Title: **Biodiversity conservation** **in an uncertain world**

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First paragraph

The dynamic nature of biological, economic, social, and political systems means that predicting outcomes of biodiversity conservation investments includes a high degree of uncertainty. Curbing biodiversity loss in a rapidly changing global environment is a complex race against time1,2. Investing in conservation projects that try to minimize uncertainty while maximizing biodiversity gains may be the most feasible mechanism to buffer high biodiversity against future change. Sources of uncertainty used here are political instability and corruption; weak governance; systemic crisis; the probability of project failure; climate change; and projected land use change. As climate change and land-cover change intensify in the coming decades, their interaction with socio-economic systems will influence the effectiveness of conservation tools such as protected areas and species management. Here we introduce a framework that can simultaneously incorporate a range of uncertainties into global biodiversity conservation planning. We highlight how incorporating these uncertainties can lead to more efficient and resilient conservation networks into the future. This represents an advancement over current practices, which identify areas crucial for conservation predominantly on the basis of measures of regional biodiversity or ecosystem services and do not incorporate multiple uncertainties at once. Our framework allows for robust conservation planning in an uncertain world.

**Main text**

Making decisions about conservation in a rapidly changing world are risky and the stakes are high (Díaz et al. 2019). As we lose biodiversity at an alarming rate2, protected areas are one of the best tools for conservation 3; however, human-caused change results in high uncertainty of the performance of conservation land in the future. Effective decision-making must operate within the context of climate change, land use change, and complex interconnected socio-economic-ecological systems that interact and result in systemic environmental risks, or Anthropocene risk (Keys et al. 2019).

To prioritize conservation investments, generally the most cost-effective actions are weighed against the biodiversity benefits. However, both cost and benefit will look much different in the future, making investing without any consideration of future conditions risky...

Biodiversity crisis

Need to make sure to maximize return on investment – investing in conservation may not make sense because in X years it will be gone.

Protection needs to be resilient re: land use change, climate effects, socio political risk

Must balance your risk as an investor with risk to biodiversity in priority places: need to incorporate risk into conservation planning

Framework to account for risk of change

We might aim to set conservation priorities that are robust to risk and uncertainty (BenHaim 2001; Nicholson and Possingham 2007). Here we need to estimate the likelihood that an unplanned but conservation relevant event may occur, such as the risk of a hurricane, fire, or coral bleaching event, or the risk that a conservation action will not be carried out correctly (the inverse of its likelihood of success). We can then either prioritize actions (or locations to carry out an action) that meet conservation targets while minimizing some combination of risk and cost (yet another trade-off ) (Game et al. 2008), or prioritize actions that maximize the expected or likely conservation benefits for a fixed budget (Joseph et al. In Press-b). Note that these solutions represent modifications of Equations (1) and (2), respectively.

Uncertainties: Sources of uncertainty used here are political instability and corruption; weak governance; systemic crisis; the probability of project failure; climate change; and projected land use change.

Climate and land use change: As climate change and land-cover change intensify in the coming decades, their interaction with socio-economic systems will influence the effectiveness of conservation tools such as protected areas and species management.

Solution: Investing in conservation projects that try to minimize uncertainty while maximizing biodiversity gains may be the most feasible mechanism to buffer high biodiversity against future change.

Here, we build on a classical problem formulation from the systematic conservation planning literature, which is the minimum set problem, where the goal is to minimize the cost of a solution, while reaching feature targets. We expand this approach to include multiple objectives in the problem formulation at the same time. Each objective represents a measure of uncertainty, we want to account for. We include i) socioeconomic uncertainty, ii) land use change uncertainty, iii) climate uncertainty, while maximizing the protection of 30930 vertebrate species globally.

**Results**

Discussion

**Main references**

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**Tables**

Table 1. Global land area required to reach 30% target. S = socioeconomic, L = land use, C = climate.

|  |  |  |
| --- | --- | --- |
| Scenario | % tot (no flip) | % increase (no flip) |
| SLCA\_0001 | 27.61 | 16.35 |
| SLCA\_1001 | 27.85 | 16.59 |
| SLCA\_0101 | 28.89 | 17.63 |
| SLCA\_1101 | 28.86 | 17.6 |
| SLCA\_0011 | 27.9 | 16.64 |
| SLCA\_1011 | 27.86 | 16.6 |
| SLCA\_0111 | 28.02 | 16.76 |
| SLCA\_1111 | 28.2 | 16.94 |

**Figure legends (+ figures)**

Figure 1: Scenario overlap. orange = protected areas. Color gradient from yellow (1 scenaris) to dark blue (8 scenarios) = ovelap.

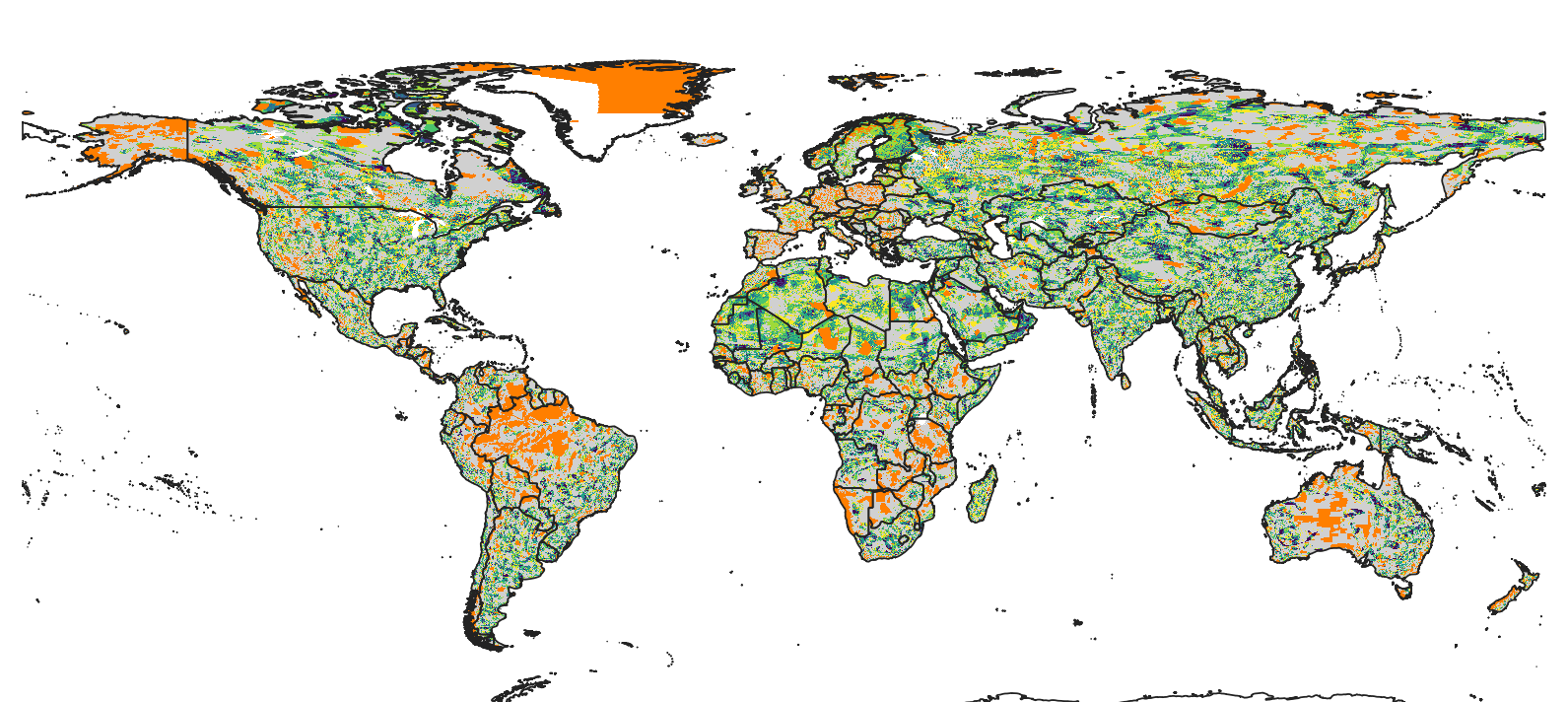
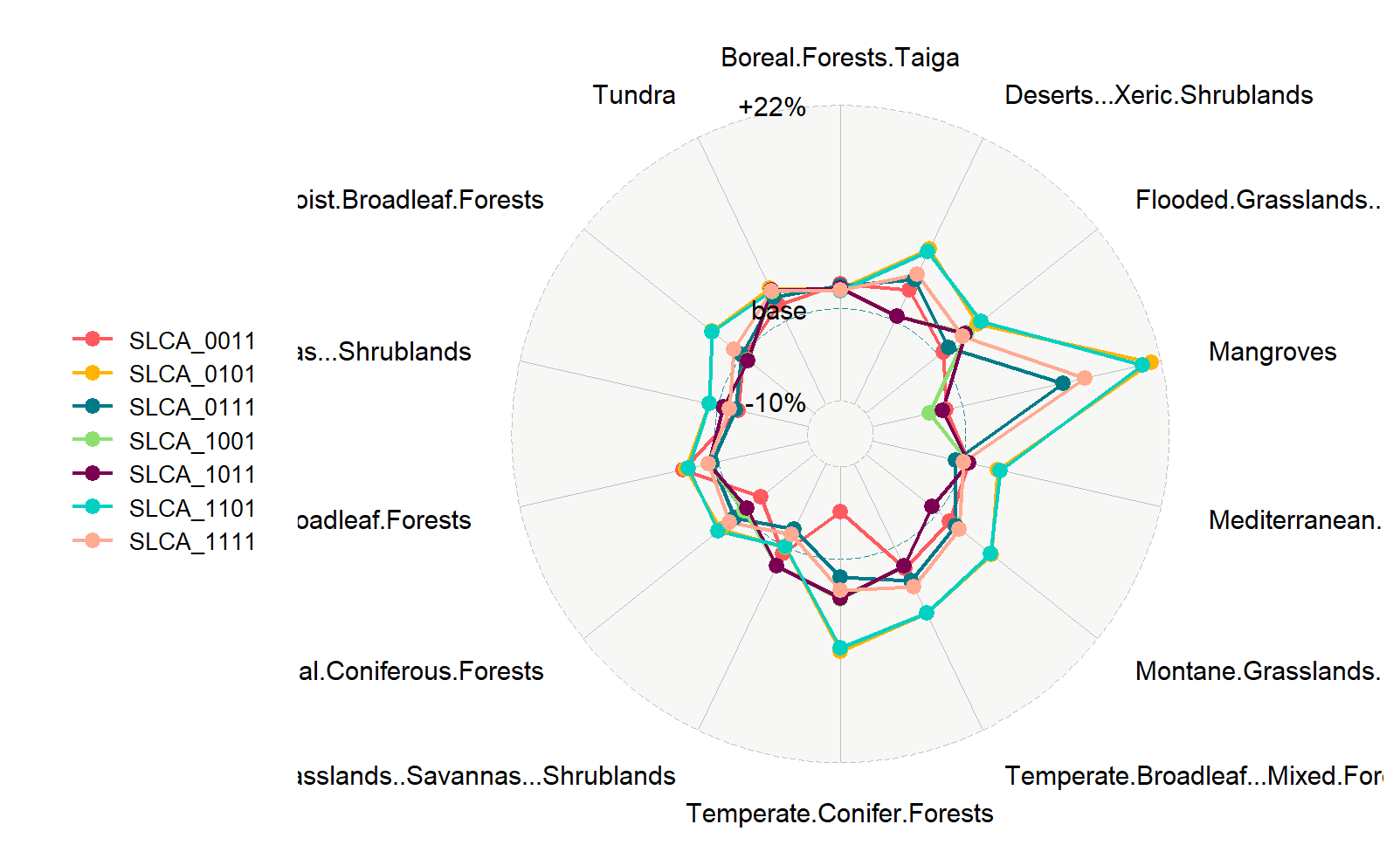
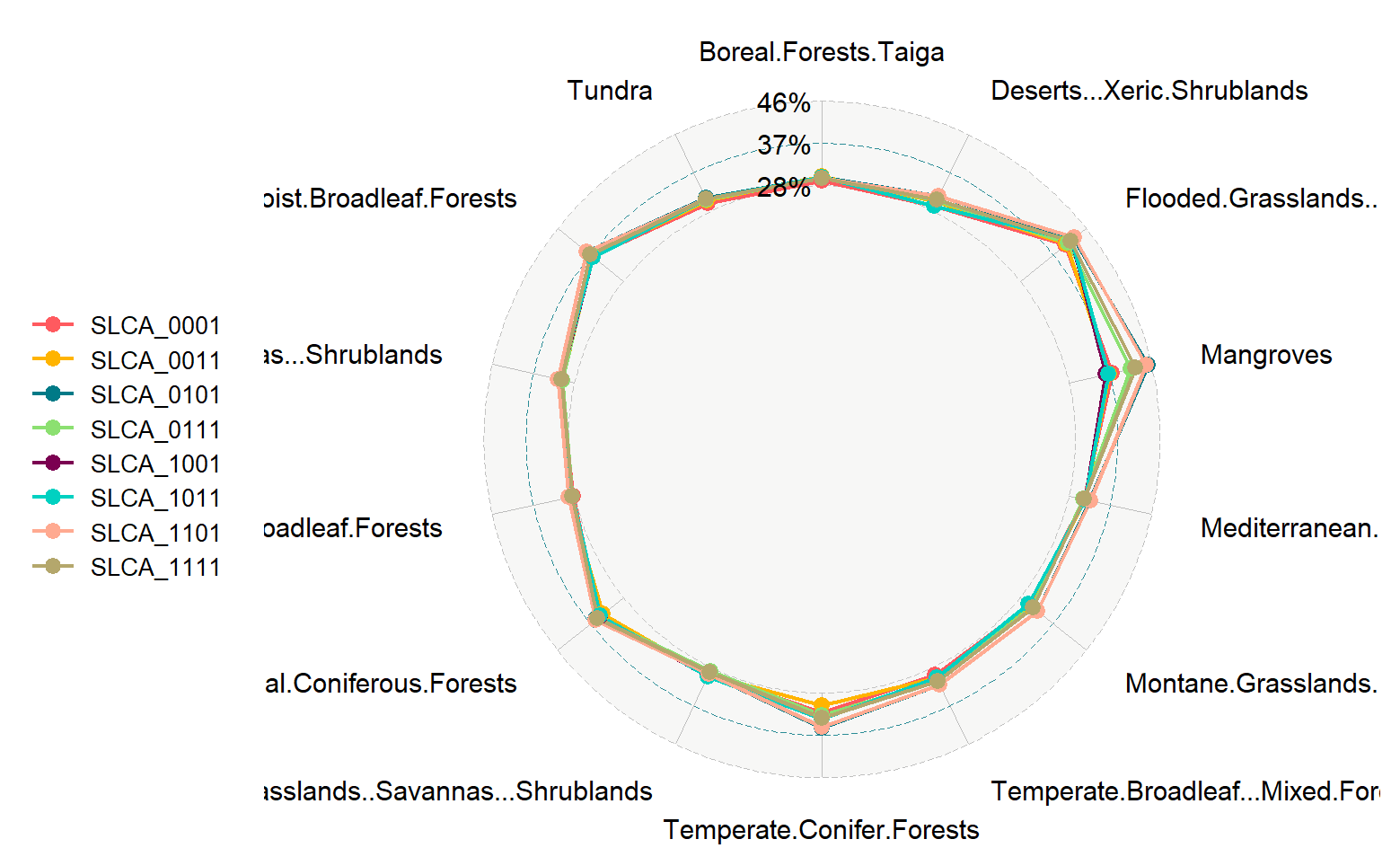


Figure 2: Spider plot biomes vs scenarios. % values are in relation to base value results. Could also do how much of each biome was selected, but that’s not very informative (see small figure below). I’m also not convinced that those spider plots are easy to read, might be better with x = biome, y = value and colors = scenarios plot.





**Methods**

*Species selection*

Our species lists were determined using the IUCN Red List of threatened species, following Pouzols et al. (2014). For mammal, amphibian and reptile species ranges, we used the IUCN Red List website (<http://www.iucnredlist.org/>, accessed 2016-09-14) and for birds we used the BirdLife International data zone webpage (<http://www.birdlife.org/datazone/home>, accessed 2016-09-14). We used these taxa because analogous data are available for a low proportion of species in other taxonomic groups. These data have certain limitations, including possible underestimation of the extent of occurrence and overestimation of the true area of occupancy 4, but have been shown to be robust to commission errors as long as the focus is on species assemblages rather than single species, 5. They are currently the most frequently used and updated source for vertebrate species distributions 6.

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: 5660, 13375, 5442, 6153.

*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 dataset, we (i) reprojected the data to an equal-area coordinate (World Behrman) (ii) excluded reserves with unknown or proposed designations, (iii) excluded UNESCO Biosphere Reserves 7, (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, we overalaid the protected area boundries with a XXX × XXXX km grid covering the Earth. These spatial data procedures were completed using ArcMap (version 10.3.1) and python (version 2.7.8).

*Socioeconomic risk*

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<https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators>

Mean World Bank Index per country.

*Land use change risk*

We used a global land systems map for the year 2000 (Eitelberg et al., 2016; van Asselen and Verburg, 2012) and a global land systems change model (CLUMondo) (van Asselen and Verburg, 2013) to examine land-use change in focal areas for the individual targets and areas of overlap. Spatially explicit land-use change models are important tools to analyze potential land-use trajectories for ecological analysis (e.g. Jetz et al., 2007; LaSorte et al., 2017) and provide information to evaluate policy options. The CLUMondo model simulates land-use change at an approximately 9.3 x 9.3 km spatial resolution based on regional demands for goods and resources dependent on factors that promote or constrain land conversion. The modelling approach goes beyond other global land-use models by distinguishing land systems that combine land cover with indicators of land use. This way we are able to distinguish more realistically the mosaics of land use that are relevant to biodiversity. Changes in land-use are simulated using empirically quantified relations between land systems, biophysical location and socio-economic factors, in combination with dynamic modeling of competition between different land systems. Model outputs are based on a land systems classification representing combinations of land cover, land use intensity and livestock presence. While the land systems classification in the CLUMondo model includes 17 categories, we aggregated these into six categories for further analysis: (1) forest and mosaic forest-grassland, (2) mosaic forest-cropland, (3) peri-urban and villages (hereafter peri-urban), (4) urban, (5) grassland-bare, (6) cropland or mosaic cropland-grassland (Table S3). The majority of the species considered in our analysis are associated with wooded habitats but many use secondary habitat types including mosaic forest-agriculture and peri-urban landscapes. Open cropland, grassland and bare land cover, in contrast, are likely to contain little to no suitable habitat for these species.

We used the CLUMondo model to simulate land system change for three shared socioeconomic pathway (SSP) scenarios, which allow us to compare the predicted change in land cover between 2000 and 2050 for each scenario. In implementing the three SSP scenarios, model settings are according to the SSP narratives (O’Neill et al., 2014) while demand for agricultural commodities and livestock are derived from assessments with the integrated assessment model IMAGE ([Stehfest et al., 201](https://www-sciencedirect-com.vu-nl.idm.oclc.org/science/article/pii/S0959378017311718#bib0265)4) at the level of world regions. Climate change is taken into account by incorporating change in temperature and precipitation drivers and in suitability for cropland conversion. Data used to determine the influence of climate change in CLUMondo was obtained from the Worldclim database (Hijmans et al. 2005) and the FAO’s database on Global Agro-Ecological Zones (IIASA/FAO 2012). Climate change radiative forcing is projected to be approximately 6W/m2 by 2100 for the three SSPs, which, by 2050 is equivalent to the RCP 4.5 and RCP 6 scenarios, or the SRES B1 scenario (IPCC 2014).

The Sustainability Scenario (SSP1) and the Regional Nationalism scenario (SSP3) represent contrasting low and high challenges to mitigation and adaptation, respectively (Riahi et al., 2017). In SSP1, development strategies shift globally towards sustainability. Investments in education and health accelerate the demographic transition amid economic growth that focuses more broadly on improving human well-being and reducing inequality among and within countries. Consumption is directed towards low material growth and lower resource and energy intensity. In SSP3, countries experience heightened nationalism, competitiveness and security concerns and regional conflicts that drive a policy agenda oriented toward domestic and regional security issues. Countries focus on achieving energy and food security goals within their own regions at the expense of broader-based development. Population growth is high in developing countries and low in industrialized countries. Environmental concerns remain a low international priority, resulting in strong environmental degradation in some regions. The intermediate scenario (Business-as-Usual, SSP2) captures moderate challenges to mitigation and adaptation, with historically consistent trends in technological, economic and societal progress. Population growth continues to rise over the next few decades before leveling off mid-century.

Each of the 23 land use classes was assigned a threat score, based on the following table. The final threat score was comprised of crop, livestock and urban components, which were added to yield a final threat score.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| No | Description | threat\_score | crop\_part | livestock\_part | urban\_part |
| 0 | Cropland; extensive with few livestock | 1 | 0.75 | 0.25 | 0 |
| 1 | Cropland; extensive with bovines, goats & sheep | 1 | 0.75 | 0.5 | 0 |
| 2 | Cropland; medium intensive with few livestock | 0.75 | 0.5 | 0.25 | 0 |
| 3 | Cropland; medium intensive with bovines, goats & sheep | 1 | 0.5 | 0.5 | 0 |
| 4 | Cropland; intensive with few livestock | 0.5 | 0.25 | 0.25 | 0 |
| 5 | Cropland; intensive with bovines, goats & sheep | 0.75 | 0.25 | 0.5 | 0 |
| 6 | Mosaic cropland and grassland with bovines, goats & sheep | 0.75 | 0.25 | 0.5 | 0 |
| 7 | Mosaic cropland (extensive) and grassland with few livestock | 1 | 0.75 | 0.25 | 0 |
| 8 | Mosaic cropland (medium intensive) and grassland with few livestock | 0.75 | 0.5 | 0.25 | 0 |
| 9 | Mosaic cropland (intensive) and grassland with few livestock | 0.5 | 0.25 | 0.25 | 0 |
| 10 | Mosaic cropland (extensive) and forest with few livestock | 1 | 0.75 | 0.25 | 0 |
| 11 | Mosaic cropland (medium intensive) and forest with few livestock | 0.75 | 0.5 | 0.25 | 0 |
| 12 | Mosaic cropland (intensive) and forest with few livestock | 0.5 | 0.25 | 0.25 | 0 |
| 13 | Dense forest | 0 | 0 | 0 | 0 |
| 14 | Open forest with few livestock | 0.25 | 0 | 0.25 | 0 |
| 15 | Mosaic grassland and forest | 0 | 0 | 0 | 0 |
| 16 | Mosaic grassland and bare | 0 | 0 | 0 | 0 |
| 17 | Natural grassland | 0 | 0 | 0 | 0 |
| 18 | Grassland with few livestock | 0.25 | 0 | 0.25 | 0 |
| 19 | Grassland with bovines, goats and sheep | 0.5 | 0 | 0.5 | 0 |
| 20 | Bare | 0 | 0 | 0 | 0 |
| 21 | Bare with few livestock | 0.25 | 0 | 0.25 | 0 |
| 22 | Peri-urban & villages | 0.75 | 0 | 0 | 0.75 |
| 23 | Urban | 1 | 0 | 0 | 1 |

To incorporate the temporal component of the SSP scenarios, we created a threat score change metric that was a combination of current (1/3 weight) and future predictions (2/3 weight). Example calculations can be found in the following example table. We created one predictive surface for each of the three SSP scenarios. In the main analysis we focus on the SSP 2 scenario (middle of the road).

|  |  |  |
| --- | --- | --- |
| current | future | **1\*a + 2\*b/3** |
| 0 | 0 | **0** |
| 0.25 | 0.25 | **0.25** |
| 0.5 | 0.5 | **0.5** |
| 0.75 | 0.75 | **0.75** |
| 1 | 1 | **1** |
| 0 | 0.25 | **0.17** |
| 0.25 | 0.5 | **0.42** |
| 0.5 | 0.75 | **0.67** |
| 0.75 | 1 | **0.92** |
| 1 | 1 | **1** |
| 0 | 0 | **0** |
| 0.25 | 0 | **0.08** |
| 0.5 | 0.25 | **0.33** |
| 0.75 | 0.5 | **0.58** |
| 1 | 0.75 | **0.83** |
| 0 | 0 | **0** |
| 0.25 | 0 | **0.08** |
| 0.5 | 0 | **0.17** |
| 0.75 | 0 | **0.25** |
| 1 | 0 | **0.33** |
| 0 | 1 | **0.67** |
| 0.25 | 1 | **0.75** |
| 0.5 | 1 | **0.83** |
| 0.75 | 1 | **0.92** |
| 1 | 1 | **1** |

*Climate risk*

For initial test purposes we have used climate change velocity from 9as the climate risk component in the multi-objective optimization formulation. We will also explore climate novelty and extreme metrics from Frank La Sorte.

*Multi-objective optimization of risk reduction*

The general problem formulation follows the min set approach, where we try to minimize the objective function, while reaching feature targets. Instead of one objective, we are expanding the formulation to include multiple objectives in the problem formulation. We use a hierarchical or lexicographic approach that assigns a priority to each objective, and optimizes for the objectives in decreasing priority order. 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) socioeconomic risk, ii) land use change risk, and iii) climate risk. To compare different risk scenarios we calculated solutions for each unique objective combination (n = 7), as well as one where we use a constant objective function as the base scenario.

For all scenarios we locked in current protected areas and used the same feature set of 30930 vertebrates. The target for each feature was set to 30% of their range. The optimality gap we use was 5% for each objective in the hierarchy. We started the hierarchy with socioeconomic risk, followed by land use change risk and climate risk to reflect the immediacy of each risk on current biodiversity (socioeconomic best predictor for success currently; land use higher current impact than climate). Sensitivity analysis showed that reversing the priority order did not influence our results (supp mat).

**Methods references**

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**Author contributions**

**Competing interest declaration**

**Parking lot**

and current patterns of land use.