The Tropical Ecology, Assessment and Monitoring (TEAM) Network: an Early Warning System for tropical rain forests

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Abstract

While there are well established Early Warning Systems for a number of natural phenomena (e.g. earthquakes, catastrophic fires, tsunamis), we do not have an Early Warning System for biodiversity. Yet, we are losing species at an unprecedented rate, and this especially occurs in tropical rainforests, the biologically richest but most eroded biome on earth. Unfortunately, there is a chronic gap in standardized and pan-tropical data in tropical forests, affecting our capacity to monitor changes and anticipate future scenarios. The Tropical Ecology, Assessment and Monitoring (TEAM) Network was established to contribute addressing this issue, as it generates real time data to monitor long-term trends in tropical biodiversity and guide conservation practice. We present the Network and focus primarily on the Terrestrial Vertebrates protocol, that uses systematic camera trapping to detect forest mammals and birds, and secondarily on the Zone of Interaction protocol, that measures changes in the anthroposphere around the core monitoring area. With over 3 million images so far recorded, and managed using advanced information technology, TEAM has created the most important data set on tropical forest mammals globally. We provide examples of site-specific and global analyses that, combined with data on anthropogenic disturbance collected in the larger ecosystem where monitoring sites are, allowed us to understand the drivers of changes of target species and communities in space and time. We discuss the potential of this system as a candidate model towards setting up an early warning system that can effectively anticipate changes in coupled human-natural system, trigger management actions, and hence decrease the gap between research and management responses. In turn, TEAM produces robust biodiversity indicators that meet the requirements set by global policies such as the Aichi Biodiversity Targets. Standardization in data collection and public sharing of data in near real time are essential features of such system.

Keywords: biodiversity, camera trapping, ground-dwelling vertebrates, human impact, monitoring, tropical forests.

1. Introduction

Biodiversity loss is quantifiably the most dramatic of the environmental changes that our planet is facing in the Anthropocene (Rockström et al., 2009; Steffen et al., 2015), with extinction rates at least three orders of magnitude higher than the background (Millennium Ecosystem Assessment, 2005). This is particularly severe in the tropical moist forests that contain more than half of the terrestrial species (Laurance et al., 2012). While the negative ecological, evolutionary and societal consequences of such biodiversity crisis are well recognized (e.g. Gibson et al., 2011; Cardinale et al., 2012; Dirzo et al., 2014), addressing biodiversity loss primarily rests on the ability to quantify and monitor changes in biodiversity, and anticipate them. Indeed the Convention on Biological Diversity (CBD)'s Aichi Biodiversity Targets include measures for preventing extinctions for declining populations of animals and plants. The degree of achievement of these targets is quantified through a number of indicators on status and trends of wild populations, effectiveness of protected area management and extent of habitat changes. However, we face a chronic lack of primary data that can, in turn, provide robust indicators of biodiversity change, and this is disproportionately severe in the tropics (Collen et al., 2008). In addition, given biodiversity loss is mostly driven by local anthropogenic activities, the need for anticipatory systems must not be limited to biodiversity components, but should encompass the coupled human-natural systems (Liu et al., 2007; DeFries et al., 2010). These are defined as integrated systems in which people interact with natural components, hence extending the ecosystem where the core biodiversity monitoring area occur to include interactions and feedbacks between ecological and human processes, due to e.g. fuelwood collection, hunting and, generally, the use of ecosystem services (Liu et al., 2007).

In this context, the Tropical Ecology, Assessment and Monitoring (TEAM) Network is a pan-tropical research programme explicitly designed as an early warning system for tropical rain forests. TEAM collects real time data for monitoring long-term trends in tropical biodiversity through a network of field stations in protected areas. Monitoring targets terrestrial vertebrates, arboreal vegetation, climate and human disturbance (see Section 2 and www.teamnetwork.org). The need for long-term, systematic and standardized monitoring of biological diversity is widely acknowledged (e.g. Lindenmayer and Likens, 2010). Robust sampling designs such as those developed by TEAM allow for inferential and question-driven studies to be conducted, and standardization in data collection routines is critical for temporal

and spatial comparisons (e.g. Ahumada et al., 2011; Beaudrot et al., 2016). Yet, there are only few monitoring programmes of this sort in the tropics. The Smithsonian Tropical Research Institute with its Center for Tropical Forest Science and Forest Global Earth Observatories (CTFS-ForestGEO; www.ctfs.si.edu) is the largest and longest tropical vegetation monitoring programme in the global tropics (Losos and Leigh, 2004). The TEAM Network, established in 2002, has grown to become one among the major ones and is contributed by CTFS at a number of sites.

The scope of this contribution is to review the achievements of the TEAM Network from local to global scales, with particular focus on the relevance to anticipating changes and hence the ability to decrease the gap between research outcomes and environmental management responses (from policy to conservation practices). We focus on two of TEAM's monitoring protocols: the first monitors terrestrial vertebrates through the use of automatic cameras (i.e. camera trapping); the second monitors the coupled human-natural systems by using a range of ground and remote sensing data.

2. Material and Methods

TEAM is a consortium of three core partners, Conservation International (www.conservation.org), The Wildlife Conservation Society (www.wcs.org), and The Smithsonian Institution (www.stri.si.edu), and over 80 academic and local partners spanning 15 countries and 17 sites in tropical forests around the world (Fig. 1). TEAM is a network by design (Andelman and Willig, 2004) to answer the question of how climate change and land use change affect biodiversity change at local, regional and global scales. The sites were chosen in a “quasi” factorial design to span moist tropical forest rainfall and seasonality gradients (Ahumada et al., 2015), land use change gradients (DeFries et al., 2005), and projected climate change gradients (Hewson et al., 2008). The sites are distributed in proportion to tropical forest cover on each continent; half of the sites are in South and Central America, roughly one quarter are in Africa, and the rest are in Southeast Asia.

2.1. Terrestrial Vertebrate protocol

The bulk of data for this protocol was collected since 2007. TEAM monitors mammal and bird communities using camera trap arrays following a standardized protocol (TEAM Network, 2011; Jansen et al., 2014). Camera traps are remotely set, automatic cameras that

take images of passing animals, and have become one of the most popular and efficient tool for wildlife research across the globe (Rovero and Zimmermann, 2016). At each TEAM site, 60– 90 camera traps are deployed at a density of one camera per 2 km², this density being lowered to 1 km² for a few sites that have less than a 120 km² in extent. Each year, each camera trap point is deployed for at least 30 consecutive days during the dry season, which is defined as months with <100 mm average rainfall, or the drier part of the year at sites with no dry season. Camera trap units are set along wildlife trails, can work in continuous with no need to check them, and store images in SD memory cards. Sampling is repeated every year in exactly the same period and at the same sampling sites. With thousands of images recorded from each site every year, timely data management is fundamental, especially to provide public access to data and summary results in near-real time. Thus, TEAM developed data management tools for processing and curating data from camera traps through technology partners Hewlett Packard Enterprise and the San Diego Super Computer Center at the University of California, San Diego (Baru et al., 2012).

Besides the baseline inventorying of medium-to-large bodied mammals and terrestrial birds, the key objectives of the analysis of TEAM data at the community level are the estimation of ‘true’ species richness and composition, and its variation with time and among sites. At the species level, the main objective is to derive a proxy of population abundance that can be analysed in time, to determine population trends, and in space, to model species’ habitat associations and study the potential effect of anthropogenic disturbances. The majority of the analyses to address these objectives are conducted in an analytical framework called ‘occupancy’ (MacKenzie et al., 2002), i.e. the probability of presence of a species across the sampled sites. Occupancy can be used as a surrogate for abundance and it is unbiased because it is corrected for the various potential sources of observation error due to ‘detectability’, i.e. the probability that a species is detected given it is present (MacKenzie et al., 2002). Indeed in most cases, species detection is imperfect, which can lead to the incorrect classification of occupied sites as empty. If imperfect detection is not accounted for, bias is induced in the occupancy estimator. Such framework is called ‘hierarchical’ because the estimation of occupancy (i.e. the abundance, or ‘state’ process) is conditional upon the ability to detect the species at the site (i.e. the ‘observation’ process). This approach at the species level is scaled up to the community level, whereby the estimation of the ‘true’ number of species in the community considers the fact that a portion of species in the area may go undetected (Dorazio et al., 2006). Analytically, occupancy estimation is based on repeated presence–

absence surveys of animals at multiple sites. The basic sampling scheme implies multiple visits to a randomly selected set of sites within a short interval of time so that sites are closed to changes in occupancy states (present, not present) within the season of sampling (O’Connell and Bailey 2011). Occupancy analysis is particularly well suited for camera trapping data, because the sampling period (i.e. the duration for which each camera trap works) is fractioned during analysis into multiple, sequential sampling occasions, e.g. 1 day. This procedure provides the detection-nondetection matrices that are used for occupancy estimation (see Rovero and Spitale, 2016, for further details).

Variations with time in estimated occupancy at both species and community level are determined using a dynamic occupancy framework (MacKenzie et al., 2003). These authors extended the static, ‘single-season’ model to the ‘multi-season’, or dynamic model by including two parameters: ϵ (probability of site extinction) and γ (probability of site colonization). The first (ϵ) is the probability that an occupied site in season t becomes unoccupied in season $t + 1$, and the second (γ) is the probability that an unoccupied site in season t becomes occupied in season $t + 1$. The analysis is used to assess trends in species and populations, and hence predict future changes. In particular, the Wildlife Picture Index (WPI) is a composite index that was specifically developed to assess changes in species’ richness and occupancy, or abundance, in the community from camera trap data (O’Brien et al., 2010). The index is based on the geometric mean, for a set of species, of relative occupancy estimates derived from camera trap sampling. Each species-specific occupancy in a time series, o_{ij} , is scaled by dividing occupancy in year j by the estimated occupancy of species i at the initial time point, o_{ij}/o_{i1} . This creates a species-specific index that measures the change in occupancy from initial conditions. The community WPI is the geometric mean of scaled occupancy statistics for n species, and it is sensitive to changes in both species’ occupancy (i.e. abundance) and number of species (O’Brien et al., 2010). The WPI was developed to meet the requirement of an indicator for monitoring progresses of Aichi Biodiversity Target 12, and we refer to Beaudrot et al. (2016) for methodological details and an example of its use with TEAM data.

2.2. Zone of Interaction (ZOI) protocol

This protocol was designed to address the question as to how human disturbances at the local scale are measured and can be monitored to interpret biodiversity trends. Hence, DeFries et al. (2010) defined the ZOI as the spatial extent of the coupled human–natural system that

strongly influences biodiversity measured within a plot, and we refer to these authors for the underlying conceptualization and methodological details. In summary, authors took a pragmatic approach to delineating the ZOI based on a combination of remote sensing data and local expert knowledge, or field data when available, of the ecological and socioeconomic features. Thus, DeFries et al. (2010) proposed four criteria for incorporating ecological and human interactions that affect biodiversity at the measurement plots: (1) extent of contiguous habitat surrounding the measurement site, (2) migration corridors used by landscape species (usually large mammals) to move between ecosystems, (3) position of watershed boundaries relative to the monitoring sites, and (4) areas around the monitoring sites where human activities have direct influence on the measurement site through impacting practices such as fires, deforestation, pollution, disease transmission, etc. (TEAM Network, 2014).

Once the ZOI is mapped using these four criteria, a set of attributes are recommended for assessing and monitoring changes in anthropogenic disturbance, such as land-cover, land-use, and landscape patterns (e.g. fragmentation, patch size, connectivity); human population density; infrastructure (e.g. the construction of roads, conversion of road from unpaved to paved, etc.); active fire and burned areas; direct human impacts, such as timber harvesting, grazing by domestic animals, and hunting (DeFries et al., 2010; TEAM Network, 2014). DeFries et al. (2010) used one of the TEAM sites in Africa, the Udzungwa Mountains of south-central Tanzania, as the model site to delineate the ZOI. Here, we will present the relevance of this framework to interpret TEAM biodiversity monitoring data. In particular, human disturbance data were collected in Udzungwa using transects running from forest edge to interior and recording all signs of illegal activities such as snares, pitsawing sites, charcoal making sites, etc. (see Rovero et al., 2012). In addition, each year during 2009-2014 all snares set for bushmeat hunting found along the fixed route walked to set and remove TEAM camera traps were scored and removed, providing an index of hunting incidence over the years.

3. Results

3.1. Assessing and predicting trends in mammals from local to global scales

At the site level, camera trapping data are used to profile mammal communities by modelling the ecological preferences of selected species and guilds, and by estimating true species

richness in the community, hence conducting a baseline against which temporal and spatial variations can be assessed. Considering the Udzungwa Mountains of Tanzania as a case study, Rovero et al. (2014) modelled at the fine scale estimated occupancy of a pool of species with enough detection events against habitat and human disturbance covariates. Such models make inference on probability of presence beyond the measurement sites hence determining species' responses to disturbance as approximated, for example, by the distance from protected area boundaries, or the preference for interior versus edge forest. In the example provided in Fig. 2, occupancy estimation is mapped for two target species against distance to forest edge, a variable that resulted significantly affecting estimated occupancy in the model selection. The two species are a common forest antelope, the Harvey's duiker (*Cephalophus harveyi*) and the Udzungwa-endemic grey-faced sengi, or elephant shrew (*Rhynchocyon udzungwensis*). Results show that these species have opposite patterns in their preference for forest edge: the duiker is seemingly an 'edge-lover', its predicted occupancy peaking near the forest edge, as also shown by the bivariate relationship in the chart; in contrast, the sengi prefers forest interior zones, hence avoiding forest edges. Given that forest edges tend to have secondary forest habitat, and that the eastern portion of the forest is under human disturbance, these analyses provide critical inference into species' ecological preferences and resilience to disturbance.

This study also used the community occupancy model developed by Dorazio et al. (2006), and estimated that the target community contained over 30 species from an observed richness of 26, with estimated median and mean species richness being 32.0 and 34.3, respectively (26–54 CRI 95%; CRI = credible intervals; Rovero et al., 2014). Estimating true richness with account for imperfect detection, i.e. correcting the observed richness for species that may go undetected (see Section 2.1), provides an 'unbiased' metric, that in turn allows for different communities to be compared. For example, Hegerl et al. (2015) replicated the sampling using TEAM's protocol in a different forest of the range. Due to logistic constraints, authors deployed 30 camera trap sites only in this second forest, and therefore the comparison was based on this re-scaled sampling effort. This forest, Uzungwa Scarp Nature Reserve, is ecologically similar to TEAM's but it lacks effective protection on the ground despite its recent upgrading of conservation status. Indeed the study shows that estimated species richness in this second forest was almost 40% lower (median 18 vs 29 species, respectively; Fig. 3), due to the combination of intensive and continuous poaching and habitat degradation over the last decades. Such threats have led to the complete extirpation of larger

mammals, as well as a significant decline in the abundance of several species (see Hegerl et al., 2015, for more details). Interestingly, community composition in trophic guilds was also altered in the disturbed forests, with a tendency to the reduction of insectivores and carnivores and an increase in omnivores and rodents (Hegerl et al., 2015). Similarly to this study, the first multi-region analysis of TEAM camera trapping data found that the observed species richness across seven sites in three continents scaled according to habitat fragmentation, with least fragmented sites holding larger communities (Ahumada et al., 2011). In addition, communities in fragmented landscapes had altered composition, lowered body size range of species, and lowered species' abundances as proxied by estimated occupancy (Ahumada et al., 2011).

In analogy with these analyses on spatial patterns, assessments of temporal trends in community size and species' occupancy have been conducted at local and global scales. For instance, Ahumada et al. (2013) used data for 5 years to assess temporal changes in Volcan Barva (Costa Rica) at species and community levels using dynamic occupancy modelling. Authors found that three out of the 13 species for which the analysis could be performed showed significant declines in occupancy, and hypothesized that hunting, competition and/or increased predation might explain these patterns. Two examples are shown in Fig. 4, with trends in estimated occupancy for the lowland paca (*Cuniculus paca*), and the nine-banded armadillo (*Dasypus novemcinctus*). The rate of decline in estimated occupancy from one year to another was statistically tested (Fig. 4; see Ahumada et al., 2013 for methodological details), providing an objective indication to detect drastic changes in abundance. Authors also found that species richness and the WPI were relatively stable at the site over the monitoring period (Fig. 4), however the pool of small herbivores, which are particularly targeted by hunting, showed a decline in richness of about 25% (Ahumada et al., 2013).

The first TEAM-wide assessment of temporal trends was recently presented by Beaudrot et al. (2016) that analysed occupancy dynamics for 15 communities across the global tropics and representing 511 populations and 244 species of terrestrial mammals and birds, monitored through camera trapping over a period of 3-8 years. Due to the standardization in data collection across the network, authors could deploy a consistent, dynamic occupancy framework (as used at the Volcan Barva site by Ahumada et al., 2013; see Fig. 4) to determine temporal trends in estimated occupancy of target populations across communities in three continents. Authors found that occupancy declined in 22%, increased in 17%, and

exhibited no change in 22% of populations during the study period, while 39% of populations were detected too infrequently to assess occupancy changes (Fig. 5). The variability in occupancy trends was large, but the study overall indicates that these 15 sites in three continents across the global tropics have not exhibited systematic declines in biodiversity (i.e., occupancy, richness, or evenness) as proxied by the community of larger terrestrial mammals and birds.

3.2. Combined biodiversity and human disturbance assessments

Based on criteria 1 (contiguous habitat where forest-dependent species occur), 2 (migration corridors used by elephants), and 4 (strong human interaction; criterion 3 – watershed - was not applied as the area falls within the upper reach of the watershed), DeFries et al. (2010) identifies the ZOI for the Udzungwa TEAM site, provide a baseline assessment of major anthropogenic drivers of disturbance and propose ground and satellite-based monitoring of a number of attributes relevant to interpret biodiversity trends. Indicators of human disturbance assessed through remote sensing included fire activity and changes in forest cover (Fig. 6). These both peaked along the eastern and southern edge of the mountains, in the large floodplain Kilombero valley, coinciding with areas of rapid agricultural expansion, including within the elephant migration corridors. Since this assessment, rapid changes in a number of these attributes in subsequent years can be traced from a number of other sources. Hence, human population increased along the eastern side of the Udzungwa mountains at an annual growth rate of at least 2.4% (Government of Tanzania 2016); mechanized rice and sugar cane production intensified in the Kilombero valley due to very recent, large investments (<http://www.sagcot.com>); this led to further deforestation in the valley, with wood fuel consumption in the study area estimated to cause net deforestation between 3.37 and 21.59 ha day⁻¹ (Mombo et al., 2014). Indeed remnant forest patches in the Kilombero valley have shrank or disappeared in recent years (Barelli et al., 2015). Two major elephant corridors that were still used until around mid 2000s have been completely closed due to encroachment of fire and agriculture in the corridor areas (Rovero and Jones, 2012).

De Fries et al. (2010) and Rovero et al. (2012) report of marked increase in human disturbance signs, as they were counted on the ground along 0.5 km transects, when moving from the national park to the southern, least protected reserves. The greatest contrast was from the TEAM site in the national park to the southern, Uzungwa Scarp Nature Reserve (see Section 3.1), with 1 versus 33.7 freshly-cut poles counted per km (trees of <15 cm diameter

at breast height, DBH) and 0.3 versus 27.3 freshly-cut large trees per km (DBH > 15 cm; N = 20 and 25 transects respectively). Similarly, Rovero et al. (2012) interviewed 110 hunters living around the southern forest and found intense hunting levels targeting both the arboreal primates and terrestrial mammals. Such ground assessment of human disturbance is especially critical to interpret biodiversity trends as indicated both by the study on terrestrial mammals by Hegerl et al. (2015; Fig. 3) and a primate monitoring programme that has also been conducted in the same two forests. This programme documented lowered diurnal primate abundance in the southern, unprotected forest relative to the northern forest, with population abundance that declined to near-extinction over the last 10 years for the arboreal monkeys (Rovero et al., 2012; 2015), mirroring the general impoverishment for ground-dwelling mammals in this forest (Hegerl et al., 2015). While hunting levels were of difficult quantification, hunting is considered the primary cause of such biodiversity loss; however, multiple regression analysis has also provided evidence for an impact on arboreal monkeys of forest degradation, as indicated by the quantification of logging, pole cutting and charcoal making recorded along transects, as well as the cover in climbers which is exceeding in the most degraded and secondary vegetation areas of the forest (Rovero et al., 2012).

In contrast, primate populations have remained stable in the TEAM monitoring site within the Udzungwa Mountains National Park, where hunting pressure is low and relatively few signs of fresh habitat degradation were recorded (Rovero et al., 2012; 2015). These results are mirrored by the temporal analysis of TEAM camera trapping data: Beaudrot et al. (2016) show that WPI did not change for the community of mammals monitored by the TEAM Network in the National Park. Indeed, preliminary, simple correlative analysis between mammals' trends in abundance and systematic data on snare removal at TEAM camera trapping sites collected during 2009-2014 indicate that stability, or even increase, in a number of species' relative abundance may be related to increased protection efficiency over the study period as approximated by a decrease in the number of snares removed per year (E. Martin and F. Rovero, unpublished data).

4. Discussion

4.1. Towards an Early Warning System for tropical forest biodiversity

While there are well established Early Warning Systems for a number of natural phenomena such as earthquakes, catastrophic fires, tsunamis, hurricanes, and volcanos, we do not have an

Early Warning System for biodiversity. This is of concern given we live in a period of unprecedented biodiversity loss. Priority should be given to tropical ecosystems, where biodiversity is both the richest and most threatened on the planet (e.g. Laurence et al., 2012). Typical warning systems are those that inform the general public of a future danger so to enable preparation for the danger and act accordingly to trigger a response that can mitigate or avoid it. Therefore, we propose that, operationally, an Early Warning System for biodiversity should comprise the following chain of functions: (1) monitoring biodiversity along with potential drivers of changes, (2) integrate these data into models that can then be used to simulate biodiversity change under different scenarios of climate change, deforestation, poaching, etc., (3) share the data, models and predictions with protected area managers, local communities, government agencies and the general public, and (4) provide recommendations based on identified or predicted changes and trigger conservation management actions. Here, we will discuss the potentials and limitations of TEAM Network towards setting up such a system.

We have shown that the TEAM Network collects standardized, near-real time data on key biological components of tropical ecosystems. The fundamental features as met, for example, by TEAM's terrestrial vertebrate protocol, are (1) the standardization in data collection across sites in the global tropics, and (2) the public sharing of data in near-real time. On the first feature, despite the wealth of wildlife studies on tropical species and ecosystems (e.g. Ghazoul and Sheil, 2010; Laurance et al., 2012), without standardization of methods across sites it is difficult to determine real patterns in the dynamics of these populations. For example, an assessment of temporal dynamics such as in Beaudrot et al. (2016) could have not been conducted before due to lack of standardized data of that magnitude; indeed an earlier pantropical study with comparable aims was primarily based on expert opinion (Laurence et al., 2012). A direct consequence of standardization is the ability to apply robust analytical approaches such as occupancy and adopt state-of-the-art modelling to explicitly test hypotheses about drivers of variations in these communities in unified analytical frameworks (e.g. Sutherland et al., 2016), making the inference process robust and reliable. On the second feature, TEAM's approach of making of public access the data in near real time represents a new avenue in ecology as it scales up the capacity of observing natural phenomena to the magnitude needed to anticipate changes. This is because the spatial and temporal scales of the current environmental crisis are larger than the average study conducted at a single site and/or by a single team of scientists. Additionally, the data sharing

coupled with the availability of platforms that provides summary analyses of easy consultation and use, such as the WPI (Fegraus and MacCarthy, 2016), have the potential to greatly augment the range of data users, from scientists to wildlife managers and from policy makers to conservation agencies, and hence the range of data uses (see examples below). While these features of TEAM Network address the bulk of operational functions of our proposed definition of an Early Warning System for biodiversity, i.e. standardized data collection, analytics, and data sharing, it remains critical to address the end functions, i.e. triggering conservation management actions based on identified or predicted changes in biodiversity.

4.2. Anticipating changes in biodiversity and identifying decision triggers

The combination of biodiversity data with data on potential drivers of changes, such as local human disturbance, opens the way to explicitly assess how biodiversity respond to local and global environmental perturbations at a magnitude not explored before. We provided examples of this potential at both spatial and temporal scales. At the spatial scale, the fine-scale occupancy models for mammals can effectively predict how a species will respond to local perturbations, providing an estimate of occupancy and associated error beyond the measurement points. For example, a species preferring forest edges will likely be more severely affected by anthropogenic pressure when forest edges coincide with protected area border, such as the case in Udzungwa Mountains (Fig. 2; Rovero et al., 2014). Similarly, the knowledge on poaching pressure at the southern, unprotected forest in the Udzungwa Mountains allowed the authors to determine how species richness and community composition changed under this pan-tropical threat (Hegerl et al., 2015). More generally, a quantification of the attributes monitored in the ZOI allowed to understand at the landscape level how a range of anthropogenic changes including increasing human population and deforestation affects local biodiversity. At the temporal scale, important conclusions can be drawn from dynamic occupancy modelling, as shown for example by the results in Fig. 4 from Costa Rica (Ahumada et al., 2013) and the global WPI study by Beaudrot et al. (2016; Fig. 5). In particular, the statistical test of rate of change in time of estimated occupancy (for single species), or in the WPI (for community or pool of species; see Fig. 4 and Ahumada et al., 2013) provides a way to detect changes in the metric that may reflect ‘true’ changes in abundance rather than natural fluctuations. This approach is of critical importance, as it offers premises for determining decision thresholds, i.e. identifying changes that should trigger conservation actions (Connors and Cooper, 2014).

The inference on occupancy provided by these methods can potentially be extended both beyond the target area (space) and the sampling period (time), an approach which is in principle relevant to anticipating changes. However, caution must be recommended as the uncertainty associated to these predictions may be large depending on the quality of data themselves (e.g. Tenan et al., 2016). Yet, the examples given indicate that the inference based on data from the sampling area, or sampling years, remain very informative to predict changes. A review of the wealth of approaches in ecology to predict species distribution and temporal trends of populations is beyond the aim of this contribution, however some of these methods such as the population viability analysis (e.g. Boyce, 1992) require a depth of demographic data which are unavailable at the magnitude inherent with a global network such as TEAM. There are also limitations associated with approaches proposed to predict species' range such as ecological niche modelling and species distribution models (e.g. Martinez-Meyer, 2005; Guisan and Thuiller, 2005), particularly the important fact that they do not account for imperfect detection (Guillera-Arroita and Lahoz-Monfort, 2012); indeed the possibility that occupied sites are classified as empty due to detection errors will bias the occupancy estimator, and this in turn will bias the spatial predictions of occupancy.

As the ultimate goal of TEAM Network is to guide conservation action, it remains critical to use the current data and analytical frameworks to develop standardized, quantitative approaches for identifying indicators of change in the biodiversity status (e.g. species' occupancy, or community's WPI) that relate to thresholds of conservation concern. In this context, receiver operating characteristic (ROC) curves represent a promising statistical approach to identify an indicator threshold that warrant conservation action, especially as they have recently been developed for conservation status that are measured as continuous, rather than discrete state (Connors and Cooper, 2014). This is typically the case with population abundance trends, when variable thresholds in their decline (e.g. by 10, 25, or 50%) over a given time period will be variably related to actual conservation concern. Given that TEAM's camera trapping protocol provides statistically robust data for assessing trends in abundance, as exemplified by the WPI, we recommend that as longer-term data series are accumulated more attention is devoted to validate statistical approaches for determining decision thresholds (see also Black, 2015). This will require robust baseline data to set trigger points in relation to natural oscillations of the study species or system (Cook et al., 2016). More generally, towards this end greater collaboration between scientists and managers will

be determinant, particularly for interpreting monitoring data and ensuring that they provide the information required for management (Lindenmayer and Likens, 2010; Lindenmayer et al, 2013).

As the Network grows in number of sites and the monitoring period extends in time, it is predictable that the capacity to achieve this ultimate goal will in turn increase. A number of examples are showing this potential. In Uganda's Bwindi Impenetrable Forest, camera trapping data showed a decline in the area occupied by the African golden cat, a threatened felid. Park managers noticed that these locations were heavily used by eco-tourists and so redirected people to different trails. Since these management actions went into effect, there has been an apparent increase in the sighting frequency of this species (Ahumada et al., 2016). In Costa Rica, results of the study conducted by Ahumada et al. (2013) were shared with park authorities and measures were taken to increase patrolling and control poaching. Following monitoring data show that two of the species that were declining the fastest (agouti and lowland paca) have at least stabilized since threat mitigation was enforced (Ahumada et al., 2016). A similar result was obtained in the Udzungwa Mountains, where after the Tanzanian Government was presented the evidence of declining biodiversity outside the National Park the protection status of two important protected areas was upgraded to a higher level, which should in turn ensure greater protection.

5. Conclusions

We have shown that standardized data collection on biodiversity components, replication at multiple sites, and advanced data analysis and management with public sharing of data and results form a system to monitor biodiversity that decreases the gap between data collection, achievement of results, and implementation of solutions in environmental conservation. In turn, a network such as TEAM can produce robust indicators that meet the requirements set by global policies such as the Aichi targets. Moreover, the integration of biodiversity data with socio-ecological assessments - such as the approach framed through the ZOI - may provide an understanding of the dynamics and future trajectories of coupled human-natural systems.

In a period of unprecedented biodiversity loss, therefore, efforts to consolidate and scale up an Early Warning System for biodiversity are within reach. However, for a programme such as TEAM to effectively become a warning system there remains a pressing need for validating statistical approaches that identify decision triggers, i.e. threshold in the biodiversity metric being measured that reflects actual conservation concern and that can, therefore, solicit conservation management action. Additional, specific issues are: (1) the number of sites currently in the network, that may limit generalizing results to the whole biome, and, related to this (2) the focus on protected areas in the tropical forests which limits the ability to understand how the full spectrum of human disturbance impacts biodiversity; (3) the time span of data currently available (3-8 years depending on sites) that limit robust temporal inference for a number of sites and (4) the difficulty of finding and setting up sustainable funding models for long-term monitoring systems. A promising new advancement in this process is represented by the increased efforts to merge data-sets from multiple sources (networks and singles studies) at global level, which is especially been pioneered for data on arboreal vegetation (e.g. Slik et al., 2015), confirming the value of data sharing and of scaling up the magnitude of scientific research. Monitoring biodiversity in tropical forests and understanding how local, regional and global drivers of change affect ecosystem structure and function is essential for improved management of these key natural habitats. This is not only key for conserving half of the biodiversity on earth, but also to ensure the livelihoods of 1 in 4 people in the planet that depend on key ecosystem services provided by tropical forests. We must find a way to continue and scale up the reach of monitoring systems like TEAM.

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Figure legends

Figure 1. Map of the TEAM sites across the global tropics.

Figure 2. Examples of fine-scale modelling of occupancy for two species of mammals detected in the Udzungwa Mountains of Tanzania through camera trapping. Modelling predicts the response of occupancy to habitat and human disturbance across the study area. In this example, occupancy is predicted for two species of mammals (the Harvey's duiker *Cephalophus harveyi*, above, and the grey-faced sengi, or elephant shrew, *Rhynchocyon udzungwensis*, below) against distance to forest edge, which is a proxy of human disturbance and habitat type. On the left are maps of predicted occupancy and on the right the relationship between predicted occupancy and distance to forest edge. Redrawn from Rovero et al. (2014).

Figure 3. Example of species richness estimation in mammal communities using camera trapping data and occupancy analysis. Charts show the Bayesian posterior distribution of species richness of mammal communities in two distinct forest blocks in the Udzungwa Mountains of Tanzania, one unprotected (above) and one protected (below, the TEAM site). The black bar indicates the observed species richness. The comparison shows that hunting in the unprotected block, considered the main driver of community impoverishment, has almost halved the estimated species richness, with several species that went locally extinct. Redrawn from Hegerl et al. (2015).

Figure 4. Examples of temporal analysis of camera trapping data in occupancy framework. Charts above: occupancy dynamics for lowland paca, *Cuniculus paca* (left), and nine-banded armadillo, *Dasypus novemcinctus* (right), detected using camera trapping at the Volcan Barva TEAM site, Costa Rica, over a period of 5 years. Observed (naïve) occupancy is shown by black dots and modelled occupancy is shown by solid black line (median or mode of the posterior distribution). The shaded grey indicates the highest posterior density intervals for occupancy. The small inset graphs on the top-right corners symbolize the statistical signal of λ , i.e. the rate of change in occupancy between any two particular years. Values of λ significantly smaller than 1 are symbolized in red; values not significantly different from 1 are symbolized by grey. Charts below: estimated species richness (left) and Wildlife Picture Index (WPI; right). The solid line shows the estimated value of richness and the shaded grey indicates the 95% confidence limits of the estimated distribution. WPI is computed for 13

species of mammals; the solid line is the mode of the posterior distribution of the WPI for each year and the shaded area indicates the highest posterior density intervals for the WPI. From Ahumada et al. (2013).

Figure 5. Results of the first analysis of TEAM's camera trapping data across the global tropics. Trends in occupancy for mammal and bird species in 15 tropical protected areas were assessed through standardized camera trapping surveys. Pie charts show the fraction of populations with unknown, decreasing, stable, or increasing occupancy for each site (see legend). The type of landscape in terms of habitat fragmentation (isolated, patchy, intact) is indicated by marker colour, and the number of years of camera trap data is indicated by the square marker. Green shading depicts tropical forest. From Beaudrot et al. (2016).

Figure 6. Zone of Interaction (ZOI) defined for the Udzungwa Mountains of south-central Tanzania, according to the combined spatial extent for (a) criterion 1 (contiguous habitat), (b) criterion 2 (migration corridors), and (c) criterion 4 (human influences; see text for details). The two maps show changes in forest cover from 1970 to 2000, reflecting the distribution of human activity in the ZOI (map above), and fire activity from Moderate Resolution Imaging Spectroradiometer (MODIS) data for November 2000 through August 2007, highlighting frequency of active fires around each 100-m cell (map below). The two black circles on the map above indicate the location of biodiversity monitoring sites, i.e. the TEAM site in the Udzungwa Mountains National Park (to the north east) and the Uzungwa Scarp Nature Reserve (to the south). Redrawn from De Fries et al. (2010); see this reference for the sources of data used in the maps.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

**Data
collection
at a TEAM
site**

**Innovative
technology to
scale up data
capture**

**Understanding
the insights
from big data
(using
innovative
analytics)**

**Translating
into decision
making**