LETTER

Projecting Global Biodiversity Indicators under Future Development Scenarios

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Abstract

To address the ongoing global biodiversity crisis, governments have set strategic objectives and have adopted indicators to monitor progress toward their achievement. Projecting the likely impacts on biodiversity of different policy decisions allows decision makers to understand if and how these targets can be met. We projected trends in two widely used indicators of population abundance Geometric Mean Abundance, equivalent to the Living Planet Index and extinction risk (the Red List Index) under different climate and land-use change scenarios. Testing these on terrestrial carnivore and ungulate species, we found that both indicators decline steadily, and by 2050, under a Business-as-usual (BAU) scenario, geometric mean population abundance declines by 18–35% while extinction risk increases for 8–23% of the species, depending on assumptions about species responses to climate change. BAU will therefore fail Convention on Biological Diversity target 12 of improving the conservation status of known threatened species. An alternative sustainable development scenario reduces both extinction risk and population losses compared with BAU and could lead to population increases. Our approach to model species responses to global changes brings the focus of scenarios directly to the species level, thus taking into account an additional dimension of biodiversity and paving the way for including stronger ecological foundations into future biodiversity scenario assessments.

Introduction

Growing concerns over the loss of biodiversity and the goods and services it provides to humankind have prompted the United Nations to establish the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), to inform global environmental decision making (Brooks *et al.* 2014). The main function of IPBES is to produce regional and global assessment on status, trends, and future scenarios of biodiversity and

ecosystem services. These assessments will advise on the policies required to achieve sustainable development goals, including the Convention on Biological Diversity (CBD) Aichi targets for 2020 and the CBD vision for 2050. These targets have an associated set of biodiversity indicators to monitor progresses (Tittensor *et al.* 2014).

Both IPBES and the CBD require a framework for producing projections about future trends in biodiversity loss under alternative policy scenarios. Until now, such projections measured via biodiversity indicators adopted by the CBD have been limited to a single study of African-protected area scenarios (Nicholson *et al.* 2012).

In order for any biodiversity scenario projection to be relied upon, it is important that the ecological response models are known to provide accurate estimates of past trends; surprisingly, there are no studies hindcasting terrestrial ecological models from past to present for models calibration and validation. Moreover, most biodiversity scenario studies have used indicators such as total number of species derived from species-area curves (Van Vuuren *et al.* 2006) and naturalness via Mean Species Abundance (MSA; Alkemade *et al.* 2009) that do not use species-specific responses to anthropogenic pressures. Species-specific ecological models improve predictions of ecological responses to global change by accounting for life-history traits, and allow understanding which species are at higher risk and why (Pearson *et al.* 2014).

Here, we assess the ecological impact of different human development scenarios with species-specific ecological models and two established species-level indicators, the Red List Index (RLI; an aggregate measure of species' extinction risk) and species Geometric Mean Abundance, (GMA) an indicator equivalent to the Living Planet Index (which is based on observed trends of populations of vertebrates species) for 440 terrestrial mammalian carnivores and ungulates (89% of the species in these groups). These two complementary indicators have been adopted by the CBD to measure progress toward global biodiversity targets (Butchart *et al.* 2010). We validate our models through hindcasting species distributions and biodiversity indicators from 1970 to the present and we provide confidence intervals around past and future modeled trends. We conclude by highlighting the step-changes required for achieving conservation goals for large mammals based on our scenario projections.

Methods

Scenario storylines

The "Business-as-usual" (BAU) scenario explores the effects of economic growth, consumption patterns, and energy mix in the absence of new policies (PBL 2012). Growing human population and economic development will increase the demand for food, energy, and other essential goods, such as clean water, fibers, and wood. These demands are satisfied by increasing agricultural productivity and expanding agricultural land and freshwater consumption; by expanding fisheries and aquaculture; by increasing the use of fossil fuels and wood products (PBL 2012). These trends largely satisfy human needs, reduce extreme poverty, and improve human health. However, they also result in ongoing decline of biodiversity measured as MSA (PBL 2012) and large increases of greenhouse gas emissions.

An alternative scenario, "Consumption Change" belongs to a family of scenarios designed to achieve a set of sustainable development goals on human well-being, climate change, and biodiversity simultaneously. Consumption Change, does so by limiting meat intake per capita, reducing waste in the agricultural production chain and adopting a less energy-intensive lifestyle (PBL 2012). The rapid adoption of these societal changes make this scenario possible but ambitious (PBL 2012). Scenario assumptions are in Table 1, trends in major land-uses projected for both scenarios are in Figures S1 and S2.

Climate change

Our baseline climate was an average of the observed bioclimatic variables between 1975 and 2005. We considered two Intergovernmental Panel on Climate Change - Assessment Report 4 climate scenarios: A1B, associated with BAU and B1 associated with Consumption Change (PBL 2012). Raw monthly temperature minimum and maximum were obtained from http://climascopewwfus.org at a resolution of 0.5° (Price *et al.* 2012). Standard bioclimatic variables (Table S1) were generated using the "climates" package in R (VanDerWal *et al.* 2011).

Habitat loss

We used the outputs from Integrated Model to Assess the Global Environment (IMAGE) version 2.5 (Bouwman *et al.* 2006) as an estimate of the area converted to or from cropland, pasture, plantation or forestry, in 24 world macroregions at any time step. These estimates from the IMAGE agroeconomic model were used as input into the GLOBIO land-use change model to derive fractions of different land-cover and land-uses within 6' grid cells (approximately 10 by 10 km at the equator) for the years 1970–2050 at decadal interval (Alkemade *et al.* 2009; Visconti *et al.* 2011). The GLOBIO land-cover and land-use data (see, e.g., in Table S6) were used together with the relevant climate for projecting species responses to global

Table 1 Assumptions of Business-as-usual and Consumption Change scenarios for the year 2050 (PBL 2012)

Assumption	Business-as-usual	Consumption Change
Access to food	250 million people globally have insufficient access to food in 2050	Inequality in access to food due to income inequality converges to zero by 2050
Consumption	+65% energy consumption, +50% food consumption	Meat consumption per capita levels off at twice the consumption level suggested by a supposed healthy diet (Stehfest *et al.* 2009) which would imply reducing meat and egg consumption in all regions by 76–88%.
Waste	Stable 30% of total production	Waste is reduced by 50% with respect to BAU by 2030
Agricultural productivity	Yield increase by 0.06% annually (+27% by 2050)	In all regions, 15% increase in crop yields by 2050, compared with the BAU scenario
Protected areas	No further protected areas respect to 2010	17% of each of the 65 realm-biomes. Expansion allocated close to existing agriculture to protect areas currently most threatened by habitat loss
Forestry	+30% in clear-cut, +35% plantation, −12.5% selective logging. No reduced impact logging.	Forest plantations supply 50% of timber demand; almost all selective logging based on reduced impact logging by 2020.

changes from past to present, thereby validating our model results against known trends ("model hindcast" Supporting Information: S5), and to model the impacts of future global change on large terrestrial mammals.

Species' response to climate and land-use change

We followed a hierarchical approach to model species distribution (Pearson & Dawson 2003). Bioclimatic envelope models were used to estimate species past, present, and future extent of occurrence (EOO) reflecting the known relationship between climate and species geographic range, (Soberón & Nakamura 2009). Habitat suitability models were used to identify the areas potentially occupied by the species within the EOO (i.e., Extent of Suitable Habitat; ESH) based on habitat preferences coded in the IUCN Red List (RL) database (IUCN 2012b) and projected land-cover and land-use.

Species data

We focused on all extant terrestrial carnivore and ungulate species of the orders Carnivora, Cetartiodactyla, Perissodactyla, and Proboscidea for which the geographic range was known and available from the IUCN (IUCN 2012b), and sufficiently large to obtain an adequate sample of presence points for fitting bioclimatic envelope models. In total, we projected the responses to climate and land-use change impact of 440 of the 493 species in these orders for which range data were available.

Bioclimatic envelope models

We simulated climate change effects on species distribution by fitting bioclimatic envelopes at 30' resolution and by projecting spatial changes to this envelope at 10-year intervals. We used seven statistical models with the R package BIOMOD (Thuiller *et al.* 2009) to fit current bioclimatic envelopes and to project these envelopes into future climatic scenarios (see Supporting Information: S2.1). The variables selected (Table S1) are those usually considered most important for modeling species distributions at large scale (Guisan & Zimmermann 2000). We transformed the probabilistic output of these models to a binary (presence/absence) output selecting for each species and model the probability threshold that maximized True Skill Statistic TSS (Allouche *et al.* 2006). We obtained a single model output by calculating the mode of the seven binary values (presence/absence) derived from individual models.

We accounted for species ability to track climate using two dispersal assumptions. The first represents a pessimistic scenario where species were unable to disperse and adjust their EOO according to climate; hence species could only lose suitable climate space within their present EOO. In the second assumption, species were allowed to track climate at the speed of one dispersal distance per generation (see Supporting Information, S2.2). This equals to assuming an intergenerational relay race to track climate change. We also considered a climate adaptation scenario in which we assumed species to be able to adapt locally to climate change and persist in their present EOO wherever the habitat is suitable.

Habitat suitability models

We used the IUCN Global Mammal Assessment habitat suitability models (Rondinini *et al.* 2011; Visconti *et al.* 2011) to quantify the ESH for each species within a species' EOO. Each combination of land-cover, land-use, and elevation within a grid cell was scored as either suitable or not according to the land-cover and altitudinal preferences of species and their sensitivity to different land-uses reported by IUCN taxonomic experts (Rondinini *et al.* 2011). The land-use classification system was a modification of the 23 Global Land Cover 2000 adopted by the GLOBIO model which included grazing areas and subclasses related to the type and intensity of agriculture and forestry, yielding a total of 66 classes (Table S5). For each species, suitable habitat within the 6' cells inside a species EOO was calculated as the proportion of suitable land-cover/land-use within the cell multiplied by the proportion of suitable altitude within the cell. The ESH was the sum of all suitable habitat within a species' EOO.

The suitable area does not reflect the actual occurrence of the species because parts might not be occupied due to other biophysical, ecological, or anthropogenic factors, including habitat fragmentation and isolation. We accounted for this by correcting the ESH with an occupancy factor ϕ to derive the Area of Occupancy (AOO = ESH*ϕ). To account for uncertainty in this parameter, we ran 1,000 Monte Carlo simulations in which ϕ was drawn from a distribution U (0.1, 1).

Red List Index

The RLI shows trends in aggregate extinction risk of species, as measured using the categories of the IUCN Red List of Threatened Species, and ranges from 0 if all species are Extinct to 1 if all are assigned the lowest possible extinction risk category ("Least Concern") (Butchart *et al.* 2007). RL categories are broad classes of extinction risk (IUCN 2012a) assigned on the basis of criteria relating to the size, structure, and trends in population and geographic range (IUCN 2012a). We estimated each species' RL category at each time-step by comparing the projected EOO, AOO, and estimated population size (number of mature individuals) against RL criteria A2 (trends in population size), B1 (EOO size), B2 (AOO size), C1 (small and declining population), and D1 (very small population). We followed IUCN guidelines (IUCN 2012a) to assign each species to the following RL categories: Least Concern, Near Threatened, Vulnerable, Endangered, Critically Endangered, and Extinct (including Extinct in the Wild), according to IUCN criteria and thresholds. To project RL categories according to criteria C1 and D1, we

first estimated the potential global population size of a species by multiplying the AOO by the average population density of the species. To account for the uncertainty in the realized density of the species and that mature individuals are a fraction of the whole population, we multiplied the observed and estimated mean density by a correction factor δ (see Supporting Information: S4). We drew 1,000 values of δ from a distribution U (0.1, 1) and applied these values to Monte Carlo simulations (together with ϕ that was sampled independently). For each combination of socioeconomic scenario and dispersal assumption, we thus obtained 1,000 time series of EOO, AOO, and population size which we used to calculate the RLI (see Supporting Information: S3.1).

After transforming RL categories into weights W from 0 (LC) to 5 (EX), we calculated the RLI following Butchart *et al.* (2007)

$$\text{RLI}_t = 1 - \frac{\sum_{s}^{S} W_{c(s,t)}}{W_{\text{EX}} S}, \tag{1}$$

where $W_{c(s,t)}$ is the weight applied to category c of species s at time t, S is the total number of species modeled, and W_{EX} is the weight applied to extinct species.

We also created spatial maps of RLI for 2010 and 2050 and its difference for each scenario and dispersal assumption (see Supporting Information: S3.2).

Geometric Mean Abundance

The GMA at time t is the geometric mean across a group of species S of the ratio between their population size at time t and their population size in 1970. This is the equivalent at the species to the LPI which is instead based on trends of single populations (Collen *et al.* 2009).

$$\text{GMA}_t = \sqrt[S]{\prod_{s=1}^{S} \frac{p_{s,t}}{p_{s,1970}}}, \tag{2}$$

where $p_{s,t}$ is the total expected population size of species s at time t, across its whole EOO obtained by multiplying the AOO of species s for its expected population density.

Indicator trends validation

We hindcasted species' responses to global changes from 1970 to 2010 and compared the predicted and observed trends in GMA and RLI for model validation and calibration (see Supporting Information: S5).

Results

When assuming that species can adapt locally to climate change, for example, through phenotypic plasticity or
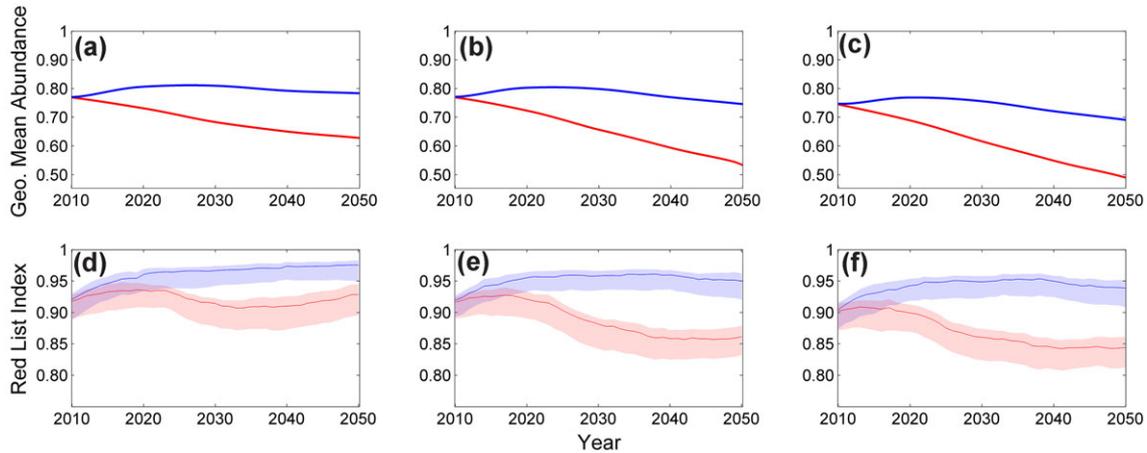
Figure 1 Projected GMA (a, b, and c) and RLI (d, e, and f) for terrestrial carnivores and ungulates under two global socioeconomic scenarios. Business-as-usual in red and Consumption Change in blue. (A and D) Species can adapt to climate change, (B and E) maximum dispersal under land-use and climate change, (C and F) and no dispersal under land-use and climate change. Shading indicates 95% confidence intervals in RLI, the dark lines within the shading represent the median RLI values. The GMA trends do not show confidence intervals because, contrary to RLI, the correction factors for population density and area occupied did not affect these indicators. This is because these factors were applied to obtain population estimates at both numerators and denominator of Equation (2), thereby cancelling each other and generating only one GMA value across all parameter tested in the Monte Carlo simulations. The GMA and RLI values in 2010 vary depending on the dispersal assumption; this affected species range dynamics during the period 1970–2010 used as "burn-in" phase thereby influencing GMA and RLI in 2010.
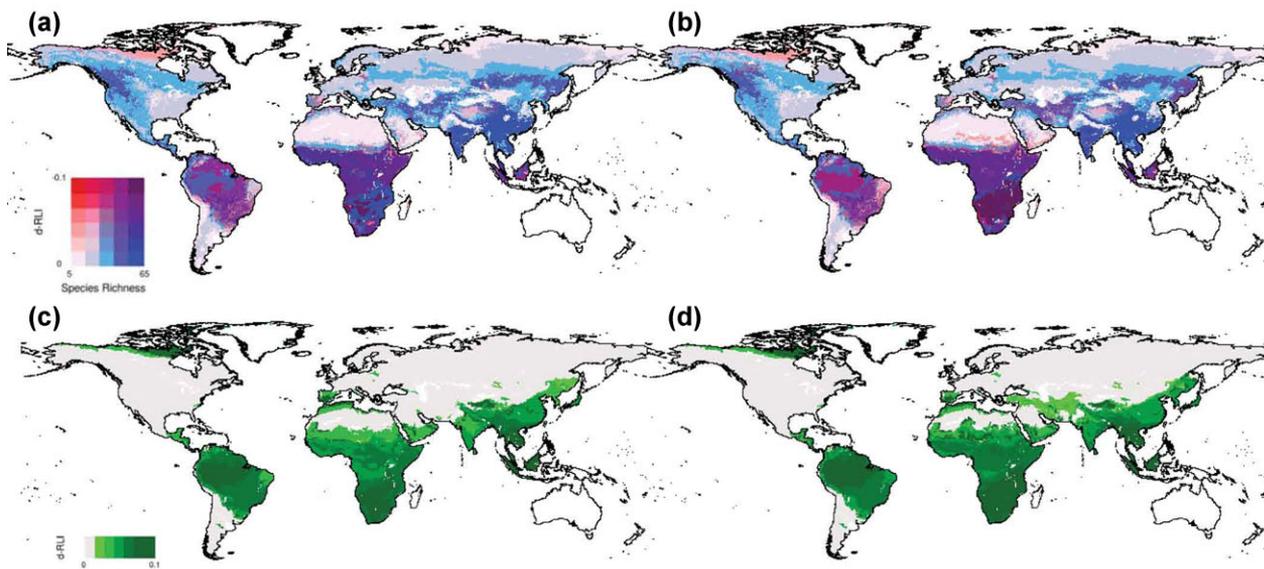

Figure 2 Spatial patterns of trends in Red List Index. (a and b) Bivariate plot showing spatial pattern in species richness and trends in the Red List Index (d-RLI) between 2010 and 2050 under the BAU scenario, with land-use and climate change and assuming maximum dispersal (a) and no dispersal (b). (c and d) Relative improvements in d-RLI for an alternative scenario, Consumption Change relative to Business-as-usual for year 2050 under maximum dispersal (c) and no dispersal (d). Areas in white contain fewer than five species per grid cell modeled in 2010.

microevolution (Boutin & Lane 2014), their EOOs remain stable, and only the area occupied within varies due to land-use and land-cover changes. Under a combination of this assumption and the BAU scenario, we found a steady global decline in mean population abundance of large mammals over the next 40 years (Figure 1a).

The 18% projected GMA decline until 2050, however is comparable to the rate observed in the last 40 years (Figure 3b), therefore it does not lead to changes in RL categories, which require an increase in the rate of decline (Figure 1d). When assuming that species cannot adapt locally to climate change, we found a decline in

the GMA in the period 2010–2050 of 31–34%, assuming respectively that species disperse to their maximum physiological capacity, or cannot disperse at all (Figure 1b and c). Extinction risk increased by at least one category for 21–23% of the species. The RLI is projected to decline by 0.055–0.0582 points (Figure 1e and f) which equates to 27.5–29.1% of the species moving one RL category closer to extinction over the time period, a trend comparable to that of the last 40 years (Di Marco *et al.* 2014). In the BAU scenario, climate change is predicted to outpace the ability of many species to shift their distributions even under the maximum physiological dispersal assumption (Figure 1b and e, Supporting Information: S2.2).

The Consumption Change scenario, regardless of assumptions concerning climate change impact and dispersal, results in an initial improvement and then stabilization in the RLI and GMA until 2030 brought about by habitat regeneration and human-driven habitat restoration assumed for this scenario (PBL 2012). When accounting for species responses to climate change, this initial improvement is followed by a decline due to the later onset of EOO contractions caused by climate change (Figure 1b, c, e, and f); which poses at risk the achievement of long-term conservation goals.

The overall trends shown by the RLI do not follow the same monotonic decline as the GMA for the BAU scenario. As the rate of habitat loss slows down toward 2050 in the BAU scenario, these species decline more slowly, eventually qualifying for lower categories of extinction risk under RL criteria A and C (Figure 1d and e). This leads to an improvement in the RLI trend, which contrasts with the GMA trend, in which the magnitude of decline reflects the total reduction in population abundance of the set of species by 2050.

Under the BAU scenario, increases in species extinction risk (i.e., declining RLI trends) are predicted in all regions of high-current mammal richness (Figure 2, Figure S6). However, particularly steep declines are predicted in the Amazon, a region with very low spatial climatic gradients that is predicted to experience no-analog future climates (Williams *et al.* 2007) and with a high richness of mammal species whose dispersal abilities are insufficient to keep pace with projected climate change (Schloss *et al.* 2012). Large declines are also predicted in sub-Saharan Africa under all scenarios. This hotspot of carnivore and ungulate species diversity is predicted to double its human population size and experience a rapid increase in per-capita growth rate from 2030 leading to a tripling of per-capita calorie consumption, and rapidly reducing the extent of natural vegetation (PBL 2012). Insular South-east Asia, which holds many currently threatened and restricted-range species (Schipper *et al.* 2008), due to the highest rates of deforestation globally (Hansen *et al.* 2013;

Abood *et al.* 2014) is also expected to face an increase in overall extinction risk under the BAU scenario due to continued deforestation (PBL 2012). Improvements in extinction risk are expected in continental South-East Asia due to the slowdown of deforestation with respect to the past 40 years (Figure S6). Compared with the BAU scenario, Consumption Change reduces aggregate extinction risks under all dispersal assumptions. Reductions are more pronounced in the tropics (Figure 2c and e), driven by measures to reduce deforestation, such as reduced meat consumption, reduced impact logging, and setting aside areas for protection (PBL 2012).

When comparing modeled and observed responses to recent (1970–2010) land-use and climate change, we found that the modeled GMA is within the large confidence intervals of the observed LPI for the subset of species for which population trends were available (Collen *et al.* 2009) (Figure 3a). Aggregate extinction risk for the period 1996–2008 (corresponding to the two published global mammal assessments), was estimated accurately and without bias after accounting for all uncertainties in parameters and models (Figure 3b).

Discussion

Our analyses show that a scenario with aggressive policies to eradicate hunger, ensure universal health, and access to modern energy can be compatible with short-term biodiversity goals. This is the first quantitative analysis in demonstrating that these potentially conflicting goals are not mutually exclusive. These ambitious goals will require rapid and widespread implementation of sustainable production practices, for example, adoption of reduced impact logging and sustainable agricultural intensification to increase crop yields. It will also require changes in consumption: low-energy lifestyle, reduce waste, and consumption of meat from industrially farmed animals. Finally, it will require progressive environmental legislation: carbon taxation (including emission from land-use change), and strategic placement of protected areas where habitat loss poses the highest threat to biodiversity. Our results also show that this might not be sufficient to stabilize long-term trends, due to the lasting effect of increased carbon emissions. BAU instead, will fail to meet both short- and long-term CBD goals.

We explored species responses to future global changes by projecting two indicators adopted by the CBD to monitor progress toward the Aichi targets. However, our approach lends itself to project any indicator based on species distribution and population abundance and is potentially applicable to any taxonomic group for which distribution data and habitat requirements are known.
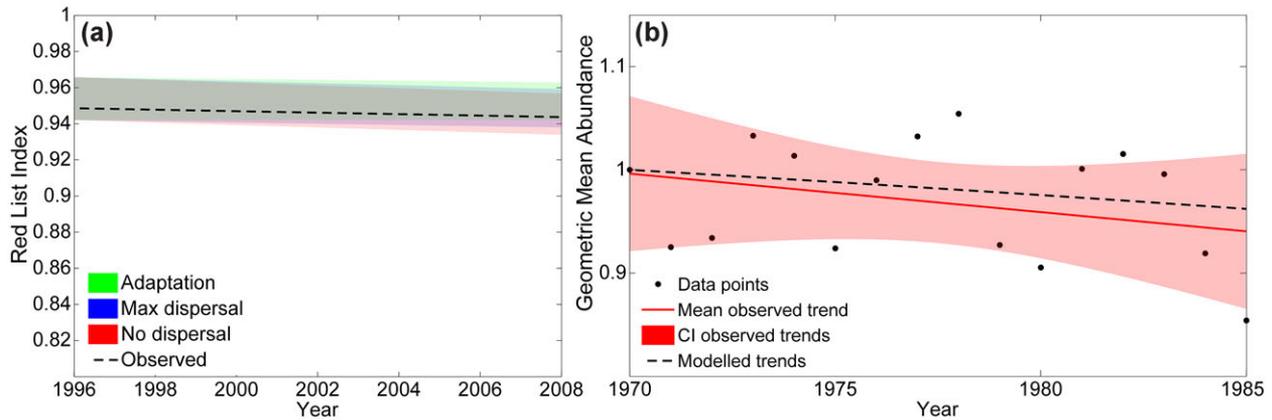
Figure 3 Validation of modeled trends in Red List Index (a) and Geometric Mean Abundance, (b). The colored bands in panel A represent the 95% confidence interval from the Montecarlo simulations of the modeled RLI (hindcast) under three assumptions of species responses to climate change: species can adapt locally to climate change (Adaptation, green band), species can colonize new suitable climatic areas that are within their maximum physiological dispersal abilities (Max. dispersal, blue band), species cannot colonize new suitable climatic areas (No dispersal, red band). The black dashed line represents the observed RLI from 1996 to 2008. The points in panel B represent observed annual GMA values for the set of carnivore and ungulate species for which population data were available. The solid line represents the trend in GMA (line of best fit across the points) and has a slope $\beta_o = -0.0037 \pm 0.061$. The modeled GMA (calculated in the same way as the LPI) has slope $\beta_m = -0.0021$ within the confidence intervals of the line of best fit of GMA values.

Our modeled responses to global changes may be overoptimistic for some species because we did not account for all threats to mammals, especially hunting which is a major threat to many of the species considered here (Hoffmann *et al.* 2011). However, we do not expect this to change the qualitative differences in projected trends between scenarios. Rather it might widen the difference between BAU and Consumption Change because low food security, poor access to food markets, a high proportion of people living in rural areas, and poorer environmental governance are more likely to exacerbate hunting in the former than the latter (PBL 2012).

Our results illustrate how detailed biodiversity indicators can be used in conjunction with coupled socioeconomic and environmental scenarios to inform the development of policies that achieve future sustainability goals. Our approach brings the focus of scenarios directly to the species level, thus taking into account an additional dimension of biodiversity and paving the way for incorporating stronger ecological foundations into future biodiversity assessments.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

S1–S6 Methods.

Table S1. Bioclimatic variables used in the species distribution models.

Table S2. Eighteen general circulation models used in the analyses.

Table S3. Description of Red List criteria and parameters used for projecting species Red List categories.

Table S4. Mean annual change in forest cover from observed and modeled data.

Table S5. Description of GLOBIO land-use categories and how they relate to GLC2000

Table S6. An extract of the GLOBIO land-cover and land-use tables for year 2000.

Table S7. Summary of the Red List Index validation for the period 1996–2008, $n = 245$ species.

Table S8. Number of species in IUCN-threatened categories (VU, EN, CR) listed under each criterion in the Global Mammal Assessment of 2008, in the model hindcast and one model forecast.

Figure S1–S2. Global trends in area covered by the two socioeconomic scenarios as modeled by the IMAGE Integrated Assessment Model platform.

Figure S3. Boxplots of Red List Index in 2008 across 1000 Monte Carlo simulations with and without the calibration of deforestation data using satellite imagery

Figure S4. Predictive ability of bioclimatic envelope models measured by True Skill Statistic.

Figure S5. Comparison of projected Geometric Mean Abundance and Red List Index for the set of species included in the validation analyses, and for the full data set of 440 species (presented in Figure 1 in the main text).

Figure S6. Richness of species subject to downlisting and uplisting of IUCN Red List categories between 2010 and 2050 under the BAU scenario.

Supplementary Data File: Supplementary Table 1 Data Sufficient Species Validation.xlsx

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