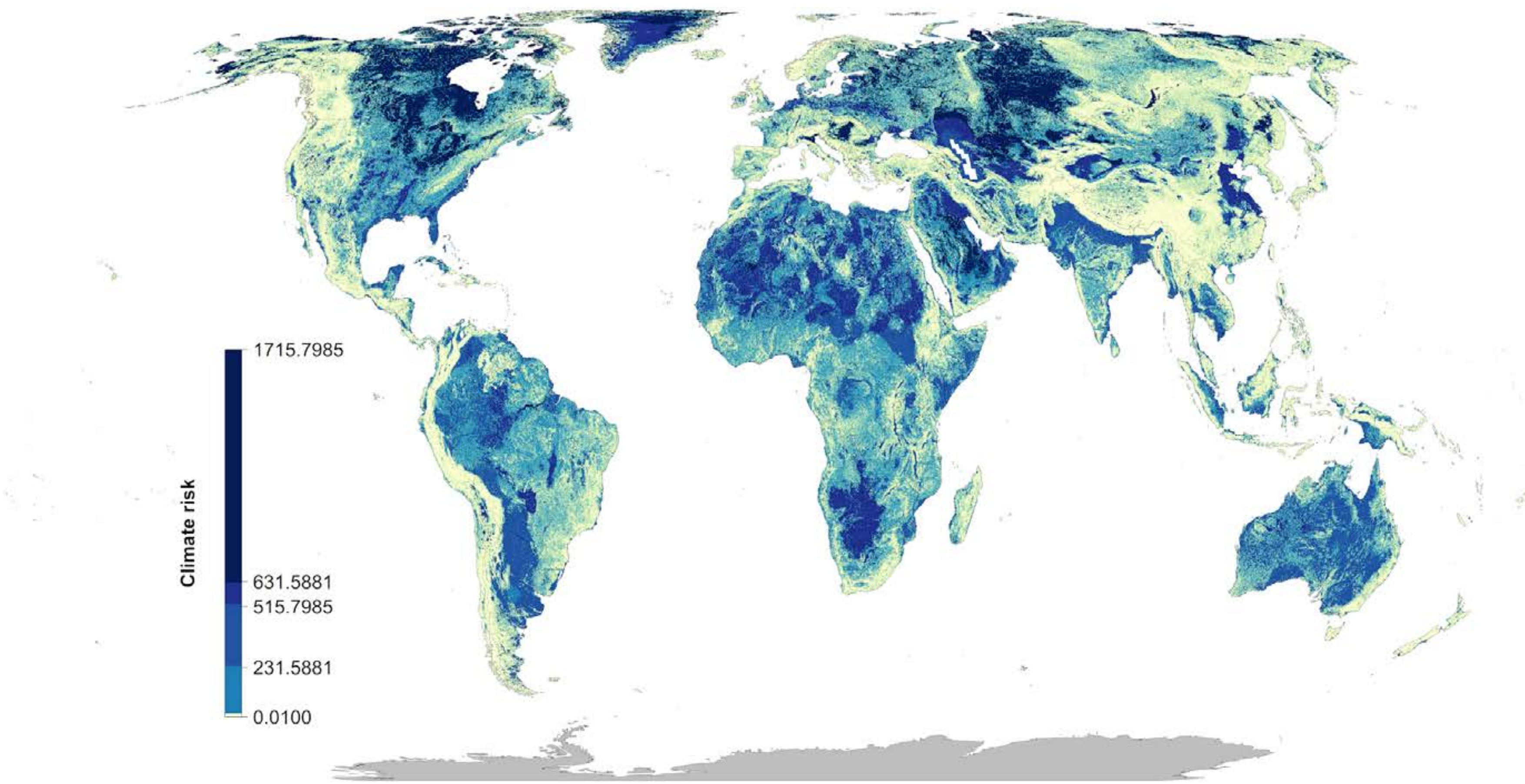

Figure S3. Climate risk (climate velocity) (yellow = low, blue= high)

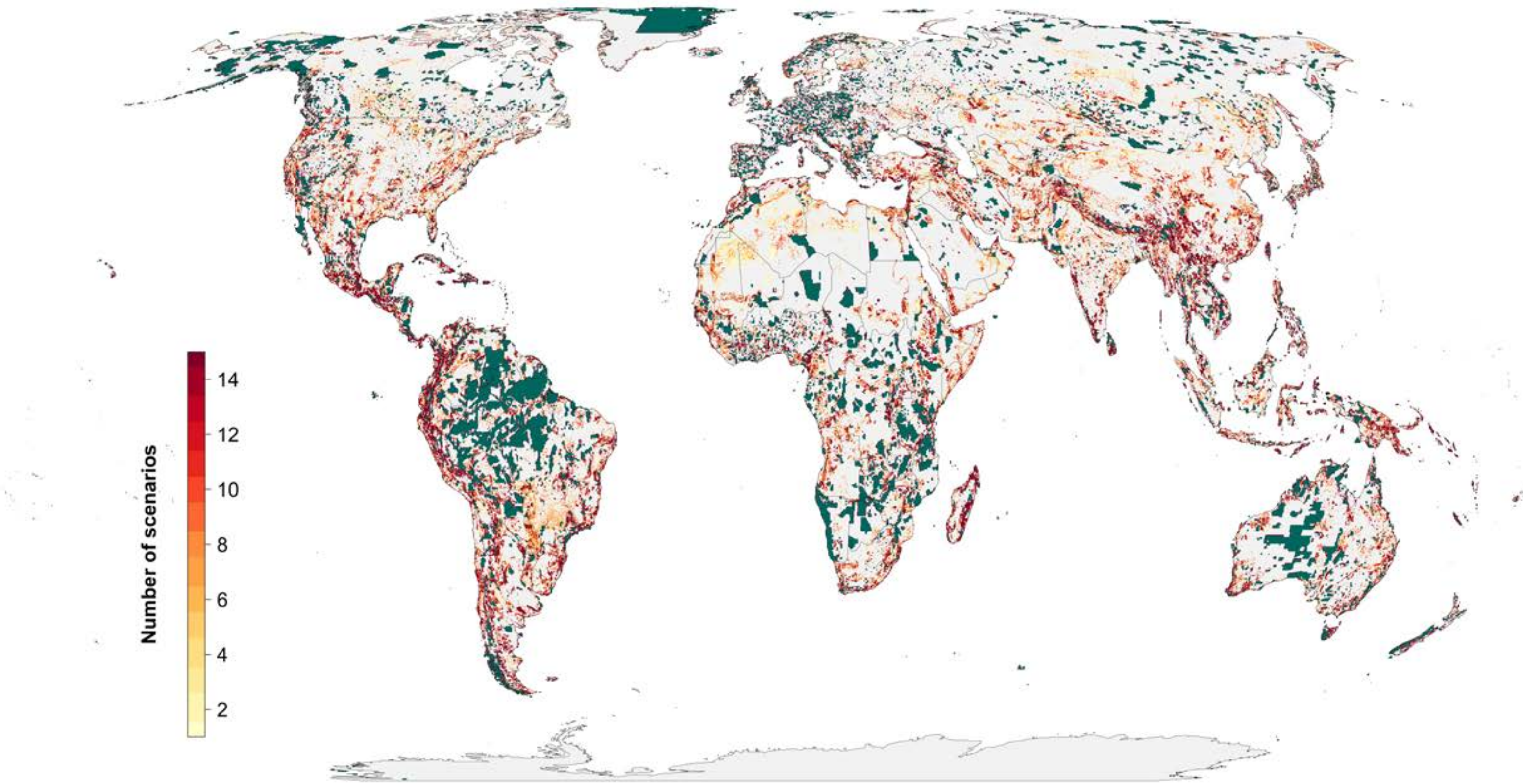

Figure S4. Scenario overlap. green = protected areas. Color gradient from yellow (one scenario) to red (15 scenarios) = overlap.

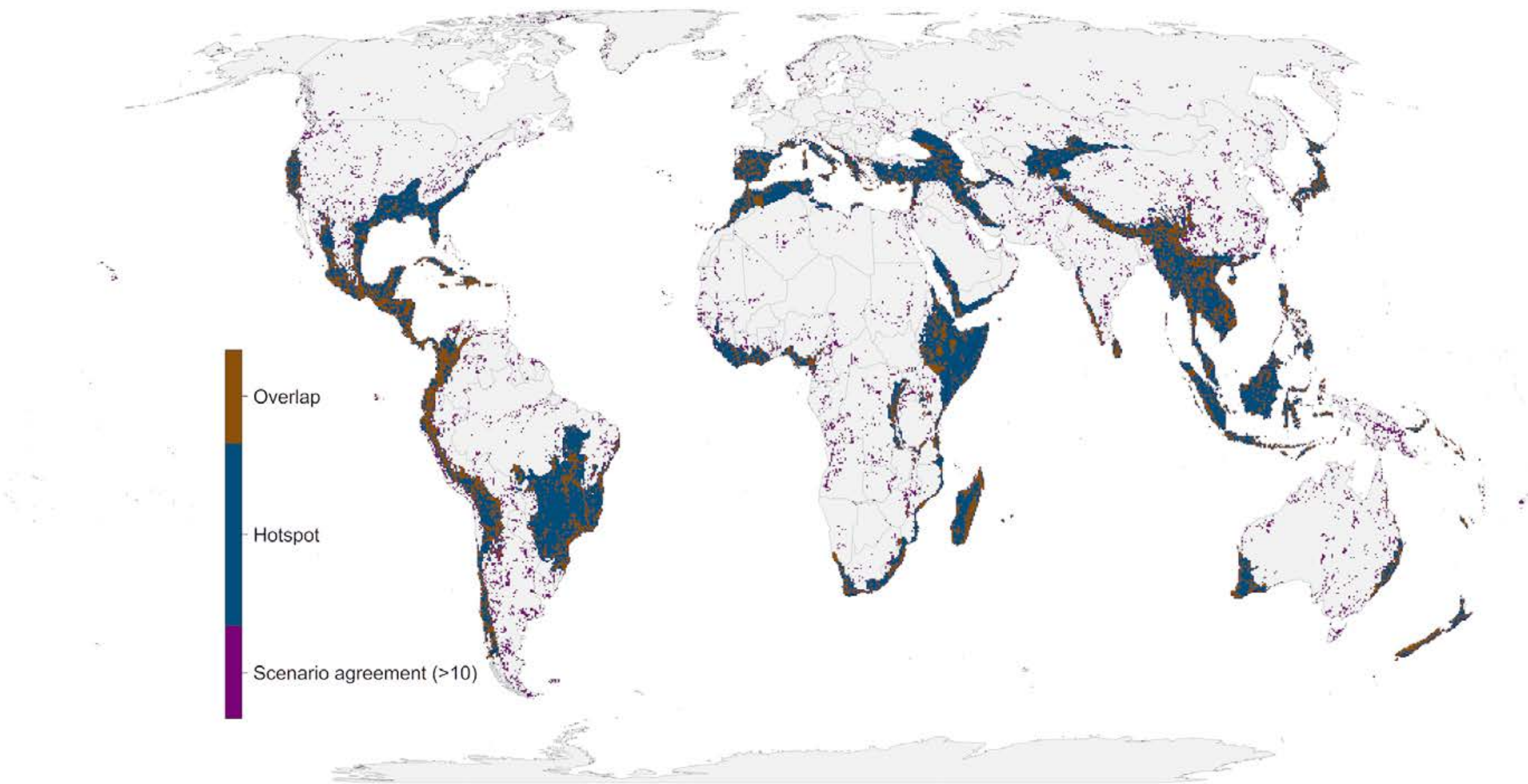

Figure S5. Areas of high scenario overlap (>10 scenarios, green) compared to biodiversity hotspots (*28*) (blue).

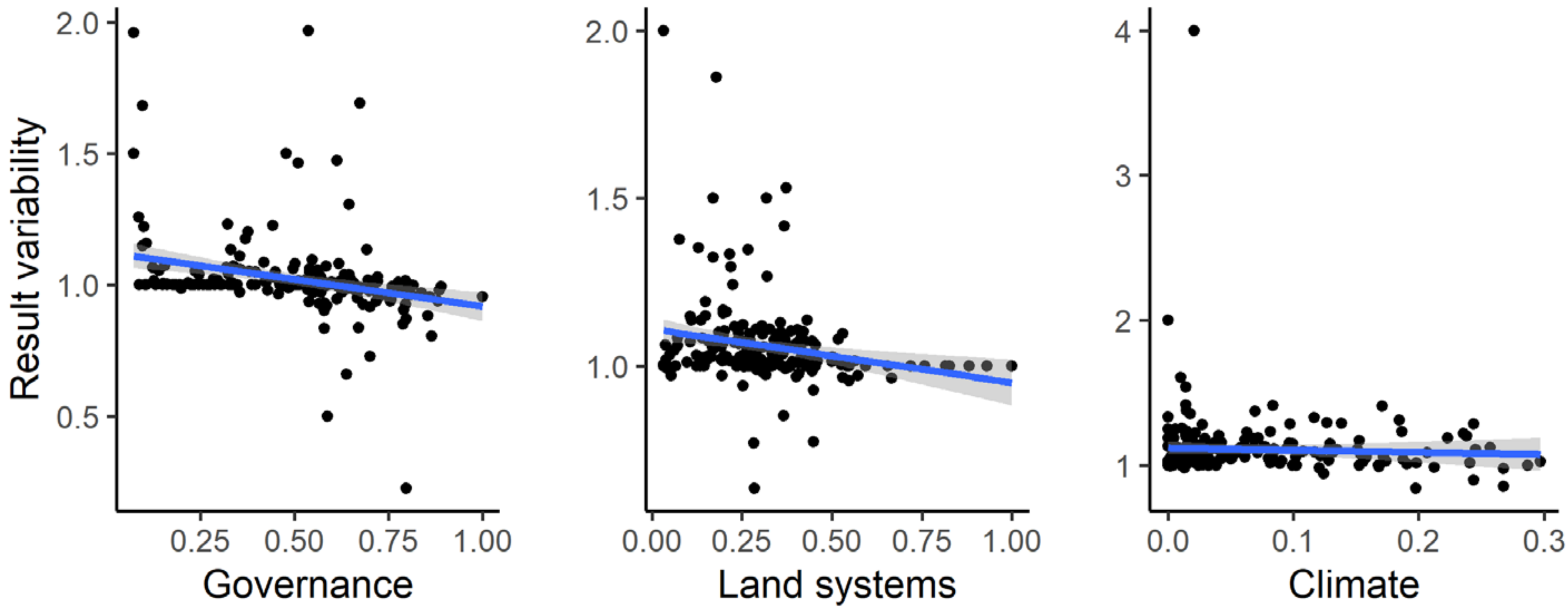

Figure S6. Influence of average country specific risk factors on the optimization outcomes compared between null scenario and the scenarios including one of the risk factors. Each data point represents the results for one country. The fitted blue lines and 95% confidence bands are from ordinary least-squares regression.

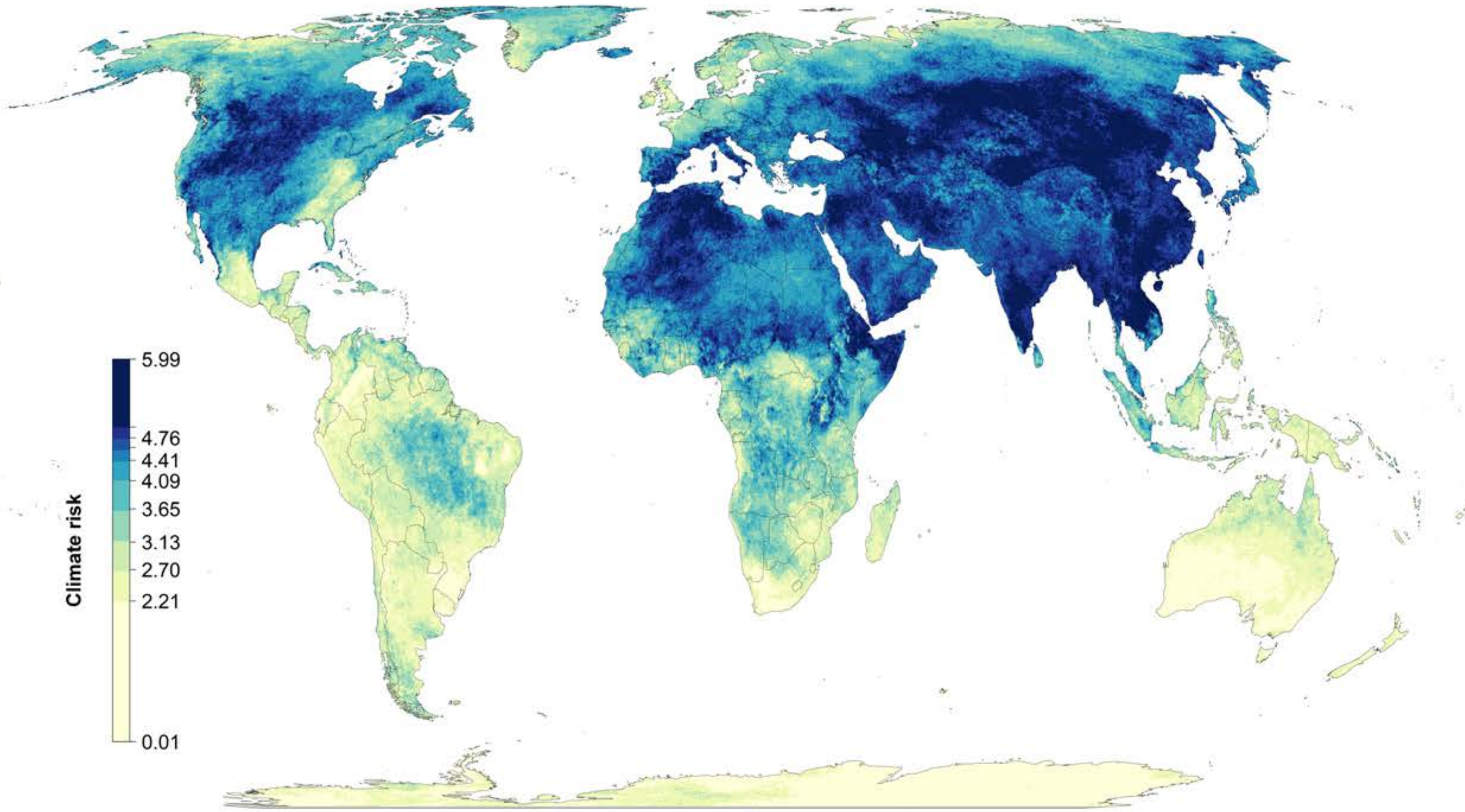

Figure S7. Alternative climate risk metric (extreme heat events) (yellow = low, blue= high)

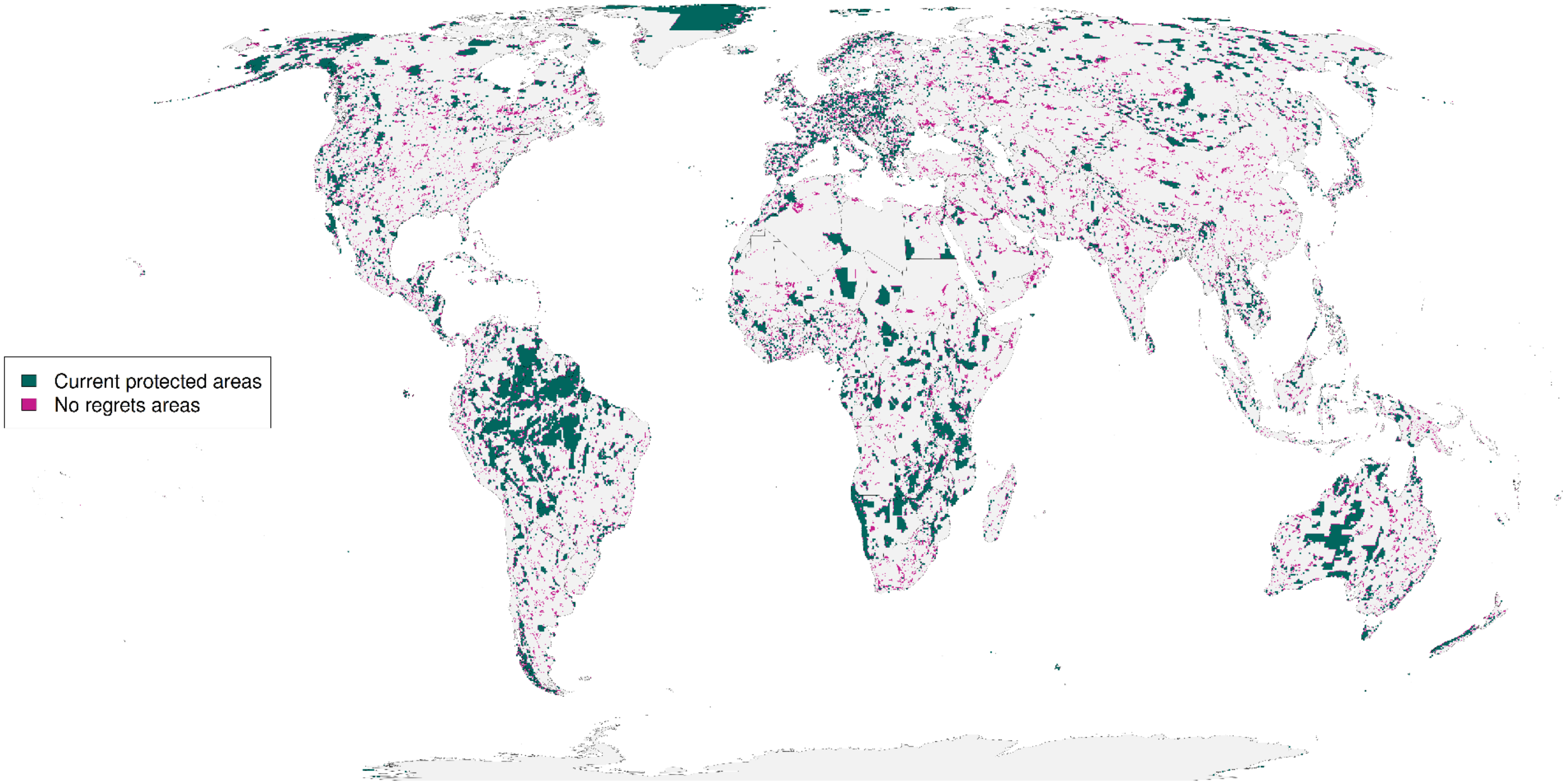

Figure S8 Alternative climate risk scenario "No regrets" areas that were identified as priority habitat for protection regardless of the risks included in our analysis.

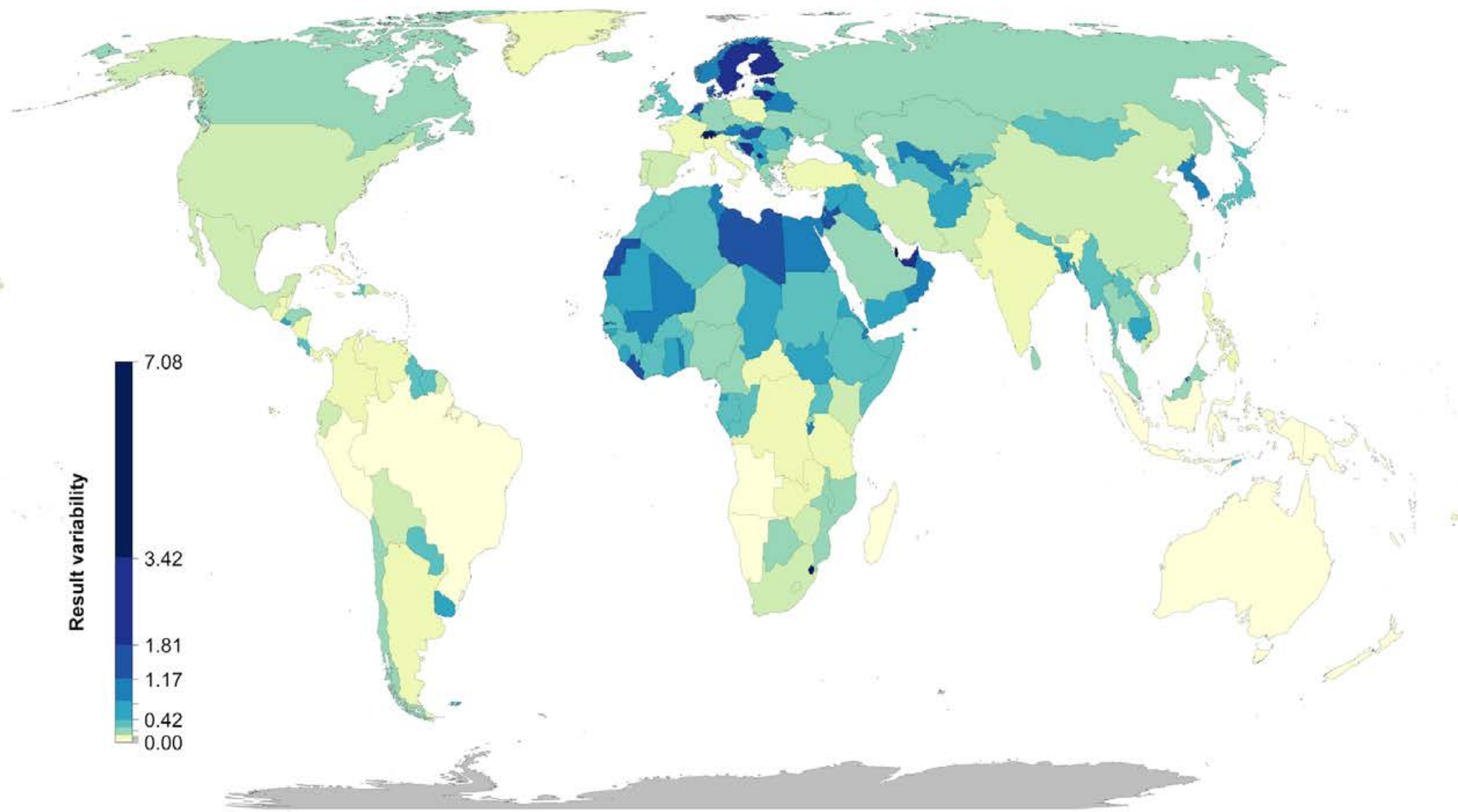

Figure S9. Alternative climate risk scenarios percent country-level variation between the null scenario and the 15 scenarios including risk. Countries whose results are consistent across the 15 scenarios (e.g., Brazil) have low variation, while countries whose results are less consistent across the 15 scenarios (e.g., Sweden) have high variation. The kmeans method (*37*) was used to generate class intervals for visualization.

Table S1. Scenarios explored and global protection results. The risk factor order represents the order risk factors were included in the hierarchical prioritization. (G = governance, L = land use, C = Climate).

Scenario	Risk factors included	Global land area protected [%]
null	-	21.27
1	G	21.35
2	L	22.31
3	C	23.79
4	G > L	21.93
5	L > G	22.18
6	G > C	23.78
7	C > G	23.31
8	L > C	23.52
9	C > L	22.99
10	G > L > C	23.52
11	G > C > L	23
12	L > G > C	23.5
13	L > C > G	23.08
14	C > G > L	22.3
15	C > L > G	22.99

Table S2. **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. N = null, G = governance, L = land use, C = Climate)

https://drive.google.com/file/d/1eD4y4K8XG4nxnRL5fNtiTqzuqfIJ_DfB/view?usp=sharing

	Afghanistan	Åland	Albania	Algeria
N	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

Table S3. 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

Table S4. **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.”