

LETTER

Global Biodiversity Indicators Reflect the Modeled Impacts of Protected Area Policy Change

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Abstract

Global biodiversity indicators can be used to measure the status and trends of biodiversity relating to Convention on Biological Diversity (CBD) targets. Whether such indicators can support decision makers by distinguishing among policy options remains poorly evaluated. We tested the ability of two CBD indicators, the Living Planet Index and the Red List Index, to reflect projected changes in mammalian populations in sub-Saharan Africa in response to potential policies related to CBD targets for protected areas (PAs). We compared policy scenarios to expand the PA network, improve management effectiveness of the existing network, and combinations of the two, against business as usual. Both indicators showed that more effective management would provide greater benefits to biodiversity than expanding PAs alone. The indicators were able to communicate outcomes of modeled scenarios in a simple quantitative manner, but behaved differently. This work highlights both the considerable potential of indicators in supporting decisions, and the need to understand how indicators will respond as biodiversity changes.

Introduction

Ambitious targets were agreed by the Convention on Biological Diversity (CBD, COP10 2010), in response to failure to meet their previous goal of reducing the rate of biodiversity loss by 2010 (Butchart *et al.* 2010). A mid-term review suggests that the prospects of achieving these targets are poor (Tittensor *et al.* 2014). Among failings that undermined attempts to reach the 2010 target was insufficient policy-specific scientific information to aid the decision-making process (Harrop 2011). Research has typically focused on measuring and predicting declines rather than evaluating the actions needed to

reverse them (Collen *et al.* 2011). Attention has recently turned to whether biodiversity indicators could be used proactively to generate predictions of different policy outcomes (Nicholson *et al.* 2012; Collen & Nicholson 2014; Visconti *et al.* 2015).

One of the main responses to biodiversity loss has been to establish protected areas (PAs; Jenkins & Joppa 2009). Two key measures of PAs' contribution to conservation are extent of coverage and effectiveness at conserving biodiversity. The CBD's latest target is for 17% of terrestrial areas and 10% of marine areas to be in effectively managed PAs by 2020 (COP10 2010). While PA coverage is measured, indicators of effectiveness remain

undeveloped (Walpole *et al.* 2009). Coverage alone does not provide an accurate barometer of protection; there are many examples of ineffective “paper parks” (Craigie *et al.* 2010; Laurance *et al.* 2012).

In this study, we tested the ability of two global biodiversity indicators, the Living Planet Index (LPI) and the Red List Index (RLI), to convey the potential conservation outcome of the CBD’s PA target in sub-Saharan Africa. The RLI and the LPI are two of the best-developed CBD indicators (Walpole *et al.* 2009). The RLI quantifies change in relative extinction risk based on changes in species’ IUCN Red List categories (Butchart *et al.* 2004; Butchart *et al.* 2007). The LPI provides an aggregated measure of change in vertebrate abundance (Loh *et al.* 2005). Combined, the two may provide an indication of whether PAs are achieving two key objectives: preventing extinctions and reducing declines in common species.

We modeled the impact of continental-scale policies for African terrestrial PAs on large mammal abundance trends (Craigie *et al.* 2010) and the two indicators. We expanded on the preliminary analyses in Nicholson *et al.* (2012) by evaluating two CBD indicators, and by modeling the effects of combinations of three policies: protecting 10% of the earth’s land area (CBD target in 2010), the updated target of 17% PA coverage by 2020, and improving management effectiveness (ME) within PAs, compared to a business as usual (BAU) scenario. We evaluated the ability of each indicator to detect species’ responses to these policies and to inform choices between policies. The aim of the exercise was not to carry out detailed modeling of the drivers of change for African wildlife, nor to assess the effectiveness of PA designs, but to assess the feasibility of using existing CBD indicators to evaluate the likely effects of different policy actions on biodiversity trends.

Methods

Overall approach

We modeled the impacts of six policy scenarios on population trends for 53 large mammal species. Our approach was to:

- (1) Estimate population size and recent trends in abundance of large mammals inside and outside PAs;
- (2) Generate projected abundance trends for each species in response to six policy scenarios for PA coverage and effectiveness;
- (3) Calculate the two indicators from generated abundance trends;
- (4) Compare resultant indicator trends, and infer their ability to reflect actual trends.

Recent abundance and trends

We collated information on recent abundance, distribution, and population trends for 53 species of large mammal from 41 countries in sub-Saharan Africa. We collated country-level data on the population size of each species inside and outside of PAs (SI1), to estimate initial population sizes prior to policy implementation (SI2).

We estimated recent population trends (1970–2005) for species in PAs using data from Craigie *et al.* (2010). Data were available for most regions (as defined by the United Nations Geoscheme), but with differing numbers of observations and time frames. Trends were aggregated to the regional level because of a lack of country-level data, by calculating the geometric mean inter-annual change in population size for each species in each region (see SI5). Where data were not available for a region but the species was known to be present, trends were extrapolated from the most closely related species in that region. The resultant trend estimates per species and region (SI3) were used in the scenario analyses.

Model abundance trends in response to policy scenarios

We modeled six PA policy scenarios:

- (1) BAU: continuation of current population trends in current PA network (2010), as documented in Craigie *et al.* (2010)
- (2) Expand PA coverage to 10%: PAs were expanded to meet the 2010 CBD target in each country, recent population trends continued;
- (3) Expand PA coverage to 17%: the 2020 CBD target, recent population trends continued;
- (4) Improved ME: all declining populations in the 2010 PA network assumed to stabilize, and undergo small annual increases (>1.7%) due to effective management;
- (5) Expand PA coverage to 10% and increase ME (as per scenario 4);
- (6) Expand PA coverage to 17% and increase ME.

The impact of each policy scenario on each species was modeled for 30 years after implementation by projecting species’ abundance trends from initial population sizes (SI2) using the annual rates of change for the relevant scenario (SI3). Each country was divided into populations inside PAs and outside PAs, which were subjected to different (but constant) rates of change.

Assumed trends outside PAs

There is a remarkable lack of research comparing population trends inside and outside PAs (Western *et al.* 2009),

although several studies have shown PAs to be more effective at conserving biodiversity than unprotected areas (e.g., Struhsaker *et al.* 2005; Setsaas *et al.* 2007; Western *et al.* 2009). Lack of data beyond PA boundaries required an assumption: that all trends would be 25% worse *outside* PAs (non-PA) than *inside*; positive trends were decelerated by 25% and negative trends accelerated by 25%. Sensitivity analyses, where differences in trends were varied (no difference, 50%, 75% worse than in PAs), suggested that relative performance of policies was insensitive to the assumed value (Costelloe 2010).

Assumed impact of effective PA management on trends

No consistent data exist on the impact of effective management on mammal populations. However, PAs in Southern Africa are considered to be particularly effectively managed (Craigie *et al.* 2010), providing a benchmark. We assumed populations in effectively managed PAs experienced the same annual population trend as the average for Southern Africa (+1.7%). Those with a more positive annual trend than +1.7% kept their current trend.

Expansion of PAs

We used Marxan (Ball & Possingham 2000) to expand the current PA network up to 10% (scenarios 2 and 4) or 17% of each country (scenarios 3 and 5), with continental-level targets for suitable habitat under protection for each species (Rondinini *et al.* 2005). We assumed suitable habitat captured within new PAs would contain the same average population densities as existing PAs, and redistributed populations from outside PAs to inside PAs so that total abundance of the species within a country remained the same upon policy implementation (detailed methods in SI6).

Calculating indicators

The RLI measures overall extinction risk of sets of species and tracks changes in that risk (Butchart *et al.* 2004; Butchart *et al.* 2007). The index is a function of the proportion of species in each category at given points in time, and changes as the status of individual species improves or deteriorates. Population projections under each scenario were used to assign each species to a Red List threat category (IUCN 2001) at decadal intervals, using criteria A2 (population reduction) and C (population size, ignoring the subcriteria), based on the total modeled population size across the continent, starting from each species' 2010 Red List status (see SI1 and SI2). The RLI

was calculated for the 53 study species in each scenario every 10 years described in SI7 (Butchart *et al.* 2007).

The LPI is an aggregated measure of proportional change in abundance (Loh *et al.* 2005; Collen *et al.* 2009), specifically, the geometric mean change in abundance. The LPI was calculated for each scenario as per the method in Collen *et al.* (2009), described in detail in SI7. Each country comprised two populations: one aggregated population inside PAs, and one population outside PAs. We averaged the inter-annual rate of change for each species first at the regional level, to counter disproportionate impacts of trends in data rich areas; the LPI data for African mammals are biased toward Southern and Eastern African populations (Craigie *et al.* 2010). We performed a sensitivity analysis to test the effects on LPI trends of giving equal weighting across populations, by ignoring region and calculating the LPI with the average rate of population change for each species across all populations; see SI7 for details.

Results

In 2010, PAs comprised 2,709,082 km², an average of 13% of each sub-Saharan country (range 0%–36%). Fifteen of the 41 study countries has less than 10% of land under protection; 29 had less than 17% (IUCN and UNEP 2010; SI4). Under the PA expansion scenarios, total PA area across the continent increased to an average of 15% of each country (range 10%–36%) under the 10% PA coverage target, and by almost half to an average of 19% (17%–36%) per country under the 17% PA coverage (SI4). Baseline rates of population change before scenarios implementation varied substantially among regions and species, with greatest declines in West Africa, followed by Central and East Africa; on average, populations were increasing slightly in Southern Africa (SI3).

Both indicators predicted that improved ME would provide greater benefits to wildlife than PA expansion (Figure 1). The indicators showed only a small predicted increase from expansion without improved management, compared with BAU, due to on-going declines in most regions, and little difference between expanding PA coverage to 10% or 17%. PA expansion in conjunction with increased effectiveness gave little benefit above increasing the effectiveness of the existing network. The two indicators differentiated similarly between policies; however, there were differences in the overall trends they displayed. The RLI was stable or marginally increased under the improved management scenarios, and declined over the first decade before starting slow recovery under the scenarios without improved management. By contrast, the LPI declined at an attenuating rate, with

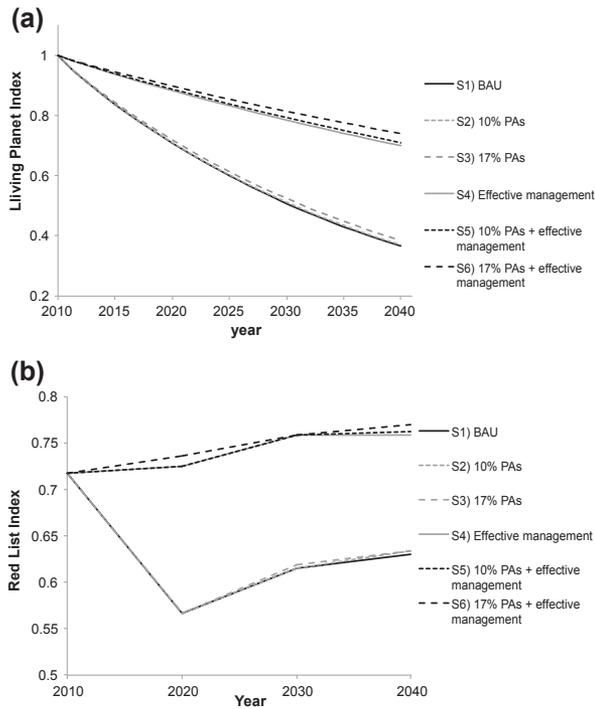


Figure 1 Comparative performance of scenarios for continental-wide indices, measured by (a) abundance trends (LPI) and (b) extinction risk trends (RLI). Scenarios 1, 2, 4, and 5 in (b) are shown in Nicholson et al. (2012).

more severe declines apparent for the scenarios without improved management.

The RLI showed an improvement in later years due to a changing ratio of abundance among regions. For illustration, we show a species-specific example under scenario 1, BAU (Figure 2). The Tsessebe (*Damaliscus lunatus*) started the simulations with a large East African population subject to a particularly strong annual decline (−13.4% p.a.) that drove the continent-wide population down at a rate sufficient to be classified Critically Endangered under Criterion A (89% decline over three generations, Figure 2a). Over time, the declining East African population comprised a smaller proportional share of the continent-wide population, with the previously smaller Southern African population increasing (positive trend +1.3% p.a.). By the final decade, the Southern African population comprised the majority of the total (albeit heavily depleted) population, resulting in a classification of Least Concern (Figure 2b). By contrast, the single-species LPI trend (i.e., geometric mean change in abundance of populations) closely mirrors the change in overall population size (Figure 2c), regardless of weighting procedure.

In some cases, the LPI was sensitive to weighting of trends in populations, particularly where trends

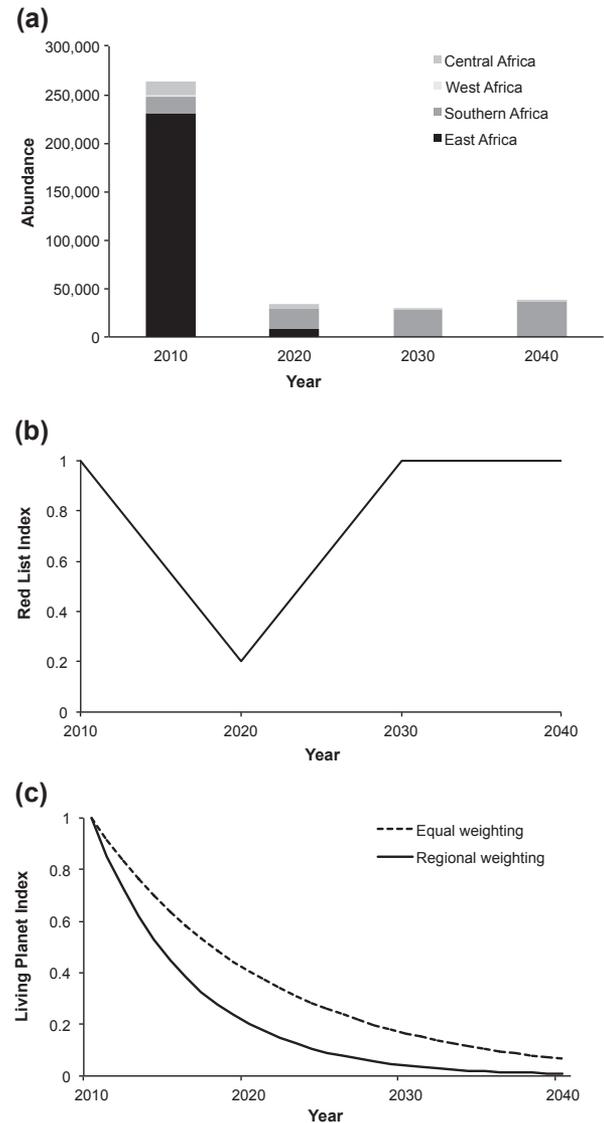


Figure 2 Impact of projected changes under scenario 1 (BAU) for Tsessebe (*Damaliscus lunatus*) for (a) total population abundance, (b) extinction risk (RLI), and (c) abundance trend (LPI) where all populations were weighted equally (dashed line) or weighted by region (solid line).

contrasted greatly. For illustration, under scenario 4, the African wild dog was predicted to decline steeply in smaller regional populations but increase in larger populations in Southern Africa; thus, the total abundance for the species increased (Figure 3a, no weighting). When changes were aggregated first at the regional level, the overall index declined (Figure 3a, regional weighting) because the modeled declines in the East, West, and Central regions were greater than projected increases in Southern Africa. Similarly, when using equal weighting across populations, the multi-species LPI showed a

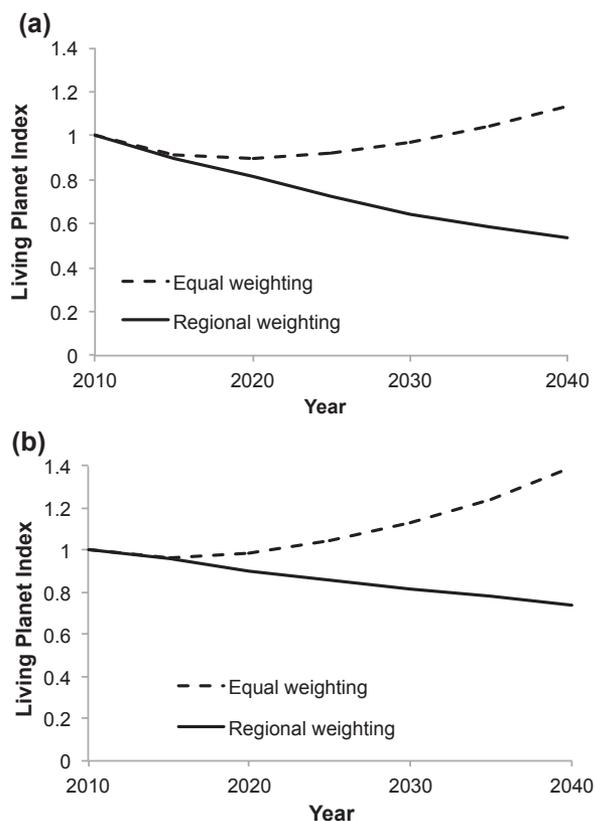


Figure 3 The sensitivity of the LPI to weighting of abundance trends when aggregating across populations for species, using two different weighting methods: where all populations were weighted equally (dashed line) or weighted by region (solid line). Results are shown for scenario 6, expand PA coverage to 17% of each country and increase ME of PAs, for (a) the African Wild dog (*Lycaon pictus*), and (b) all study species.

different trajectory to the regionally weighted index (Figure 3b).

Discussion

An indicator used to inform decision makers about the most effective policy must be able to discriminate among the predicted impacts of different policy options (Collen & Nicholson 2014). For our highly stylized model, both CBD indicators clearly demonstrated that policies to increase ME were more beneficial for biodiversity than those that only expanded PA coverage. Although both indicators ranked the scenarios in the same order, the difference in their behavior reflected the way they utilize underlying data. The RLI was less sensitive to abundance changes, in part because it measures extinction risk (which has a loose association with abundance; Purvis *et al.* 2000), and in part because of the coarse nature of the Red List categories (Mace *et al.* 2008); changes in Red

List status only occur when a species moves between classification thresholds. By contrast, the LPI detected broad scale population trends, and was sensitive to small and large changes in common and rarer species (Buckland *et al.* 2011).

The indicators also differ in the timeframes over which assessment occurs. The LPI is assessed annually and considers change in abundance relative to a reference year, whereas Red List assessments occur less frequently (modeled here as decadal intervals), with declines assessed over species-specific timeframes (10 years or 3 generations). Declines prior to the assessment window are therefore “forgotten” by the RLI, resulting in a shifting baseline, exemplified by projected changes in status for the Tsessebe. The impacts of shifting baselines may be considered a weakness of the RLI, however, the aim of the Red List is to evaluate extinction risk, in part a function of steep declines as well as absolute population size. These results show the potential risks of building an indicator from measures designed for other purposes, without examining the impacts on indicator behavior.

Our sensitivity analysis showed that the way in which species trends are aggregated is critical in determining overall aggregated trend. The LPI has been criticized for treating all proportional decreases in population size equally, regardless of absolute numbers (Pereira & Cooper 2006). The potential impacts of this on aggregated trends has been investigated, but absolute abundance data are rarely available (Collen *et al.* 2009). Giving equal weight to average trends across species and by region has merit when data are biased toward well-studied species and regions; weightings can be readily altered if data allow.

We focused on the ability of the indicators to reflect population trends under deterministic conditions with perfect knowledge. Real world data are imperfect and frequently biased, so the robustness of indicators to varying data quality and availability must be further explored. In this study, we did not evaluate the impacts of bias in sampling (all modeled species were represented in the indicators) or imperfect detection; both affect indicator behavior (Fulton *et al.* 2005; Branch *et al.* 2010; Nicholson *et al.* 2012).

We used trends to assess the impacts of policies, ignoring system dynamics. To do otherwise would be difficult for large numbers of species at the continental scale. We assumed trends remained the same inside expanded PAs, ignoring effects of size and suitability for each species, and that all study species fared worse outside PAs. Although our predictions appear relatively insensitive to assumed trends under effective management (Costelloe 2010), the assumption that all study species will respond equally is unlikely; in reality, species will respond differently

to management, and their response will vary spatially depending on ecological processes, including species interactions (e.g., predator–prey and inter-predator), and the distribution of threats. A thorough exploration of impacts of management on species trends, and subsequently on biodiversity indicators, requires extensive analyses of data on threats and responses to management, and the modeling of species-specific responses. Such analyses would help identify the management actions required to halt declines.

It is unsurprising that improving ME was predicted to be more beneficial than expanding the coverage of PAs, given the assumptions in our relatively simplistic model, designed to examine indicator behavior rather than examine on-the-ground management options. On average 81% of species' populations were already in PAs, meaning that the PA expansion often saw relatively small increases in protected abundance, in contrast with considerable improvement in both indicators from a reduction in declines from better PA management. Ineffective management is cited as the main factor behind the rapid population declines in African PAs (Craigie *et al.* 2010). Our findings support assertions that shifting effort toward better management of existing PAs is preferable to simply annexing more land for protection (Jenkins & Joppa 2009), and raise doubts over the likely efficacy of CBD Target 11 in helping to meet the mission of “halting biodiversity loss” (COP10 2010). Indeed, the use of PA coverage as both a conservation target and a measure of conservation success, without measuring effectiveness, raises the risk of countries increasing paper parks to meet global targets with minimal biodiversity benefit. Goodhart's law states that when a measure becomes a target, it ceases to be a good measure; this may be a manifestation of that law for biodiversity indicators (Newton 2011).

The different behavior of the indicators tested, based on their underlying structure, show the importance of using multiple indicators to measure complementary aspects of biodiversity change (Purvis & Hector 2000). Both indicators are used to engage policy makers and the public by communicating simply complex measures of biodiversity change (Jones *et al.* 2011); our results show that they may also be used to summarize and communicate projected changes and potential policy outcomes. Although our model assumptions were simplistic, our analyses show how evidence-based modeling can allow the causal relationships between policy actions, biodiversity change, and indicators of change to be better understood (Nicholson *et al.* 2012; Collen & Nicholson 2014). Then indicators can start to tell us how we can best conserve biodiversity, not simply that we are failing to do so.

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Supporting Information

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

List of all species and key references for estimates of population size and distribution

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