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The Wildlife Picture Index: A Biodiversity Indicator for Top Trophic Levels

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Introduction

Most conservationists agree that tropical regions harbor most of the Earth's biodiversity. Two of the most important biomes in the terrestrial tropics are the rainforests and the tropical savannas. Tropical rainforests occur in five major tropical regions, covering 6.25 million km² (~4.1% of the Earth's land surface) and contain >50% of total biodiversity, including the majority of birds and mammals. Tropical savannas occur in six major tropical regions covering 27.6 million km² (~18.5% of the Earth's land surface) and, while less diverse than rainforests, they contain significant numbers of mammals and birds, especially the large iconic species. Forests and savannas face severe threats from the usual agents of biodiversity loss including human population growth, biomass consumption for fuel, natural resource extraction, habitat loss, agricultural development, and climate change (Millennium Ecosystem Assessment, 2005).

Recognizing the threats to the Earth's biodiversity, the Convention on Biological Diversity committed 190 countries to achieve a significant reduction in the rate of loss of biodiversity by 2010 (Decision VI/26; CBD Strategic Plan). Along with this commitment came the realization that monitoring change in biodiversity was an extremely complex issue, and that a toolkit of monitoring techniques was needed to track all the different components that make up our notion of biodiversity (Dobson, 2005). As a first step to developing this toolbox, the CBD encouraged the compilation of existing datasets into composite indicators to establish the baseline of knowledge about biodiversity change and to track that change into the future. Problems with this

approach have been recognized and discussed (Balmford *et al.*, 2005; Dobson, 2005; Mace and Baillie, 2007) along with the recognition that new indicators may be needed that directly address the needs of biodiversity monitoring.

The CBD call for action presents an opportunity and a dilemma for conservation. The chance to collate the body of acquired knowledge should not be passed up, nor should methods for analysing this wealth of data. But, as Balmford *et al.* (2005) and Dobson (2005) point out, most species and habitats have not been evaluated once, and we require three time steps to detect a change in the rate of change. While the evaluation of existing data is a necessary short-term solution, we need new methods for rapidly collecting new data on species not currently under the microscope of conservation. It is unlikely that we will find datasets that are long-running, unbiased, sensitive to change, and relevant to biodiversity monitoring sitting unused on the shelves in a backroom. We therefore need new data, collected using methods consistent with the goals and objectives of biodiversity monitoring, to address these issues (Collen *et al.*, 2008b). We also need new indicators that are designed to be informative, sensitive, and robust to variation in the underlying data.

A number of authors have tackled the question of ideal datasets and ideal indicators. Yoccoz *et al.* (2001) and Balmford *et al.* (2005), for example, stress the need for indicators based on a representative, randomly selected subset of taxa, collected at a stratified random sample of habitats or sites of interest and corrected for detection bias. Buckland *et al.* (2005) outline desirable statistical properties of indicators. For a group of species, appropriately sampled, the index should not show a trend when abundance of individual species varies but number of species, overall abundance, and species evenness stay constant; the index should decrease if overall abundance, or species evenness, or number of species decreases; and the index should be insensitive to sample size and should have good and measurable precision.

It is unlikely that such an ideal indicator can be developed using available data (Dobson, 2005). The spatial coverage of current datasets is uneven and unrepresentative (Collen *et al.*, 2008b). While most biodiversity resides in the tropics, most data come from the temperate region. We have no Brazilian Wild Bird Index to compare to the UK Wild Bird Index (Gregory *et al.*, 2003). The rate of data publication is slow and uneven, and many relevant datasets are not publicly available. Often, the ability to even search for datasets published in the grey literature and for unpublished datasets is not available. Finally, there is no control over the data collection of published datasets, requiring untestable assumptions about the underlying data quality in order to justify comparisons (O'Brien *et al.*, 2010).

Looking beyond the near-term needs of the CBD to develop 2010 indicators from available data, many have called for the development of new indicators that are designed to meet the specific goals and objectives of biodiversity monitoring. One such proposed composite indicator is the Wildlife Picture Index (WPI: O'Brien *et al.*, 2010; O'Brien, 2010a), based on detection-nondetection data for mammals and

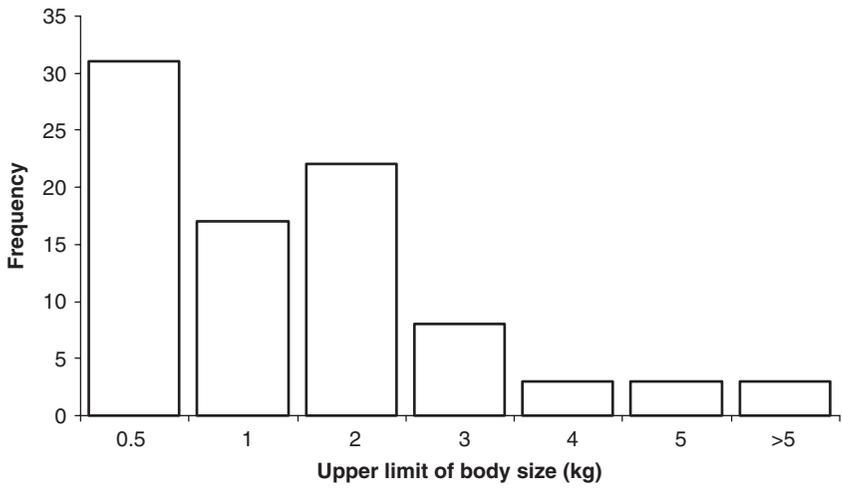
birds provided by camera trap surveys. The WPI targets communities of terrestrial forest and savanna birds and mammals that occupy top trophic levels in their ecosystems, and are often the target of exploitation and management. The WPI is based on the collection of primary data in a statistically rigorous manner designed to meet the needs of a composite biodiversity indicator. Here we describe some of the properties of the WPI.

Component of biodiversity: medium to large terrestrial birds and mammals

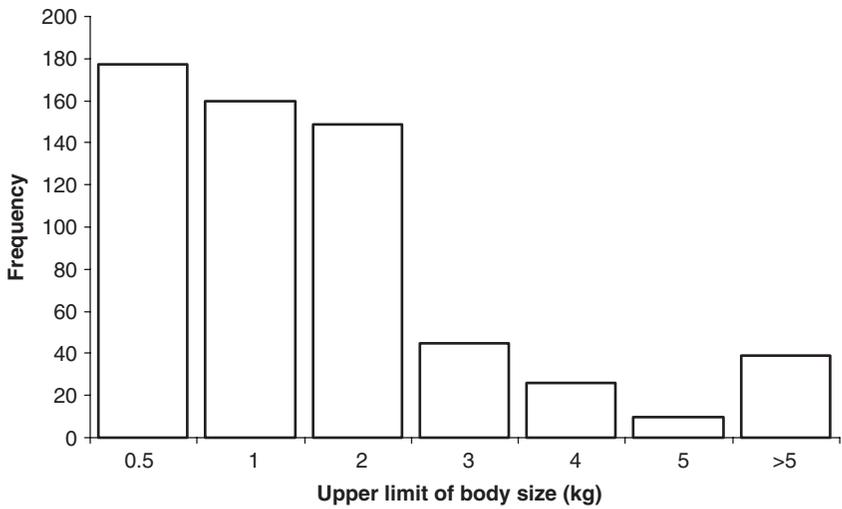
Of the currently recognized 9702 species of extant birds (Sibley and Monroe, 1990), ~600 species are found in tropical regions and spend a considerable amount of time resting, foraging, and moving on the ground. The average bird (excluding rhea, cassowary, and ostrich) weighs approximately 0.04 kg, so a 0.1 kg bird (30% of species) might be considered a large bird (Dunning, 2008). Camera traps have photographed birds as small as 0.013 kg *Muscicapa* flycatchers and as large as ostriches (O'Brien and Kinnaird, 2008). If we examine the size distribution of tropical terrestrial birds and tropical birds that appear in camera traps (Figure 3.1), we see that, although the 0.5–0.999 kg birds are underrepresented, the overall size distributions of large tropical birds and tropical birds in camera traps do not differ significantly ($\chi^2 = 5.44$, $P = 0.49$). Importantly, it appears that birds in the 0.1–0.499 kg class may be captured reliably by camera traps.

Of 5488 recognized mammals, one-quarter may be considered terrestrial or semi-terrestrial tropical, and weigh more than 0.1 kg. Within this subset, the average body mass is 32 kg (median 0.9 kg, Figure 3.2), with 59% of species weighing 0.5 kg or more (MOM vers. 3.1: Smith *et al.*, 2003). Although not all of these species can be monitored adequately using camera traps, many can. O'Brien *et al.* (2010) have previously defined the Wildlife Picture Index as appropriate for medium- to large-bodied terrestrial birds and mammals. Based on observations from many camera trap datasets (compiled primarily from large felid studies), we believe that the appropriate range of body size for mammals is 0.5 kg upwards, and may be as low as 0.1 kg.

Many of the bird and mammal species in the larger size classes are considered strong interactors (Power *et al.*, 1996) and occupy top trophic levels in their respective food webs. They perform important ecosystem services such as predation, grazing, browsing, seed dispersal, and ecosystem engineering (Dobson *et al.*, 2006). Many of these species also are important to humans as food, pests, and objects of tourism, and therefore are vulnerable to exploitation, consumptive use, and habitat loss. Finally, many of these species are the object of management interventions and regulations, an indication of their importance to humans.



(a)



(b)

Figure 3.1 Body size distribution of tropical birds (a) in camera traps and (b) of terrestrial tropical birds >0.1 kg. From O'Brien & Kinnaird 2008, unpublished data.

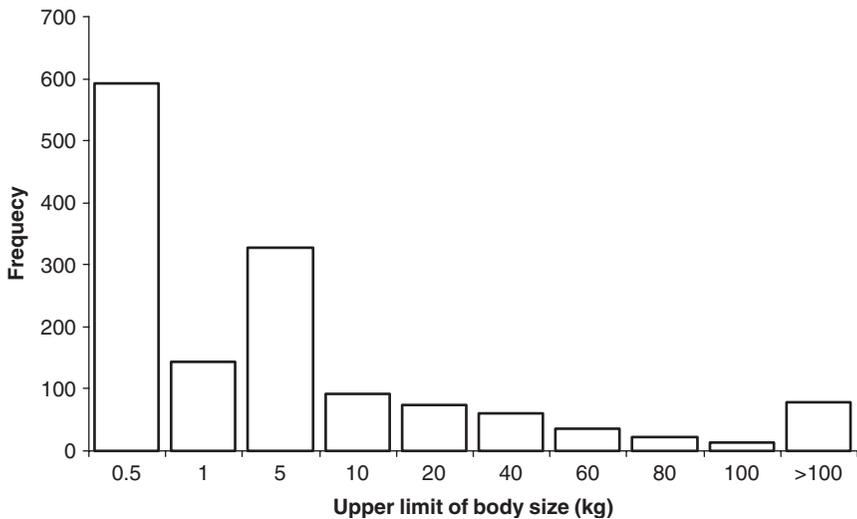


Figure 3.2 **Body size distribution for mammals.**

Terrestrial birds and mammals can be difficult to study in rainforest and savanna ecosystems. Many species are nocturnal, which presents special challenges for monitoring. Many species are rare and/or cryptic, requiring specialized sampling techniques relative to more common species in order to collect comparable data (Thompson, 2004). Many species react negatively to humans, either fleeing or hiding. To adequately sample this diverse group of mammalian and avian species might require a combination of live-trapping and mist-netting, cue counts and sign counts, line transects, and point counts. Low encounter rates can result in imprecise abundance estimates and in some cases might preclude abundance or density estimation. Remote and rugged terrain can compromise coverage, and wariness of humans may reduce detections. Use of indices based on sign and counts violates many principles of monitoring (Yoccoz *et al.*, 2001; Pollock *et al.*, 2002; Buckland *et al.*, 2005) because detection probability is not properly considered.

One solution to the problem of multiple sampling methods in multispecies surveys is to use camera traps as the sampling method (Karanth *et al.*, 2004). Camera traps have a number of features that make them useful as a data collection tool. They are passive data collection units that sit quietly in the study area. Most digital cameras use a silent electronic shutter and an infrared flash that do not scare animals. Camera traps are increasingly designed for deployment in extreme habitats under wet and hot conditions. New generation models employ digital camera technology and the latest

advances in battery and power consumption technology, enabling them to be deployed continuously for months before batteries and memory cards need to be downloaded (www.trailcampro.com). Prices of camera traps have declined as more models have become available, and high-quality digital camera traps are now priced at US\$200 or less. Using camera traps in conjunction with a randomized or systematic sampling design at an appropriate spatial scale should result in the generation of representative data on terrestrial bird and mammal communities that can be incorporated into a composite index of state variables of interest.

The Wildlife Picture Index

The Wildlife Picture Index (WPI) has been described in detail in O'Brien *et al.* (2010) and O'Brien (2010a). The WPI is a composite index similar to the UK Wild Bird Index (Gregory *et al.*, 2003), or the Living Planet Index (Loh *et al.*, 2005; see also Chapter 4). It is based on the state variable of occupancy, rather than abundance (or density) because of the difficulty of developing unbiased estimates of abundance for a set of species when animals are not individually recognizable. Typically, a community of terrestrial birds and mammals will contain a few species that can be recognized as individuals and tracked through space and time. For these species, it is possible to develop unbiased estimates of abundance or density using capture-recapture methods and spatially explicit capture-recapture models. Many other species, however, are difficult to identify reliably as individuals, and some relative abundance index must be used in place of density or abundance estimates. The result is a set of abundances composed of unbiased estimates and many relative abundance indices with unknown, species-specific biases. A composite index based on such a mix of biased and unbiased estimates will be biased to an unknown degree, and trends developed from such indices will be open to several interpretations, depending on the strength of the underlying assumptions (O'Brien, 2011).

Occupancy data are easily collected using camera traps, and the area occupied by a species, or a community of species, is a useful metric for monitoring biodiversity (Yoccoz *et al.*, 2001; Buckland *et al.*, 2005). We can develop unbiased estimates of occupancy for most species possessing detection probabilities greater than 0.02 and true habitat occupancy greater than 10%, given sufficient sampling (O'Brien, 2010a). Occupancy can be sensitive to changes in abundance and is sometimes used as a surrogate of abundance (MacKenzie *et al.*, 2006; Royle and Nichols, 2003; see also Chapter 11). This makes sense when we consider that the more individuals using a point, the more likely we are to detect at least one of them at least once during a sample. Expanding populations tend to occupy more space over time, whereas contracting populations tend to occupy smaller areas. Occupancy modeling also allows the incorporation of covariates that may help to explain some of the underlying variation

in the proportion of habitat occupied and the detection probabilities. For species that are especially cryptic and/or rare on the landscape, O'Brien (2010a) discusses methods for improving these species' occupancy estimates by borrowing information from similar species, post-stratification, and, in extreme situations, substituting observed occupancy.

The choice of species to include in a WPI is subjective and a function of the characteristics of the sampling and the assumptions of occupancy analysis. Camera trap model, setup, and trap sensitivity may all affect the size range of species detected. More importantly, a species' preferred substrate may influence its suitability as a target species. While we may be able to photograph a siamang (*Symphalangus syndactylus*) any time it crosses the camera, this strictly arboreal species is unlikely to be moving terrestrially and is not regularly available for sampling. Alternatively, many macaque species (*Macaca* spp.) spend a significant amount of time on the ground and do not violate closure assumptions regarding movement in and out of the sampling area. We refer to the target community as terrestrial birds and mammals of medium to large size, to emphasize that this is the group of species that we are most likely to include in a sample. We do not, however, exclude semi-terrestrial species that spend considerable time on the ground and are regularly exposed to the possibility of detection, and we rely on local knowledge of the species in question to decide whether to include it.

The index is constructed following the methods of Fewster *et al.* (2000) and Buckland *et al.* (2005). Buckland *et al.* (2005) found that a modified Shannon Index and the geometric mean of relative abundance (defined as abundance at time t divided by abundance at time $t = 1$) were most satisfactory for composite indices of biodiversity. We chose the geometric mean because the modified Shannon Index had no theoretical justification other than fitting Buckland *et al.* (2005) performance criteria for well-behaved composite indices. We substitute the state variable of occupancy for abundance and use a relative occupancy index as the basic measure. Note that the form of the relative occupancy index anchors the index to the initial value of the occupancy estimate at time $t = 1$.

To develop a WPI, we begin with a set of n species-specific occupancy estimates (each denoted by ψ_{ijk} for the species i at location j in year k) calculated using closed season models over k years. A species that is present but not detected has an occupancy estimate of zero for the season. The geometric mean is restricted to values greater than 0, however, so the occupancy estimates must be adjusted to eliminate 0-values. Adjustment terms are arbitrary, and O'Brien (2010a) recommends that all estimates of $\psi = 0$ be adjusted by:

$$\psi^* = \psi + \frac{1}{2x} \quad (3.1)$$

for an occupancy estimate based on x camera trap points. This ensures a distribution of ψ values that is strictly non-zero, non-negative and has minimal effect on the variance of the distribution. The next step is to develop an index of relative occupancy for each

species i at survey site j in year k . We do this by dividing occupancy in year k by the estimated occupancy at the initial season:

$$o_{ijk} = \frac{\hat{\psi}_{ijk}}{\hat{\psi}_{ij1}} \quad (3.2)$$

This creates a relative occupancy index that measures the change in occupancy from initial conditions for each of n species. The estimate for $k = 1$ is always 1. The WPI for year k and site j and n species is the geometric mean of scaled occupancy statistics for n species:

$$WPI_{jk} = \sqrt[n]{\prod_{i=1}^n o_{ijk}} \quad (3.3)$$

Equation 3.3 can also be expressed as:

$$WPI_{jk} = \exp\left(\frac{1}{n} \sum_{i=1}^n \log(o_{ijk})\right) \quad (3.4)$$

This formulation has several advantages. First, it possesses most of the favorable characteristics of a biodiversity index outlined by Buckland *et al.* (2005). Second, it is intuitively understandable, since each point is expressed as a proportional shift from initial conditions for the n species. Third, the index can be disassembled and restructured to develop associated indices that track subsets of the community. For instance, it would be relatively straightforward to develop a tiger prey index by restricting the analysis to those species at a site that are considered tiger prey. Fourth, the index is insensitive to species-specific variation in abundance and occupancy, because each species is scaled before entering the site index. Finally, by scaling to the initial year, the ratio is robust to missing years of data. Most ratio estimators use a process called chaining that requires evenly spaced observations because ratios are calculated sequentially. Missing data in one year affect the ratio estimates for two years. The WPI does not depend on chaining as all estimates are calculated based on the temporal distance from the initial condition (Fewster *et al.*, 2000).

Community dynamics and sampling error can create situations in which a species may disappear (local extinction) or appear (local colonization) or simply be missed (sampling error) during some sampling period. An example is the Sumatran short-eared rabbit (*Nesolagus netscheri*) that was photographed at two locations during a camera trap survey in Bukit Barisan National Park in 2000, missed during three subsequent surveys, and photographed again in 2007 (T.G. O'Brien, unpublished data). For species that are first recorded at time $t > 1$ as a result of colonization or sampling error, we follow the recommendation of the LPI (Collen *et al.*, 2009) and

recalculate the WPI with the new species' pre-detection occupancy estimates set to ψ^* . For species that disappear from the index due to extinction or sampling error, we face the subjective problem of deciding when a species is extinct. IUCN (2001) defines a species as presumed extinct when 'exhaustive surveys in known and/or expected habitat, at appropriate times . . . have failed to record an individual. Surveys should be over a time frame appropriate to the taxon's life cycle and life form.' Local extinction, however, is more closely related to the loss of populations (Ceballos and Erhlich, 2002) and should be easier to detect than global extinction. For the purposes of the WPI, we consider a species to be locally extinct if it has not been detected in a survey for 5 years. Until that time, a species in the index that becomes a non-detected species should be assigned a value of ψ^* . For any species believed to be locally extinct or present but undetectable using camera trap survey methods, more intensive surveys using methods appropriate for the species should be undertaken to confirm its status. If intensive targeted surveys indicate local extinction, then the species should be removed from the index.

Measuring the WPI

To develop a WPI, we begin with a camera trap survey designed to be (i) spatially representative of the area of interest, (ii) of sufficient sampling intensity to detect a representative sample of the species in the target community, and (iii) of sufficient duration to develop unbiased occupancy estimates for the sampled species. Spatial coverage and representativeness is, to some degree, a function of the species in the target community. A community of Malagasy birds and mammals, for example, is restricted in body size to less than 5 kg, and typical home ranges of lemurs, the dominant mammals, rarely exceed 1 km². Such a community might be adequately sampled at a scale of 100 km², whereas a community of birds and mammals that includes African elephants (*Loxodonta africana*: home range 10–8700 km²) and cheetahs (*Acinonyx jubatus*: home range 34–1500 km²) may require sampling at a landscape scale of several hundred km². O'Brien (2010a) recommends a sampling area (or site) of 200 km² as a compromise between adequate coverage, logistical feasibility of sampling, and maintaining population closure. Within this site, occupancy surveys are relatively easy to carry out and to interpret. We start with the objective of estimating the proportion of area occupied at a site by each target mammal and bird. The sampling units are camera trap points within the site that are arranged in a random, stratified random, or systematic fashion at a density of 1 point/2 km². Stratified random or systematic designs are preferred since they have desirable statistical properties and ensure uniform coverage of the site. Cameras are deployed by navigating to a predetermined sampling point using a GPS unit, and then setting the camera at an optimal location within 50 m of the predetermined point. The new point is georeferenced and this becomes

And finally, we take the geometric mean of these relative occupancies across species to develop k WPI estimates, denoted as I here:

$$I_1 \ I_2 \ I_3 \ \cdots \ I_k$$

Trend analysis using the WPI

To determine trends in the WPI, we follow Fewster *et al.* (2000) and Buckland *et al.* (2005). They recommend generalized additive models (GAMs) to model trends as a smooth non-linear function of time. GAMs are similar to regressions but they do not require that the data be normally distributed and they assume that the relationship between the index and time is smooth but not necessarily linear. GAMs incorporate smoothing procedures into the model fitting process, allow a range of curves to be considered, and allow for direct incorporation of covariates to test hypotheses of factors influencing trends. GAMs also allow for a statistical test of changes in direction of the index trajectory, thus satisfying the criteria of a CBD 2010 indicator.

A simple regression model has the structure $y_i = \alpha + \beta x_i + \varepsilon_i$ with the assumption that the error terms ε_i are normally distributed. Generalized Linear Models (GLMs) are structured in this manner but allow the distribution of the error term to vary (McCullagh and Nelder, 1989). Braak *et al.* (1994) used log-linear Poisson regression models, a type of GLM, to fit count data of birds. They assumed that an observation y_{it} at site i and time t comes from a Poisson distribution with mean μ_{it} . Their model resembles a linear regression:

$$\log(\mu_{it}) = \alpha_i + \beta_t \quad (3.5)$$

where α_i is called the site effect for site i , and β_t refers to the year effect for year t . Both the normal linear regression and the log-linear Poisson regression model can be considered as types of general additive models. In a generalized additive model:

$$y = \alpha_i + f(t) + \varepsilon \quad (3.6)$$

the error terms are not assumed to be normally distributed, and the $f(t)$ is some non-linear smoothing function of time. The predictor function $f(t)$ is the principal difference between a GAM and a GLM. The GAM is fitted by estimating the parameters α_i and the smooth function f in the same way that a linear regression is fitted by estimating the parameters α and β . For a linear trend over time, the regression $f(t) = \beta t$ has a single parameter β to be estimated. For an annual model, the regression $f(t) = \beta_t$ has many β parameters. In this case, the function is jagged and represented by joining β s with straight lines. Between these limits (linear and maximally jagged)

are functions that are non-linear, smoother than the annual model, and of greater utility for detecting long-term, non-linear trends.

Before the function f can be estimated, the level of smoothing must be specified. This is a subjective process that has few agreed guidelines to assist decision-making. The degree of smoothing is flexible and controlled by the degrees of freedom (df) in the time series dataset, ranging from a linear trend ($df = 1$) to an unsmoothed trend representing the annual change during a time series of k years ($df = k - 1$). Between these two extremes, the function f is determined non-parametrically from the data. GAMs thus allow us to explore linear trends in short time series and develop more complicated non-linear trends as the time series increases. The choice of df value is an important part of the modeling process and depends on the objectives of a particular analysis as well as the length of the time series. GAMs are used to separate underlying trends from short-term fluctuations (noise in the data), but the point at which this separation occurs is subjective, relating to the desired level of detail that is to be retained in the trend. For long-term trends, a smooth index curve is desirable and df should be set low. If information about annual fluctuation is required the index should be set high at $k - 1$ to produce a curve of maximum fluctuations. The length of the time series is also important; it will be hard to detect non-linear trends in short time series. Fewster *et al.* (2000) have suggested that a df of $0.3k$ be used for long time series, but caution that this is based on the needs of their analyses. They avoid setting rules for model selection and advise plotting indices from GAMs with a range of df values before settling on a final value.

The 95% confidence limits for the GAM trend are determined by a non-parametric bootstrap process. To develop a bootstrap confidence interval, we first select a random sample with replacement from the species that make up the sample for a specific time point. We repeat this process 999 times. We then analyse each sample as if it had been our real data. The variation in estimates of the index among bootstrap samples should give a good guide to the variation we would expect if we could take new samples of the community. The standard deviation of the bootstrap samples is used to estimate the standard error of our index at each time step. If we take the 999 bootstrap estimates for each year in the time series, and order each bootstrap sample from smallest to largest, the 25th smallest and 25th largest estimates represent the lower and upper 2.5% quantiles and are approximate 95% confidence limits for the index at each point in the time series.

The rate of change in the diversity index is measured by the slope of the smoothed trend. The rate of change of a non-linear trend is measured by the slope of a line tangent to a point in time along the curve. Non-linear trends allow for changes in the rate of change over time. Changes in the rate of change (a benchmark of CBD 2010 indicators) are measured by deriving a numerical estimate of the second derivative of the trend. A crude approximation of the second derivative of the slope at time t can be obtained using three points and the equation:

$$D_t = I_{t-1} - 2(I_t) + I_{t+1} \quad (3.7)$$

where D_t is the second derivative evaluated at time t , and I is the smoothed index value at $t - 1$, t , and $t + 1$. If the time series is lengthy, a more precise second derivative can be estimated using the index value at $t - 2$, $t - 1$, t , $t + 1$, and $t + 2$ (R. Fewster, personal communication):

$$D_t = 2(I_{t-2}) - 1(I_{t-1}) - 2(I_t) - 1(I_{t+1}) + 2(I_{t+2}) \quad (3.8)$$

A negative D_t indicates the rate of decline is accelerating, and a positive D_t indicates the rate of decline is slowing. To test the significance of the D_t value, we develop a bootstrapped 95% confidence interval around the second derivative. If, in a given year t , the confidence interval does not include 0, then we have evidence that the rate of change is changing. The sign (+/−) of the confidence interval indicates the direction of the change. If the interval includes only negative values, the change is for the worse; if the interval includes only positive values, the change is for the better.

All procedures for implementing an occupancy analysis are available in the free software package PRESENCE (<http://www.mbr-pwrc.usgs.gov/software/presence.html>). GAM modelling software is available in the mcgv software package (Wood, 2006) in R (R Development Core Team, 2012; check the R website for the latest version: www.R-project.org). Rachel Fewster provides GAM modeling software for monitoring of wildlife populations on her website (<http://www.stat.auckland.ac.nz/~fewster/gams/R/>). Jorge Ahumada, technical director of the Tropical Ecology, Assessment and Monitoring Network (TEAM), has written a program in R to calculate the WPI, the bootstrap confidence intervals, and the significance of changes in slopes (O'Brien, 2010a).

Implementation of the WPI

Unlike most CBD 2010 indicators, implementation of the WPI is still in its infancy. Much of the development of the WPI (O'Brien *et al.*, 2010; O'Brien, 2010a) arose from the challenges of monitoring tigers and prey (O'Brien *et al.*, 2003) and species richness (O'Brien *et al.*, 2011) across large landscapes in a representative manner using camera traps (Karanth *et al.*, 2008). Our demonstration project was based on the sampling methods outlined in O'Brien *et al.*, (2003). In this study, we set up a monitoring programme for Sumatran tigers (*Panthera tigris sumatrae*) and their prey. The sampling took place in the Bukit Barisan Selatan National Park (BBSNP), a 3568 km² park in southwest Sumatra. BBSNP is one of the largest remaining blocks of lowland rainforest on Sumatra and home to a wide variety of terrestrial mammals and birds, including species of global priority such as Asian elephant (*Elephas maximus*), Sumatran rhinoceros (*Dicerorhinus sumatrensis*) and Sumatran ground cuckoo (*Carpococcyx viridis*). We set up 10 sampling blocks at 10–15 km intervals oriented from the edge of the park to the interior. Within each block, we

randomized 20 camera trap point coordinates within 1 km² subunits in each block. This allowed for a uniform coverage of the park along an elevation gradient south to north, and an edge gradient west to east. The project eventually conducted five park-wide surveys between 1998 and 2006, along with five additional camera trapping surveys at the Way Canguk Research Station. We photographed 12 bird species and more than 40 mammal species (not all identifiable to species). It was the surprising amount of data generated by the camera traps that inspired us to evaluate the potential further and develop the WPI. O'Brien *et al.* (2010) details an application of the WPI to BBSNP. The results indicated a continuous decline in wildlife diversity in BBSNP that has accelerated over time. The linear rate of decline has exceeded the rate of forest loss during the same period suggesting that other factors, most likely hunting for commercial purposes as well as subsistence and pest control, contributed significantly to the decline (Kinnaird *et al.*, 2003; O'Brien *et al.*, 2010)

The TEAM programme is a consortium consisting of Conservation International, the Missouri Botanical Garden, the Smithsonian Tropical Research Institute, and the Wildlife Conservation Society, along with many partner institutions around the world (www.teamnetwork.org). The mission of TEAM is 'to generate real time data for monitoring long-term trends in tropical biodiversity through a global network of field stations, providing an early warning system on the status of biodiversity to effectively guide conservation action.' TEAM's Terrestrial Vertebrate Monitoring Protocol (TEAM Network, 2008) is designed to be compatible with the WPI sampling design and analysis. This protocol currently is being implemented annually at 16 sites in Central and South America, Africa, and Asia, with plans for implementation at 50 sites by 2015.

The Zoological Society of London (ZSL) has initiated a number of projects using the WPI sampling protocol. Collen *et al.* (2009) have developed a biodiversity monitoring programme built around an Evolutionarily Distinctive Globally Endangered (EDGE) priority species (Isaac *et al.*, 2007), the pygmy hippopotamus (*Choeropsis liberiensis*) in Sapou National Park, Liberia (Collen *et al.*, 2011). The Steppe Forward Program is a ZSL project to measure and monitor biodiversity in the Mongolian grasslands (Townsend and Baillie, 2009). Both projects use the WPI sampling protocol and are introducing camera trap monitoring to national protected area staff. Wachter *et al.* (2008) have implemented WPI monitoring in Niger in conjunction with protected area development and an addax (*Addax nasomaculatus*) conservation programme.

Finally, the Mpala Research Centre and Wildlife Conservation Society are using the WPI sampling and analytical protocols to monitor carnivore, grazer, and browser communities in the rangelands of Laikipia District Kenya, and to evaluate the impact of livestock management practices on wildlife (Kinnaird and O'Brien, in press). Results to date have shown that the WPI methods are equally useful in rainforest and savannas. While it is too early to evaluate the implementation of the

WPI globally, we expect that such an evaluation will be possible within the next few years.

Preliminary simulations

We conducted a preliminary bootstrapping analysis of the WPI to examine the precision and robustness of the index. We approached the problem in two ways:

1. evaluating the usefulness of the geometric mean as a way to track changes in community composition; and
2. evaluating the ability of the WPI to track a constant decline of occupancy across species similar to a scenario of forest conversion that affects all species equally.

We developed a community of 104 species (Figure 3.3) representing cryptic ($0.02 < P \leq 0.2$) and detectable species ($P > 0.2$) that are rare ($0.1 \leq \psi \leq 0.2$), common ($0.3 \leq \psi \leq 0.5$), and widespread ($0.6 \leq \psi \leq 0.8$). We then use the simulation function in PRESENCE to estimate a distribution (mean \pm SD) for 500 simulated occupancy estimates based on each species' true occupancy and detection probability, and a sampling effort of 100 camera points over 30 days. For the bootstrap analysis, we first set the size (n_s) and composition of the community of species (# rare

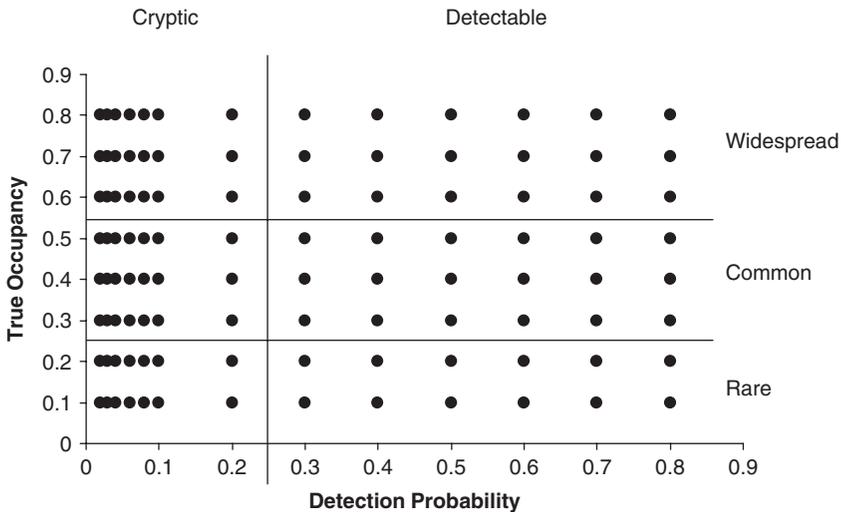


Figure 3.3 Simulated community of 104 species (represented by the closed circles) characterized by area occupied and detection probability.

cryptic species, . . . , # detectable widespread species), and the number of species detected out of the total community (n_d). We then sampled with replacement for n_d times, selecting a species' true occupancy and a random estimated occupancy from a uniform distribution bounded by the 95% confidence interval based on the estimated occupancy for the species from the PRESENCE simulation. We then calculated a geometric mean based on the true occupancies and a geometric mean based on the simulated occupancy. We repeated this process 10 000 times to give us a distribution of true occupancies and simulated occupancies that could be compared for accuracy and precision.

We chose as an example a community of 60 species with four community compositions:

- 20 rare, 20 common, and 20 widespread species;
- 30 rare and 30 common or widespread species;
- 40 rare and 20 common or widespread species;
- 40 rare and 20 common species but no widespread species.

We simulated the effect of detecting 60, 50, 40, 30, and 20 species on the estimated geometric mean of occupancy and compared that to the true geometric mean of occupancy for each example (Figure 3.4). In each test, there was a small positive bias in the estimated geometric mean. This may reflect the tendency for positive bias in occupancy analysis estimates as true occupancy declines. When the number of rare species was less than or equal to the number of common and widespread species (Figure 3.4a,b) the bias was less than 5% at all levels of species detection. When the number of rare species was twice the number of common species (Figure 3.4c,d), the bias was between 5% and 10%. Precision (as measured by percentage of coefficient of variation (CV)) of the simulated geometric mean was between 5% and 17%, with precision declining (%CV increased) as the number of detected species declined. We conclude from this preliminary example that the geometric mean performs well, even in the presence of a large proportion of rare species, although accuracy and precision do decline as rare species increase.

We next asked how well the WPI would perform when a community of species was losing habitat and all species are affected equally by this loss. We examined the full community of 104 species and estimated the WPI for a simulated habitat loss equal to a loss of 1%, 2.5%, 5%, 7.5%, and 10% of occupancy (Figure 3.5). Because all species' occupancy values were reduced by the same amount, habitat loss had a greater impact on rare species than common and widespread species. When habitat loss reached 10%, 13 species disappeared from the community. We looked at two levels of species representation, 80 and 60 randomly selected species in the sample, to see how declining representativeness of the sample might affect the index. In both examples, the simulated WPI accurately tracked the true value of the WPI with a small positive bias that averaged 2.4%. Precision of the simulated WPI varied between 11%

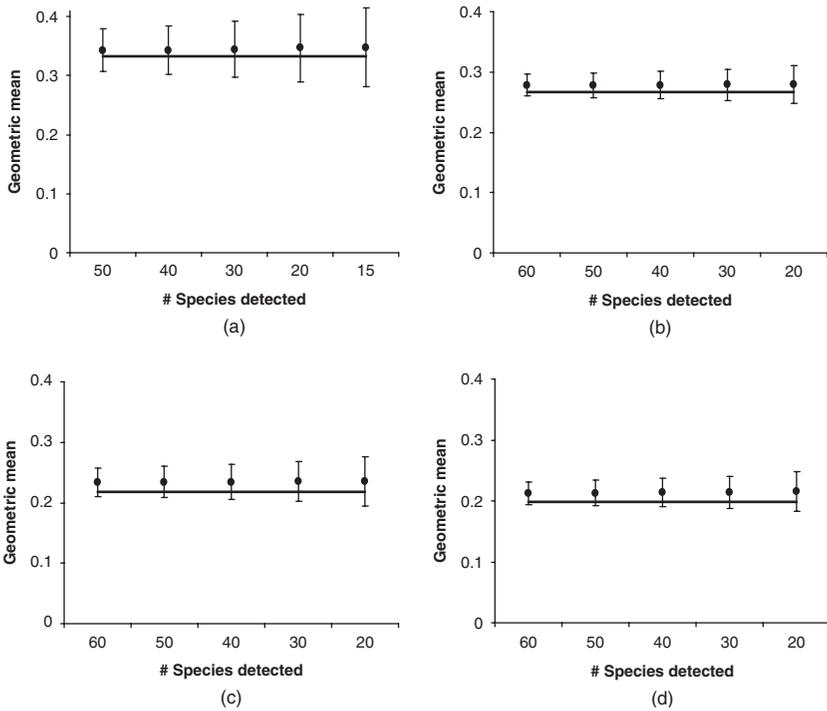


Figure 3.4 True (lines) and simulated (filled circles) geometric means (\pm SD) of occupancy for a community of 60 species composed of (a) 20 rare, 20 common, and 20 widespread species; (b) 30 rare and 30 common or widespread species; (c) 40 rare and 20 common or widespread species; and (d) 40 rare and 20 common species. The x -axis is the number of species from the community detected in a sample.

and 22%, increasing as the true index declined and as the number of species detected declined. With 80 species in the sample, a significant ($P < 0.05$) decline in the WPI was detected by the 5th time step. With 60 species in the sample, a significant decline was detected by the 6th time step.

Cost of implementation

To evaluate the cost-effectiveness of the WPI, we considered the implementation of a 100-point WPI survey compared to a line transect survey of 100 2-km-long transects,

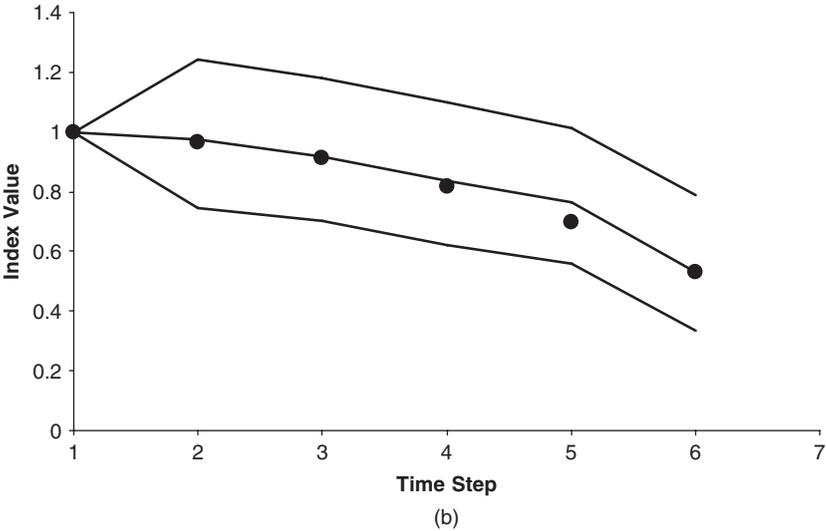
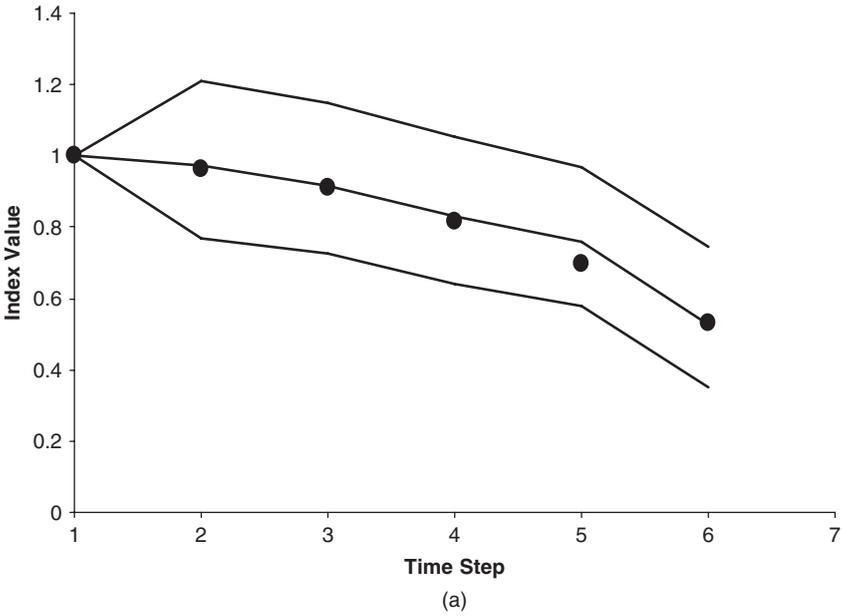


Figure 3.5 True (filled circles) and estimated (lines) values of a wildlife picture index (WPI) with 95% confidence limits when (a) 80 of 104 species are detected, and (b) 60 of 104 species are detected.

in Asian forest of Lao PDR and rangeland of Laikipia, Kenya. The WCS Lao PDR Program provided the cost data for implementing a camera trap survey versus a line transect survey in forest. We developed the rangeland budgets based on personal experience and knowledge of field expenses charged by biologists at the National Museum of Kenya. We calculated the fixed cost of 5 years of surveys in 2010 US dollars and pro-rated the equipment over that time. We ignored inflation because inflation affects all rates similarly. Equipment costs were set as one-time startup costs of US\$6860 for camera traps plus accessories, and \$1750 for laser rangefinders, binoculars, and digital compasses for line transect surveys. We assumed no loss or replacement of equipment during the 5 years (= five surveys). For the rangeland surveys, we used standard salaries, per diem, and minor equipment, fuel, and vehicle rental rates. For the forest surveys, we used standard transportation, per diem, field rations, camping equipment, and minor equipment. The key differences in the cost of implementation of camera trap surveys versus line transect are the startup cost (higher for camera trap surveys) and cost of keeping people in the field (higher for line transect surveys).

We estimate that the cost of implementing a single camera trap survey and line transect survey in rangeland condition averages \$5750 and \$7500, respectively, per year over a 5-year period. In the forest conditions of Lao PDR, we estimate the average costs at \$15 900 for camera trapping and \$18 400 for line transects. In savanna, a WPI survey is 30% less expensive than a line transect survey. In the forest, the cost saving for a WPI is 15% compared to a line transect survey. The similar costs in forests are due to the fact that camera trap deployment in the forest requires more time than in the savanna due to lack of roads and the rugged terrain. If we consider data returns, a line transect survey in Laikipia rangelands typically accumulates data on 28 large birds and mammals whereas a camera trap survey accumulates 59 large birds and mammals, primarily due to capturing nocturnal mammals. In the forest example, a line transect survey might encounter 20 species whereas the camera trap survey might encounter more than 40 species, again due to capturing the nocturnal community and animals that might flee humans. We expect that these figures would vary with the specifics of a deployment strategy, but the key features of startup and daily costs of conducting the surveys determine the relative cost advantage. We conclude that the WPI is a cost-effective alternative to line transect surveys, and probably other labour-intensive surveys, producing more data and more representative data for less cost.

Weaknesses and strengths

The WPI has been developed to monitor the terrestrial component of diversity represented by medium- to large-sized birds and mammals in the data-deficient

tropics. The degree to which these two groups represent trends in the broader bird and mammal communities at the monitoring sites is unclear (Collen *et al.*, 2009). There is reason to believe that larger terrestrial birds and mammals might face more threats than small birds and mammals in the same ecosystem. In areas where wildlife is hunted for food, larger body size and a terrestrial habit increase vulnerability to a wider range of hunting methods (Robinson and Bennett, 2000). Larger birds and mammals also require more habitat per unit animal (Haskell *et al.*, 2002; Jetz *et al.*, 2004). These same traits, however, make the larger taxa sensitive indicators of habitat and exploitation threats in forest and savanna ecosystems (Dobson *et al.*, 2006).

We also do not know whether changes in the community of terrestrial birds and mammals are representative of changes in other vertebrate taxa, particularly reptiles, amphibians, and fish, in forest and savanna ecosystems. The long search for indicator, flagship, and umbrella species has been frustrated by the lack of congruence in species response to common threats across taxa within an ecosystem (Simberloff, 1998; Caro and O'Doherty, 1999; Andelman and Fagan 2000; Williams *et al.*, 2000). We have some understanding of why taxa differ in response to common threats but more work is needed to determine if the lack of congruence in response to common threat is due to time lags or genuine differences in taxa responses.

The WPI targets tropical rainforests and savannas because of data deficiencies in these ecosystems. It may be subject to criticism for ignoring coverage in other tropical ecosystems and the temperate equivalent of these tropical ecosystems. To date, we do not know the extent of geographical coverage represented by current camera trap programmes, although we suspect it is biased towards the tropics and it is widespread. There is no reason why the WPI could not be applied in other ecosystems, especially in temperate forest and grasslands, and where the fauna contains a large number of nocturnal species. A global data registry similar to Ecological Archives would help track camera trap programmes and coverage.

The success of the WPI will ultimately depend on contributions and participation by a network of voluntary data providers who adopt the WPI sampling protocol in their programmes. We do not know the degree to which ongoing camera trap programmes, many of which target single species and sample accordingly, produce data that are comparable and compatible with WPI data. For example, a long-term tiger monitoring programme in Nagarhole National Park, India, is designed to maximize detection probabilities of tigers (Karanth and Nichols, 1998). The camera trap locations in this study are not systematic and not optimal for sampling chital (*Axis axis*) and several other ungulate species in the park (K.U. Karanth, personal communication). Consequently, occupancy estimates for these species may be biased low compared to true occupancy due to unrepresentative sampling. If the bias is systematic, however, the trends in occupancy estimates may still be unbiased, and a WPI based on a combination of unbiased and systematically biased occupancy

estimates would still contain useful information (O'Brien, 2010b). For camera trap studies not designed with WPI objectives in mind, the sampling designs and datasets will have to be scrutinized to determine if and where biases occur in the representation of the medium- to large-sized bird and mammal community. The usefulness of this retrospective analytical approach needs to be evaluated.

Basing the WPI on occupancy rather than abundance means that the index responds to spatial distributions rather than abundance distributions. While there are many reasons to assume that occupancy and abundance should be positively associated (Royle and Nichols, 2003; Royle, 2004; MacKenzie *et al.*, 2006), situations may arise that cause abundance and occupancy to be out of synchrony. We can imagine situations in which a population is declining uniformly across a region. Its occupancy may stay relatively constant as the population size declines. This might manifest itself as a declining point abundance but stable occupancy. We can also imagine a situation where a recovering population is growing but has not reached the size where dispersal or recolonization of old habitat becomes detectable in the occupancy estimates. In both cases, however, we should observe changes in detection probabilities associated with changing abundance (Royle and Nichols, 2003) and we expect that the WPI will respond to changing abundances though not necessarily in the same way that a relative abundance index might.

Two final weaknesses of the WPI are shared by many biodiversity indicators. First, the WPI may include many rare species at some sites and few at others. This may affect the local precision of the WPI, making it more difficult to detect changes in the trend at some sites compared to others. Preliminary bootstrap simulations on the effect of community structure (measured by true occupancy of species), detectability, and number of species detected in samples suggest that the accuracy of the WPI is fairly insensitive to rare species in the sample. The precision of WPI estimates, however, remains sensitive both to rare species and to the number of species detected. Second, the WPI weights each species in the community equally. Declining rare and endemic species are treated the same as abundant and widespread species. Although some may argue that declines in rare and endemic species are more important than declines in widespread species (loss of evolutionary distinctiveness: Mace *et al.*, 2003; Isaac *et al.*, 2007) or that declines of widespread, abundant, or top trophic level species are more important to ecosystem processes (Ray *et al.*, 2005; Sergio *et al.*, 2005; Dobson *et al.*, 2006), these are arguments based on different, often qualitative, notions of biodiversity and there are no agreements on how weighting schemes should be assigned. Buckland *et al.* (2005) recommend that weighting schemes be avoided altogether.

A significant strength of the WPI is that it monitors a component of biodiversity that is seen as important to governments and the public. The carnivores, large ungulates, seed dispersers, and seed predators are not only important components

of terrestrial biodiversity, they are often the target of exploitation, management (to promote or to limit populations), and tourism (Norton-Griffiths, 2007). Wildlife species occupying the top trophic levels are an important component of agricultural landscapes, where they may prey on livestock or crops. They can be important to local or national economies where wildlife viewing earns tourism revenues. They also provide important sources of protein and hunting revenues where permitted. Top carnivores and herbivores also are vulnerable to consumptive exploitation, habitat deterioration and loss, and their disappearance is often associated with trophic cascades as their ecosystem services are lost (Dobson *et al.*, 2006). Because of their economic, ecological, and aesthetic importance, we believe that wildlife managers may find the WPI especially useful to their monitoring efforts.

The future

Clearly, the WPI is a work in progress. We are still a few years away from a complete evaluation of the index using real data. We need to develop a network of WPI practitioners, although the coordinated camera trap monitoring programme by TEAM and ZSL will soon provide the critical nucleus of this community. Work on a full simulation of the accuracy and precision of the WPI under a variety of community structures is underway. More data are needed on the cost of implementation of WPI surveys. The use of camera traps in ecological studies is expanding rapidly (Rowcliffe and Carbone, 2008) in all major biomes of the world. Also, ecologists are making great progress in the development of hierarchical models of abundance and occupancy (Royle, 2004; Royle and Dorazio, 2008; MacKenzie *et al.*, 2006) as well as in trend estimation with imperfect detection (Kéry *et al.*, 2009). We agree with Rowcliffe and Carbone (2008) that an important next step is a global databank for camera trap information, where studies from around the world can be connected and integrated. Several efforts are underway, and we look forward to the time when the WPI becomes a useful indicator of changing biodiversity.

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