**Biodiversity conservation in an uncertain world**

**Materials and Methods**

We used a multi-objective optimization approach that incorporated governance, land use and climate constraints to prioritize the conservation of 29,350 vertebrate species. All scenarios we investigated assumed the current global protected area portfolio is locked in. We further created representation targets for each species on the basis area of habitat maps. Targets for the unpartitioned habitat maps were set following standard practices for global gap analyses and prioritizations, except that instead of using the range sizes of species to set the targets, here we used the total extent of suitable habitat for each species following Hanson et al..

*Species selection*

Our species list included all terrestrial vertebrate species from the IUCN Red List of threatened species, following Pouzols et al.2. For mammal, amphibian and reptile species ranges, we used the IUCN Red List website (<http://www.iucnredlist.org/>, accessed 2019-11-14) and for birds we used the BirdLife International data zone webpage (<http://www.birdlife.org/datazone/home>, accessed 2019-11-14). We used these taxa because no analogous data are available for a high proportion of species in other taxonomic groups such as insects39. These data have certain limitations, including possible underestimation of the extent of occurrence and overestimation of the true area of occupancy2, but they have been shown to be robust to commission errors as long as the focus is on species assemblages rather than single species7. They are currently the most frequently used and updated source for vertebrate species distributions40.

For each taxonomic group, we restricted our analysis to species that fell into the presence category of ‘Extant’, the origin categories of ‘Native’ or ‘Reintroduced’ and the seasonality categories ‘Resident’, ‘Breeding Season’ or ‘Non-breeding Season’, thus only focusing on stationary periods of the life cycle of migratory species. This resulted in the following final numbers of amphibian, bird, mammal and reptile species ranges: 6254, 13415, 5219, and 4462, respectively.

*Basic administrative delineations*

National boundaries were derived from the Global Administrative Areas database (<http://gadm.org/>, accessed 2019-10-31). We obtained protected area boundaries from the World Database on Protected Areas (WDPA, [https://www.protectedplanet.net](https://www.protectedplanet.net/)). Following standard procedures for cleaning the protected area dataset41,42, we (i) projected the data to an equal-area coordinate system (World Behrman), (ii) excluded reserves with unknown or proposed designations, (iii) excluded UNESCO Biosphere Reserves43, (iv) buffered sites represented as point localities to their reported area, (v) dissolved boundaries to prevent issues with overlapping areas, and (vi) removed slivers (code available at https://github.com/jeffreyhanson/global-protected-areas). After the protected area data were modified as described above, we overlaid the protected area boundaries with a 10 x 10 km grid covering the Earth. These spatial data procedures were implemented using ArcMap (version 10.3.1) and python (version 2.7.8).

*Governance risk*

Conservation risk due to governance can affect the outcomes of strategies, and effective governance can promote the resilience of conservation in the face of sociopolitical and economic shocks. We used worldwide governance indicators from the World Bank18 to capture these pressures. The indicators include six scaled measures: voice and accountability; political stability and absence of violence; government effectiveness; regulatory quality; rule of law; and control of corruption (see Table S4 for definitions). We chose these indicators because evidence suggests that they reliably predict protected area effectiveness44 and state investment and efforts for biodiversity conservation8. For each country, we used a mean of annual averages of all six measures8 (Figure S1).

*Land use risk*

We used a recently developed global land systems map produced by Kehoe et al.19 to incorporate the risk of land-use change. This map is based on a global land systems map for the year 200045 at a 9.25 km2 spatial resolution, but is refined based on recent land-cover and land-use datasets to a spatial resolution of 1 km2. Kehoe et al.19 further estimated the impact of land use and land use intensity on biodiversity, with data originating from the PREDICTS project46. They first matched their land-systems classes to varying intensity levels for each land-use type (for detailed conversion table, see ref47). This allowed Kehoe et al.19 to calculate average biodiversity loss per land system (relative to an unimpacted baseline) by taking the mean model estimates of biodiversity loss per land-use intensity class from previous work47. The result gives average relative biodiversity gain or loss per land-system class. Here, we used their modelled mean estimates (following Newbold et al.47) of relative percent biodiversity change for each land-system class for species abundance as a measure of the land-use pressure (Figure S2).

*Climate risk*

[Placeholder – Richard mentioned Patrick could provide. Would be one small paragraph re why climate velocity important, then one paragraph description of method.]

We also explored an alternative measure of climate risk: exposure to extreme events. Anthropogenic climate change is affecting the frequency and duration of extreme heat events48,49. Exposure to these events can adversely affect human populations50–52 and natural systems13,53. For species in natural systems, these events can further the decline and extirpation of populations, increasing the chances of extinction13,54. EHE and ECE can also promote the formation of novel ecosystems53, generate enhanced selection pressures55,56, and change the phenology of life history events57,58. There are a number of climate indices that have been used to estimate the occurrence of these events59,60. These indices are often context specific and there is little consensus on the most appropriate technique61.

We estimated climatic risk based on the estimated trend in the annual proportion of days containing extreme heat events from 1979 to 201917. 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 (DOI: 10.24381/cds.adbb2d47). The temperature data was acquired from the European Centre for Medium-Range Weather Forecasts (ECMWF) fifth generation atmospheric reanalysis of the global climate (ERA5)62,63. 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)64,65. 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 model66,67. (Figure S3). See La Sorte et al.20 for additional details.

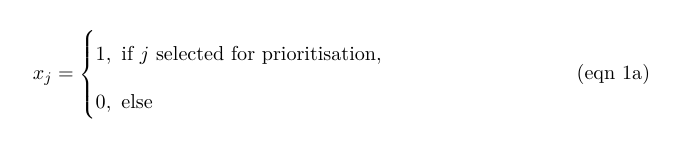
*Multi-objective optimization of pressure reduction*

We processed all data described previously to a 10 x 10 km resolution and clipped data to the extent of land based on the global administrative areas database. We then developed an extension on the minimum set problem, which has the goal to identify a set of sites within a planning area that represents all conservation targets in the fewest number of sites24. Instead of including a single objective in the problem formulation, we expanded it to include multiple objectives. Specifically, we used a hierarchical (lexicographic) approach that assigns a priority to each objective, and sequentially optimizes for the objectives in order of decreasing priority. At each step, it finds the best solution for the current objective, but only from among those that would not degrade the solution quality for higher-priority objectives. We considered up to three objectives in our prioritization scenarios, i) governance risk, ii) land-use risk, and iii) climate risk. To compare different scenarios, we calculated solutions for each unique objective combination (n = 15), as well as one where we use a constant objective function as the null scenario, as the order of the hierarchy can influence the results.

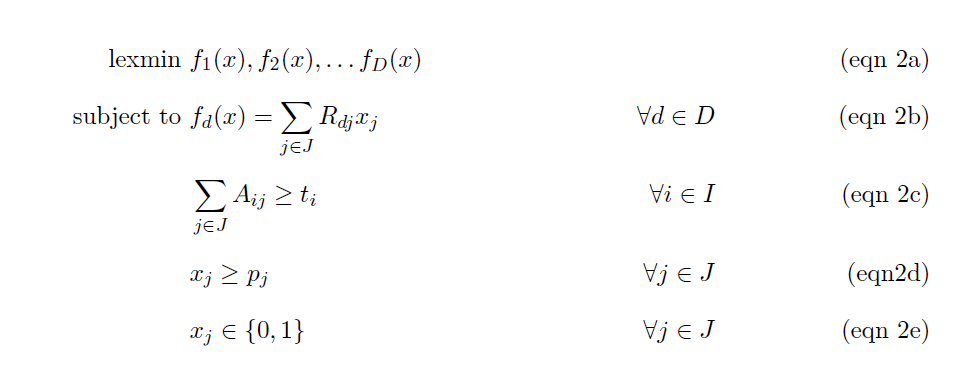
In systematic conservation planning, conservation features describe the biodiversity units (e.g., species, communities, habitat types) that are used to inform protected area establishment. Planning units describe the candidate areas for protected area establishment (e.g., cadastral units). Each planning 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 pj indicate (i.e., using zeros and ones) if each planning unit j ∈ J is already part of the global protected area system. To describe the spatial distribution of the features, let Aij 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 ti denote the conservation target for each feature i ∈ I. Next, let D denote the set of risk datasets (indexed by d). To describe the relative risk associated with each planning unit, let Rdj denote the risk for planning units j ∈ J according to risk datasets d ∈ D.

The problem contains the binary decision variables xj for planning units j ∈ J.



The reserve selection problem is formulated following:



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 (ti ) 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 xj contain zeros or ones.

For all scenarios we locked in current protected areas and, following Hanson et al.[cite], we used flexible targets for suitable habitat based on species’ ranges. Species with less than 1,000 km2 of suitable habitat were assigned a 100% target for their unpartitioned map (1,802 amphibians, 893 avian and 645 mammalian species), species with more than 250,000 km2 of suitable habitat were assigned a 10% target for their unpartitioned map (712 amphibians, 4,518 avian and 1,868 mammalian species) and species with an intermediate amount of suitable habitat were assigned a target by log-linearly interpolating values between the previous two thresholds (2,683 amphibians, 5,190 avian and 2,557 mammalian species; migratory bird species were assigned targets for each seasonal distribution separately). Additionally, to prevent species with very large suitable habitats from requiring excessively large amounts of area to be protected, the targets for species’ distributions larger than 10,000,000 km2 were capped at 1,000,000 km2. This cap affected only 206 (1%) species, and sensitivity analyses showed that it had little effect on our results. We acknowledge that these targets are arbitrary; however, they are more precise than previous targets based on species’ ranges (which can contain a large amount of unsuitable habitat), and accounts for the increased vulnerability of species with smaller range sizes, as well as the difficulty in conserving all habitat for species that occur over large areas.

**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.  
(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)**

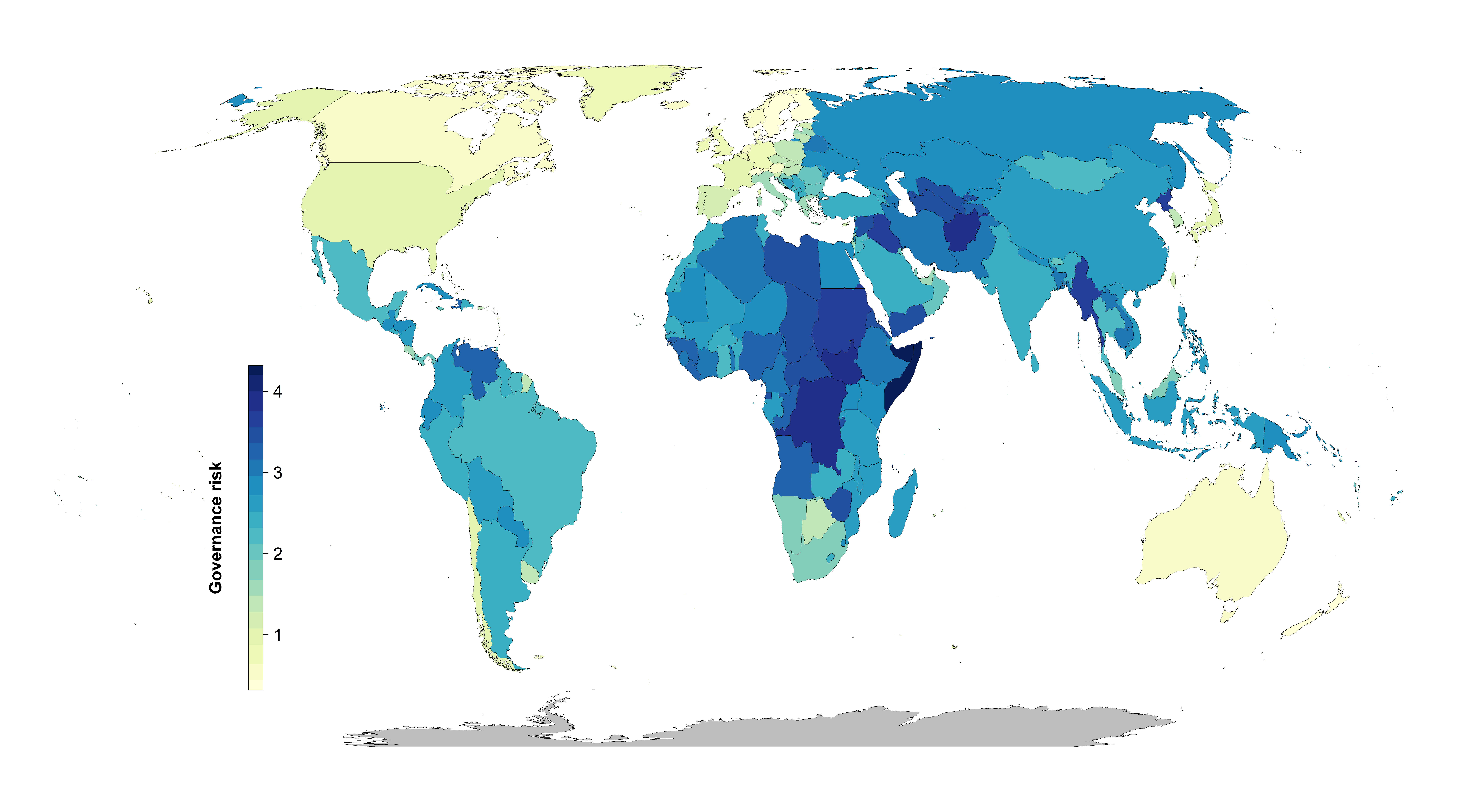
(As an example Afghanistan – Barbados are included below)<https://drive.google.com/file/d/1g_LePBfCbphXzTiCOXCzQtNLSSYoV6me/view?usp=sharing>

|  |  |  |  |
| --- | --- | --- | --- |
| 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 |

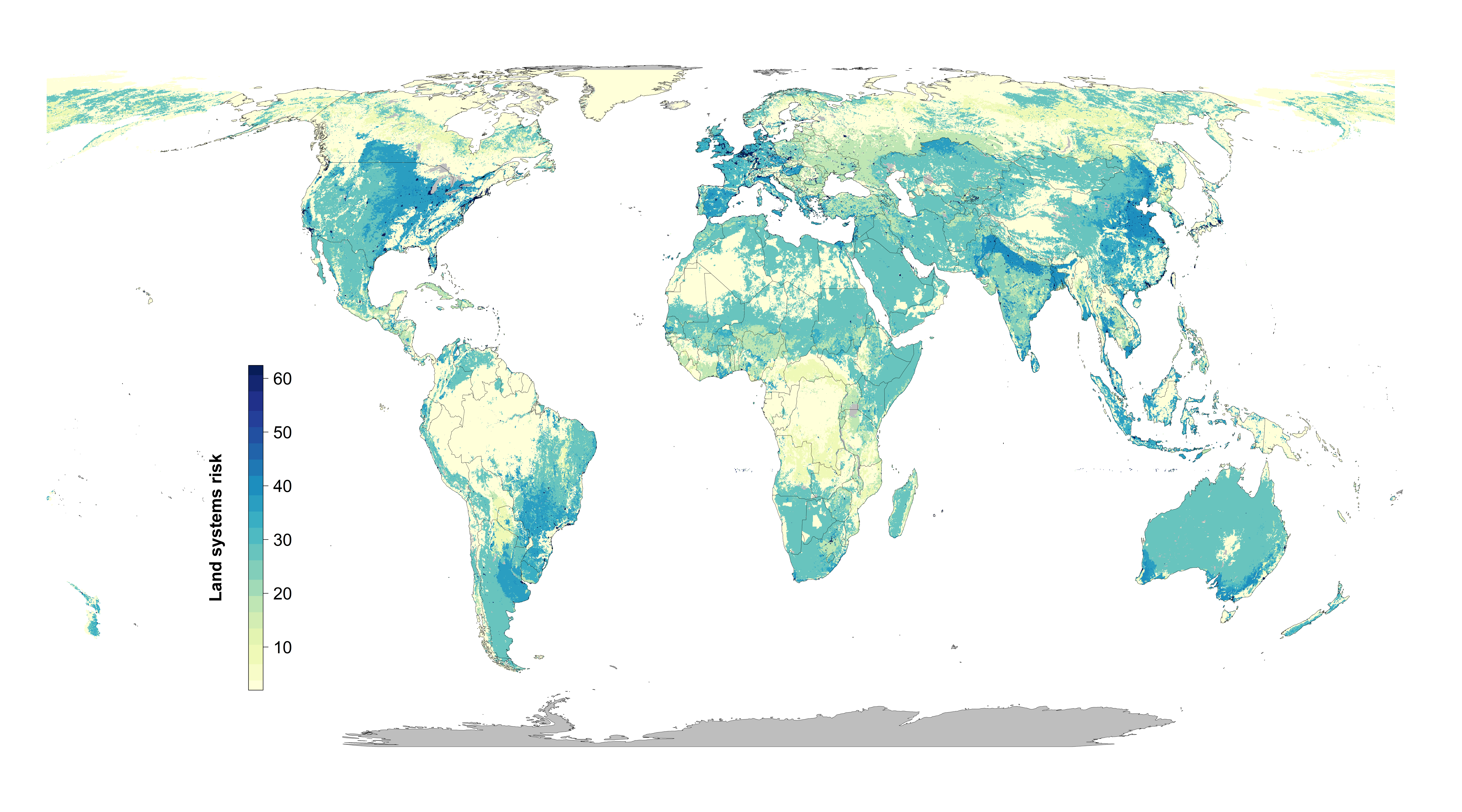
**Table S4.**

|  |  |
| --- | --- |
| **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.” |

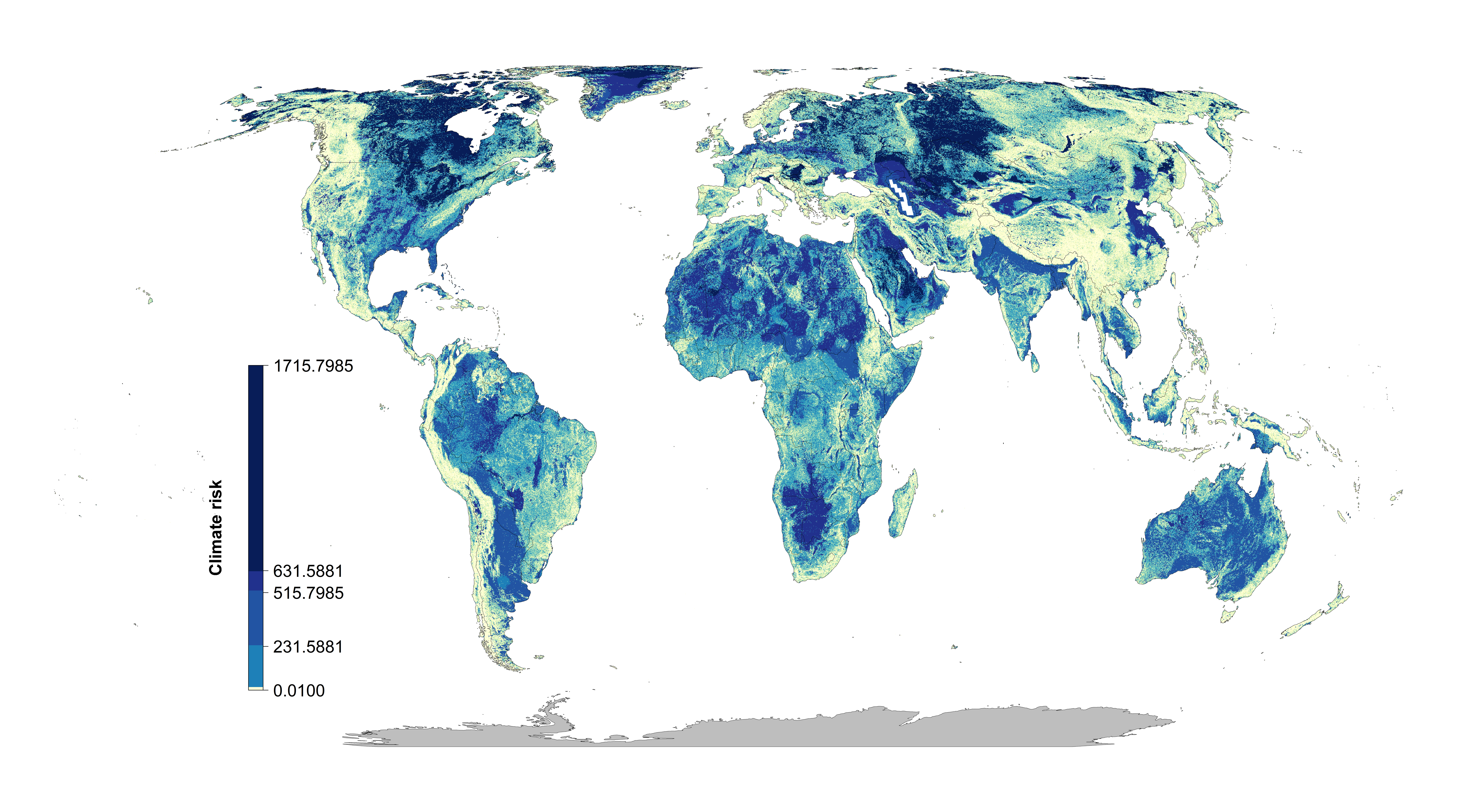
**Figure S1. Governance risk (yellow = low, blue= high)**



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



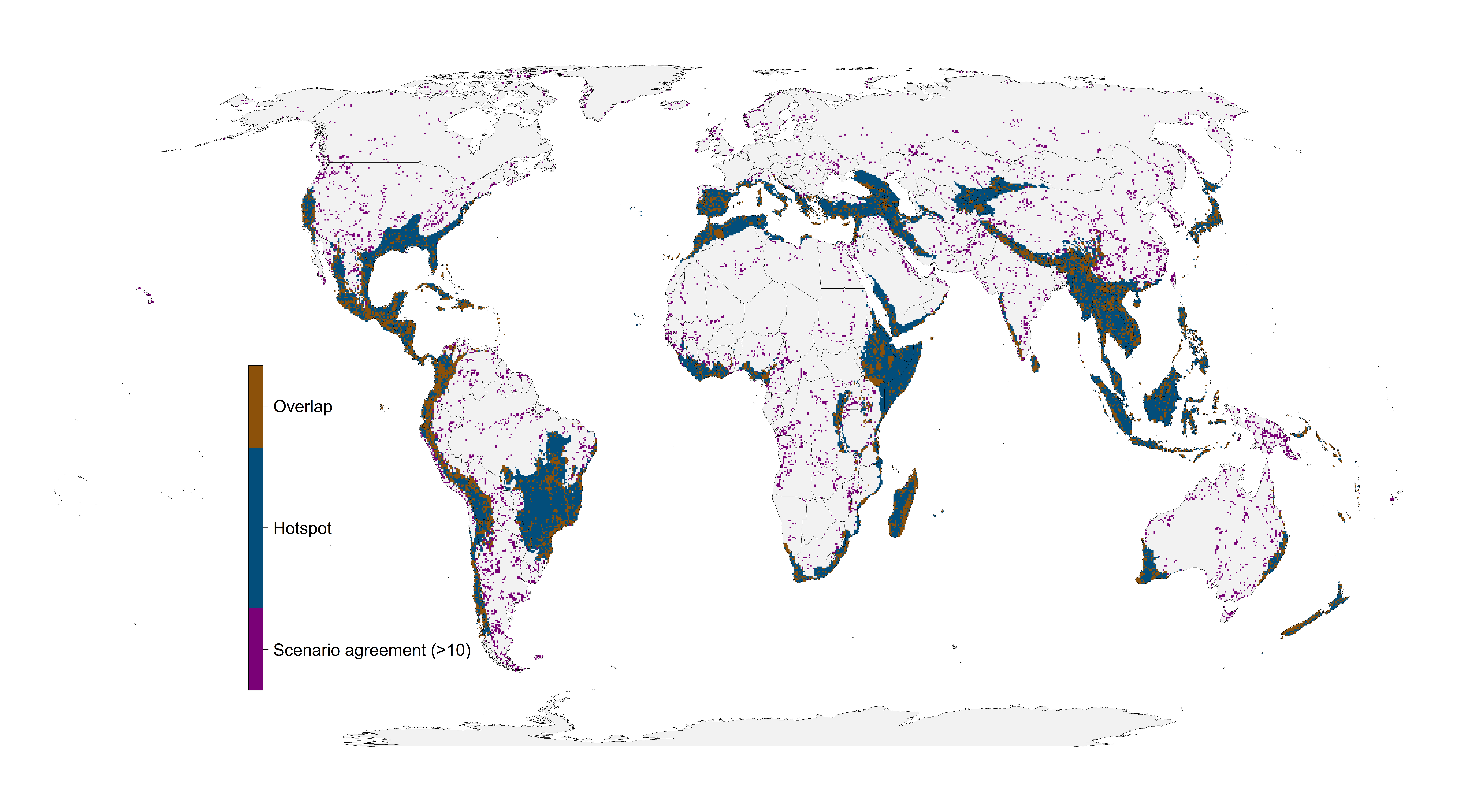
**Figure S3. Climate risk (extreme heat events) (yellow = low, blue= high)**



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



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

Chart, scatter chart

Description automatically generated