Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote sensors

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Countries committed to implementing the Convention on Biological Diversity's 2011–2020 strategic plan need effective tools to monitor global trends in biodiversity. Remote cameras are a rapidly growing technology that has great potential to transform global monitoring for terrestrial biodiversity and can be an important contributor to the call for measuring Essential Biodiversity Variables. Recent advances in camera technology and methods enable researchers to estimate changes in abundance and distribution for entire communities of animals and to identify global drivers of biodiversity trends. We suggest that interconnected networks of remote cameras will soon monitor biodiversity at a global scale, help answer pressing ecological questions, and guide conservation policy. This global network will require greater collaboration among remote-camera studies and citizen scientists, including standardized metadata, shared protocols, and security measures to protect records about sensitive species. With modest investment in infrastructure, and continued innovation, synthesis, and collaboration, we envision a global network of remote cameras that not only provides real-time biodiversity data but also serves to connect people with nature.

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Declining biodiversity is a reality of the Anthropocene, and society is failing to meet international biodiversity targets (Butchart *et al.* 2010; SCBD 2014). From Carnivora to Coleoptera, biodiversity losses are across the globe due to human activities (Butchart *et al.* 2010). Rare species are becoming rarer, geographic ranges are constricting, and species are going extinct (Dirzo *et al.* 2014). Monitoring these changes to biodiversity is a global priority required by international treaties (SCBD 2014) and coordinated by international networks such as the Group on Earth Observations Biodiversity Observation Network (GEO BON; earthobservations.org/geobon.shtml), which has called for the focused monitoring of variables that capture the largest dimensions of biodiversity change, ie Essential Biodiversity Variables (EBVs; Pereira *et al.* 2013). Amid growing concern and limited funding for maintaining the health of the planet (Tittensor *et al.* 2014), real-time biodiversity monitoring is key to identifying and addressing large-scale ecological threats.

The Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) was created in 2012 with the explicit goal of strengthening the interface between science and policy to improve biodiversity conservation outcomes, emulating the successful issue-specific policy focus of the Intergovernmental Panel on Climate Change (IPCC; Mooney and Tallis 2014). An important distinction between IPBES and the IPCC, however, is that the latter has a global network of standardized weather sensors to track changes and inform predictions about future climate. Conversely, biodiversity data are typically collected to serve local objectives, and may not be suitably standardized to provide effective measures of global change. An international biodiversity network remains a major gap, which must be filled to improve our

In a nutshell:

- A standardized worldwide system of sensors to monitor the trends and drivers of biodiversity change will be required to help achieve the objectives of the Convention on Biological Diversity and the Intergovernmental Platform on Biodiversity and Ecosystem Services
- The rapid growth of remote-camera technology has the potential to contribute to such a network at the planetary scale (similar to the global meteorological sensor network)
- A growing number of case studies demonstrate the feasibility of using large-scale camera networks to monitor biodiversity trends across thousands of square kilometers of diverse habitats, including tropical forests and alpine ecosystems
- Modest investment in infrastructure combined with ongoing collaborative efforts to standardize metadata, field protocols, and databases could harness the power of remote-camera technology
- There is also a great opportunity to integrate the burgeoning interest of citizen scientists in remote-camera monitoring

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understanding of ecological patterns and processes at adequate spatial scales, and to quantify how human activities affect them (Schmeller *et al.* 2015).

To meet the global challenges in monitoring and conserving biodiversity, scientists and resource managers must evaluate changes in species composition, distribution, abundance, and response to anthropogenic impacts (Pereira *et al.* 2013). Technological, financial, and organizational constraints restrict most monitoring initiatives to one or a few species of concern over relatively small areas, thereby incorporating only a small selection of ecological processes. The result is a mismatch between the global scale of conservation needs and the localized availability of ecological data (Fraser *et al.* 2012). Data on ecological communities across multiple scales are vital to fully understand and anticipate anthropogenic effects, establish baselines, identify mechanisms of species decline, and formulate effective mitigation actions (Hampton *et al.* 2013). Remote sensing offers a promising means to integrate local in situ biodiversity data with globally available environmental data to test hypotheses about the effects of changing environments on biodiversity (Turner 2014).

Autonomously triggered cameras (also known as remote cameras or camera traps) are effective at sampling communities of medium- and large-sized birds and mammals, and we suggest that they can help biodiversity monitoring initiatives expand to the necessary scales and meet these global challenges. With recent advances in camera technology, reductions in cost, and increased interest in wildlife images as an outreach and education tool, the use of remote cameras has grown exponentially for the past 10–15 years, doubling every 2.9 years (Burton *et al.* 2015). The magnitude of current camera trapping efforts (eg Figure 1) demonstrates the broad geographic distribution, taxonomic diversity, and breadth of conservation issues that can be addressed with remote cameras. In this small sample of global camera studies (only those conducted by coauthors of this paper) there are on average 78 cameras deployed per study, totaling over 8000 camera sites (WebTable 1). We estimate that this represents, at most, 5% of present global efforts, and Burton *et al.*'s (2015) 10-year review included 20,000 camera locations – meaning that tens of thousands of cameras are already deployed across the planet.

Despite this increase and the concomitant accumulation of remote-camera data, coordination between camera studies rarely occurs, and resultant datasets can be fragmented, unstandardized, and difficult to integrate for broader biodiversity assessment and conservation (Meek *et al.* 2014). However, we draw attention here to a growing number of examples that illustrate regional, coordinated applications, and thereby demonstrate the global potential of remote cameras as a standardized monitoring platform for terrestrial vertebrate biodiversity. The recent emergence and coordination of remote cameras may, to some extent, mirror the coordination efforts of the world's earliest meteorological network in the late 19th and early 20th centuries. Progressing from disparate hand-calculated local forecasts early on, to using new computers emerging after World War II to provide medium-range forecasts, weather and climate forecasting data are now consolidated globally by the World Meteorological Organization, which combines data from ~20,000 weather stations, including many satellite sensor networks (Smith and Roulston 2002).

The complexity of ecosystem responses to human stressors, and the multiple spatial and temporal scales at which ecological processes affect biological conservation, require substantial amounts of data to be collected, stored, and processed (Kelling *et al.* 2009). Ecology is rapidly becoming larger scale in terms of collaborative networks, data intensification, and application (Peters *et al.* 2008; Reichman *et al.* 2011). Here, we review the present state of remote-camera use in ecology and conservation and provide a vision for expanding from individual, localized camera studies to coordinated regional and global camera networks. Surmountable gaps remain in our ability to effectively use these data to measure changes to regional and global biodiversity. Extant regional networks have worked through many of these challenges, which we review in part, and we suggest strategies for overcoming other real and perceived barriers to further growth. We conclude with recommendations on how to translate remote-camera science into effective tools for management and conservation.

Current applications of remote cameras to biodiversity conservation

Given the pressing need for biodiversity monitoring, an increasing number of remote-camera studies are now focusing on multiple species (Figure 1). Studies have progressed from the measurement of biodiversity's basic components (eg species abundance, distribution, richness) to applications that address underlying causes of biodiversity change. For example, remote cameras are an ideal tool to measure the effectiveness of highway crossing structures to improve multi-species landscape connectivity (Barrueto *et al.* 2014), test corridor models (McShea *et al.* 2016), and evaluate the effects of forest fragmentation on tropical species diversity and dominance (Ahumada *et al.* 2011). Camera surveys can also highlight how different life-history stages respond to disturbances; in one instance, cameras have identified key habitats linked to higher reproductive success in female grizzly bears (*Ursus arctos*; Fisher *et al.* 2014). Remote cameras are also increasingly used to address complex ecological interactions between animal behavior and climate change. For example, cameras helped to assess the impacts of climate change and trophic interactions on elk (*Cervus canadensis*; Brodie *et al.* 2014), to measure plant phenology and climate (Morisette *et al.* 2008), and to determine how large-mammal food webs respond

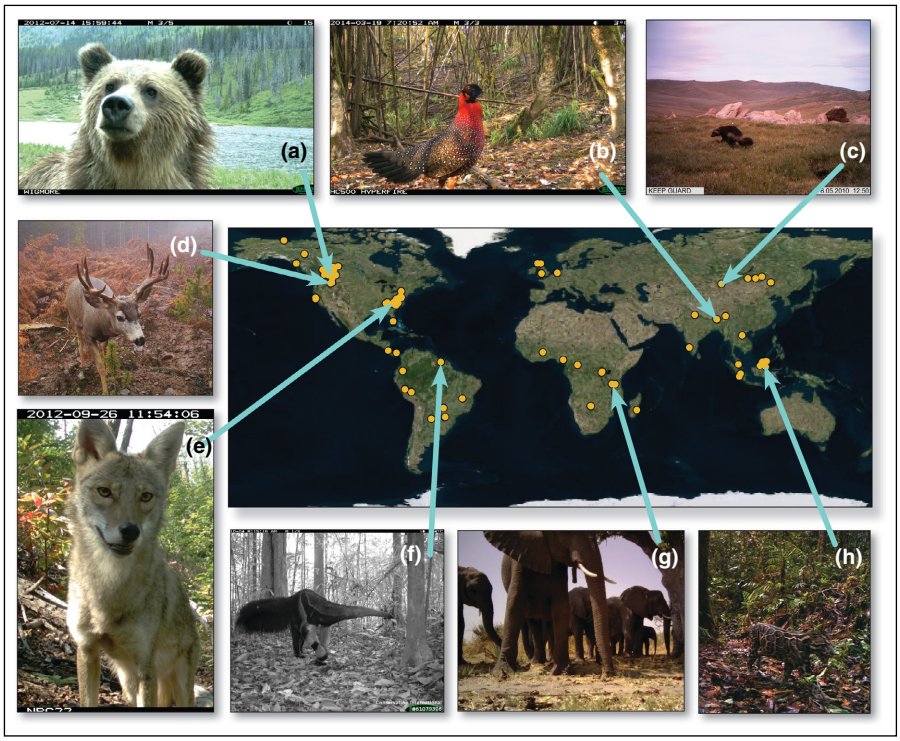

Figure 1. *Snapshot of recent global remote-camera studies. All study area locations where selected authors have used cameras to ask large-scale ecological questions are shown (on average, 78 cameras at each point; range 11–600), providing a glimpse of the ubiquity and diversity of current efforts around the world to collect ecological data using remote cameras. Cameras studies used in eMammal and TEAM projects are included. Focal species include: (a) grizzly bear* (Ursus arctos)*, (b) tragopan* (Tragopan blythii)*, (c) wolverine* (Gulo gulo)*, (d) mule deer* (Odocoileus hemionus)*, (e) coyote* (Canis latrans)*, (f) giant anteater* (Myrmecophaga tridactyla)*, (g) African bush elephant* (Loxodonta africana)*, and (h) clouded leopard* (Neofelis nebulosa)*. See WebTable 1 for more details.*

to forest fragmentation (Brodie *et al.* 2015). Furthermore, because they can measure the success of conservation actions (Dajun *et al.* 2006), including protected area effectiveness (Burton *et al.* 2011), cameras have been highlighted as tools to monitor local or regional biodiversity (Tobler *et al.* 2015). In fact, the Tropical Ecology Assessment and Monitoring Network (TEAM; www.teamnetwork.org) developed a conceptually simple camera-specific diversity metric called the Wildlife Picture Index (WPI; O'Brien *et al.* 2010), which summarizes the average proportional change in occupancy among species, and has been used to measure trends in the large-mammal communities of Mongolia (Townsend *et al.* 2014), Costa Rica (Ahumada *et al.* 2013), and most recently an entire network of forested tropical protected areas (Beaudrot *et al.* 2016).

Remote-camera projects usually target ground-dwelling vertebrates (mostly mammals), although some projects focus on arboreal mammals (Gregory *et al.* 2014), and "phenocams" are an emerging technology for monitoring phenology, snow cover, and disturbance events (Brown *et al.* 2016). Species commonly documented in remote-camera surveys, including large carnivores and herbivores, represent a critically important group for biodiversity maintenance (Ripple *et al.* 2014, 2015). Even small changes in vertebrate community composition can have large cascading effects throughout lower trophic levels in food webs, including affecting rates of primary productivity and decomposition (Hooper *et al.* 2012). Early detection and mitigation of population declines may be crucial to conservation. Moreover, active engagement among decision makers and citizen scientists in conservation is enhanced by photographs of these charismatic megafauna, because these species can act as effective conservation surrogates for large-scale conservation efforts across taxa (Di Minin and Moilanen 2014).

Many applications of camera data have yet to be fully exploited. Cameras are key to fill knowledge gaps in mammal distributions. As an example, Moriarty *et al.* (2009) used cameras to document the first evidence of wolverine (*Gulo gulo*) recolonization in California. Cameras can potentially assess range changes due to climate change. Photographic evidence could also be used to populate a skin coat database to assess the origins of poached animals, similar to contemporary genetic analogues (Mondol *et al.* 2014) but with the additional benefit of providing spatiotemporal data to help locate poachers.

As with museum specimens, the core data collected by remote cameras are spatiotemporally referenced "voucher" specimens documenting the occurrence of a species in situ. The Smithsonian Institution has started archiving remote-camera data, in the same way that specimens are preserved in museum collections (McShea *et al.* 2016; eMammal, emammal.org), and the Global Biodiversity Information Facility (GBIF; www.gbif.org) provides international open-access infrastructure to store and share such data – including imagery obtained from remote cameras – on all species. The digital specimen is an unobtrusive documentation of an animal in situ, in its habitat, with associated spatiotemporal data on behavior, temporal activity, heterospecifics, and environmental covariates.

Public interest in remote-camera imagery continues to grow, with coffee-table books now featuring remote-camera photography (Kays 2016). A frequent ancillary

goal of remote-camera projects is the production of imagery for use in communicating science and building support for biodiversity conservation. Many studies have harnessed the keen interest of citizen scientists to help maintain cameras (eg replacing batteries, memory cards; Barrueto *et al.* 2014; McShea *et al.* 2016) and to classify camera images (see below). Thus remote cameras contribute substantially to attainment of the first goal of the Aichi biodiversity target of the Convention on Biological Diversity's (CBD's) 2011–2020 Strategic Plan: "Address the underlying causes of biodiversity loss by mainstreaming biodiversity across government and society" (SCBD 2014).

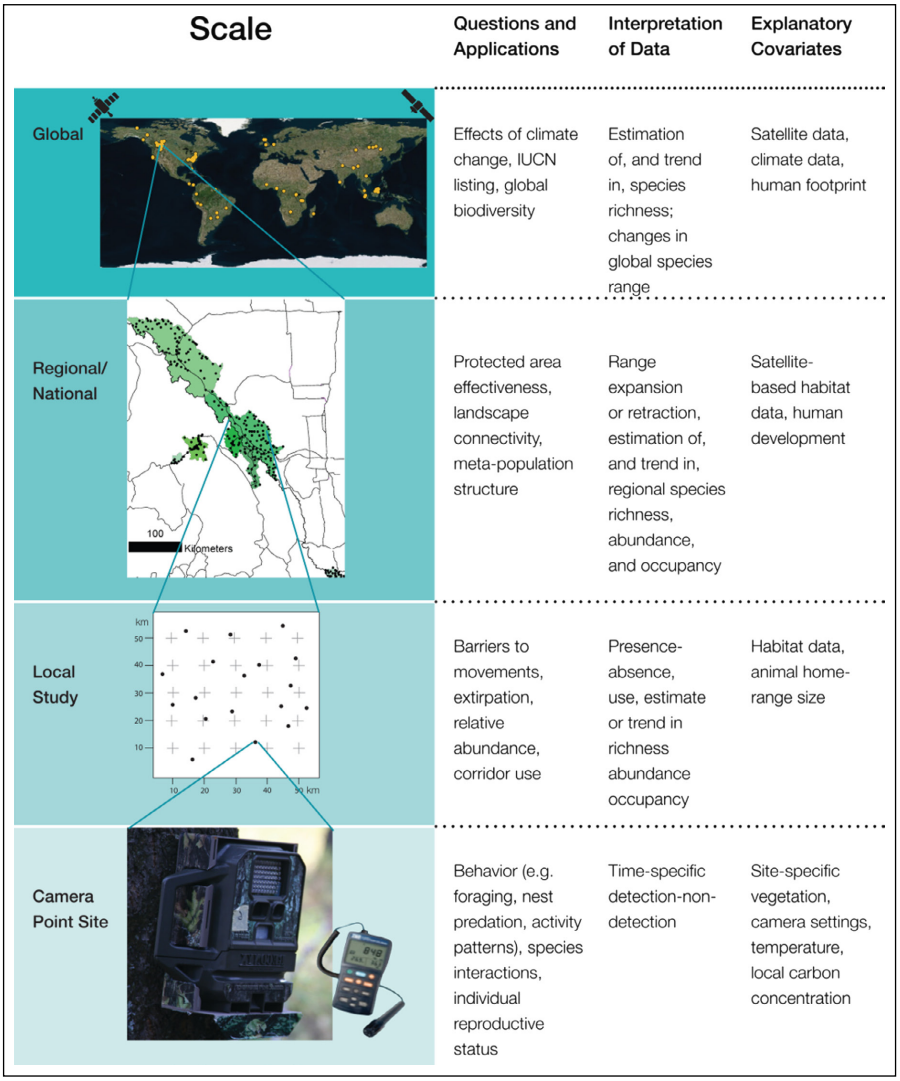

Figure 2. *How scaling up data collected from local in situ camera sites to higher levels of organization results in changes in the interpretation of the data, the ecological and conservation questions that can be asked, and the explanatory covariates required to answer these questions. The spatial scale of interest determines the meaning of data collected, availability of analyses, and the needed explanatory variables – all of which guide the application of camera data. The smallest scale is the local in situ camera site, which can be combined with other point data such as carbon metrics. Next, cameras are often deployed relative to an idealized camera trap grid. These grids can be coordinated across a network such as the Canadian mountain parks network and have the potential to be integrated across the globe with ever-increasing satellite-based data.*

Future vision: moving from local to global scales

Global policy frameworks, such as the CBD and IPBES, require ambitious and large-scale monitoring tools to ensure progress toward meeting their goals. To that end, ecological monitoring networks are striving to match the capacity of global weather monitoring by deploying ecological sensors, building data infrastructures, and refining statistical models for prediction (Keller *et al.* 2008). The first step toward an equivalent standardized global network for biodiversity is to link current in situ data streams with global-scale data, such as satellite-based remote sensing (Figure 2; Turner 2014). Linking and expanding current local remote-camera projects into nationally or internationally coordinated efforts permits continental and global-scale questions to be asked from locally point-sampled data (Figure 2). This scaling up from local to global requires not only time and money but also innovation and cooperation. Obstacles to the formation of a global remote-camera network – including standardization of field protocols and metadata, coordination among regional and international partners, and long-term funding for field and data management – are common to many forms of large-scale monitoring (Lindenmayer and Likens 2009). However, with the number of existing networks growing, as reported below, the barriers to a global biodiversity network are falling away. With more than 100 years of combined remote-camera experience, we offer suggestions on how to overcome the obstacles associated with starting regional-scale camera networks.

Getting on the same page: increasing sample size and standardizing protocols

Often, a perceived (or real) impediment to starting an individual camera study is the initial cost associated

with camera purchase. Improvements in camera technology continue to reduce their cost (as low as US$100), giving this technology a low cost per unit of sampled area and per species. Moreover, with proper protocols, personnel – including local wildlife guides, park rangers, anti-poaching patrollers, or volunteer citizen scientists – can be trained at a relatively minimal expense to service cameras, further reducing costs per sample, thereby facilitating larger sample sizes. For example, the eMammal project enlists more than 400 volunteers to maintain cameras in over 2000 locations across six US states (McShea *et al.* 2016); the Snapshot Wisconsin project also makes effective use of citizen scientists to maintain cameras across the state (www.snapshotwisconsin.org). Thus, financial and logistical barriers for operating cameras at large scales are becoming smaller and smaller.

Experimental design should be dictated by research objectives (Figure 3; Meek *et al.* 2014). Once a design is chosen, metadata reporting is critical for compiling image data for larger-scale analyses (Meek *et al.* 2014; Burton *et al.* 2015). Project metadata should include camera model and settings, number of camera sites, length of deployment, sampling design, and protocol, while site metadata should provide information such as GPS location, vegetative communities, and environmental conditions (Meek *et al.* 2014). TEAM is the world's largest remote-camera network, with 17 large camera arrays (~60 sampling points each) distributed across 15 countries (WebTable 1). Each site follows an identical standardized protocol to collect data on multiple vertebrate species, ensuring coordinated collection of metadata; other projects could follow this cohesive example. Similarly, Parks Canada provides a classic example of how local networks can scale up in spatial extent. With cameras emerging as a new tool to monitor biodiversity in the early 2000s, staff at Canadian national parks began experimenting with cameras for park-wide monitoring. With increased deployment came increased coordination and collaboration. Now, 10 years later, park personnel are using standardized methods to systematically distribute 350 cameras for year-round multi-species monitoring at seven national parks covering ~23,000 km^2 (Steenweg *et al.* 2016; see WebTable 1 for a list of similarly coordinated networks). Global integration of camera networks will ultimately require collecting equivalent metadata across camera studies. Metadata description standards for camera studies are now available (Meek *et al.* 2014; www.wildlifeinsights.org).

Statistical analyses and scaling up image classification

The first step in turning pictures into data is classifying the images, which can be labor intensive. With proper management, large volumes of photographic data can be rapidly catalogued using standard software: up to 1000 images per hour using minimally trained technicians or volunteers (Meek *et al.* 2014). eMammal capitalizes on its network of volunteers to help with this process and has classified over 2.6 million images (McShea *et al.* 2016). TEAM uses specialized software (Wild.ID), now available to any remote-camera project, to classify images and provide a project management framework for remote-camera projects to keep track of sampling periods, personnel, and even individual pieces of equipment (Fegraus *et al.* 2011; https://github.com/ConservationInternational/Wild.ID/archive/master.zip). Further efficiencies come with crowdsourcing image analysis, often with double classification techniques to reduce error (eg www.chimpandsee.org, www.chicagowildlifewatch.org, and www.snapshotwisconsin.org). One of the best-known projects is Snapshot Serengeti (www.snapshotserengeti.org), which includes 28,000 registered online volunteers and 10.8 million classified pictures from their park-wide camera project (Swanson *et al.* 2015). Software to allow researchers to crowdsource image processing is also freely available via www.zooniverse.org/lab.

There are a growing number of statistical approaches available to estimate abundance, distribution (occupancy), or species diversity from camera data (Figure 3). A major milestone in the development and application of camera data was the use of capture–recapture methodology to estimate density and other demographic parameters of tigers (*Panthera tigris*; Karanth 1995). This advancement contributed to the rapid and widespread adoption of remote cameras in population studies of species with uniquely identifiable individuals and has fueled the growth of spatially explicit capture–recapture methods (Royle *et al.* 2013). For all camera data, one key challenge is accounting for occasions when species were present but not detected at a sampling site (Royle and Dorazio 2008). One approach applied to camera data is to divide up the data that is continuously sampled over time into, for example, 1-week intervals, to mimic repeatedly sampling for abundance or occupancy estimation (Figure 3). In some circumstances, other methods using continuous detection probabilities can be more appropriate (Guillera-Arroita *et al.* 2011). Using raw detection rates as a measure of abundance is generally not recommended because it confounds true absence and undetected presence, ignoring detection issues (Sollmann *et al.* 2013). Nonetheless, use of these uncorrected relative abundance indices continues (Burton *et al.* 2015), perhaps because more sophisticated approaches require fine-scale understanding of how animals move in front of cameras to estimate animal density (eg Random Encounter Model; Rowcliffe *et al.* 2008) or necessitate the use of complicated hierarchical models. Hierarchical models are ideal for camera data analyses because they can contain two nested models: the first of the imperfect observation processes that led to the observed data, which is nested within a second model of the ecological process of interest

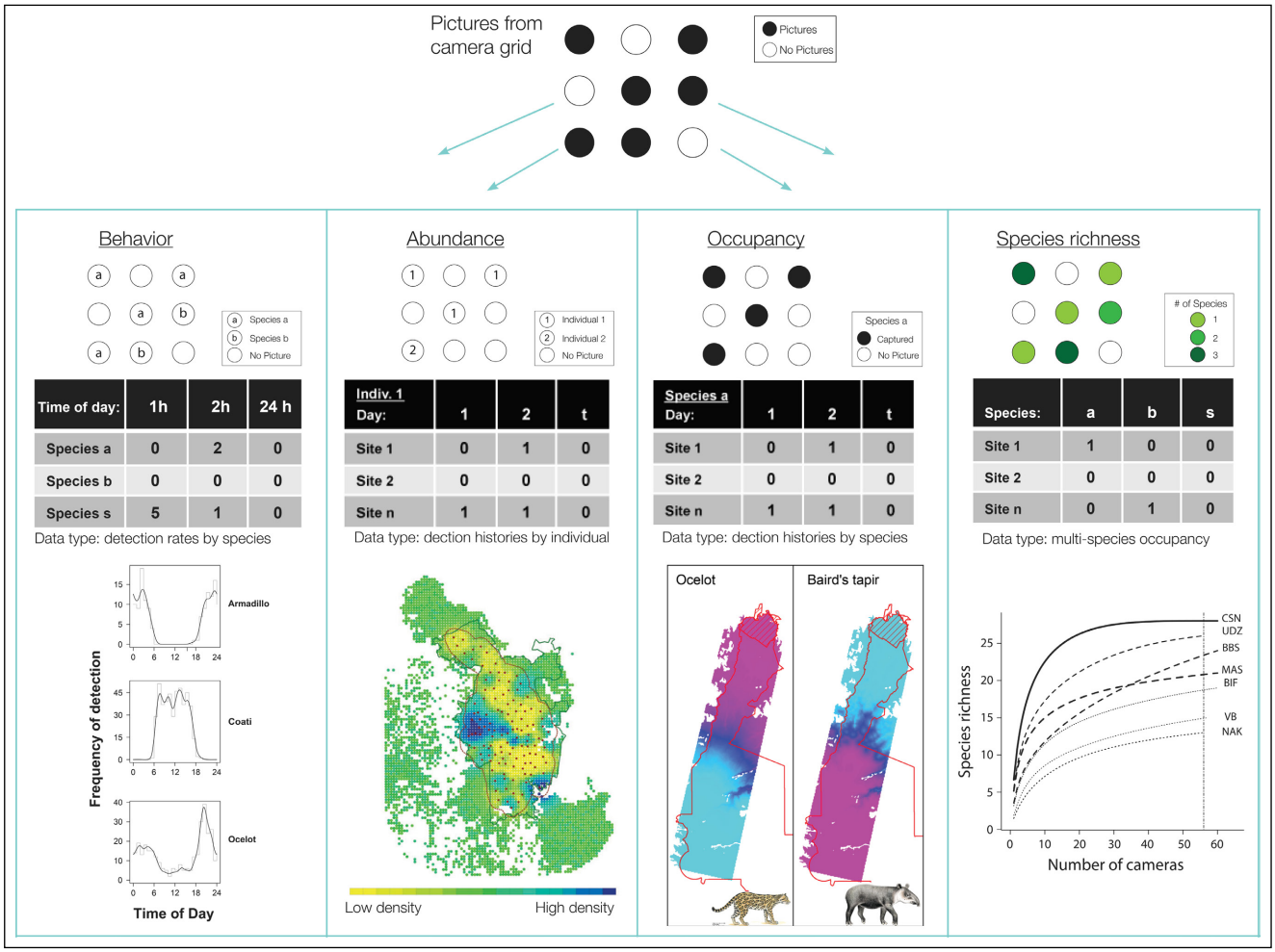

Figure 3. *Common groups of statistical analyses performed on camera data. Data collected from the same local camera grid can be easily analyzed to answer many different types of questions including: temporal and spatial behavior patterns (subfigure modified from Rowcliffe* et al. *[2014]), spatially explicit abundance (Gopalaswamy* et al. *2012; reproduced by permission of John Wiley and Sons), occupancy (Ahumada* et al. *2013), and species richness (Ahumada* et al. *2011; reproduced by permission of the Royal Society).*

(eg how abundance changes over space; Figure 3). Hierarchical models have been used to scale up regional estimates of species occupancy and relative abundance to large-scale assessments of factors affecting species richness (Tobler *et al.* 2015; Sutherland *et al.* 2016). These models are now becoming more widely available with the release of recent books (eg Kéry and Royle 2016), open source software (eg White and Burnham 1999; Fiske and Chandler 2015), and active web forums (eg groups.google.com/forum/#!forum/unmarked and groups.google.com/forum/?hl=en#!forum/hmecology).

One challenge with camera data is communicating how the distribution and abundance of multiple species change across numerous regions over time. One proposed solution is the aforementioned WPI (Figure 3; O'Brien *et al.* 2010). Trends in WPI can be examined at multiple scales of interest to understand scale-specific causes of decline. WPI is one of the indicators for CBD's Target 12 (preventing species extinctions), fulfilling a critical need in tropical terrestrial biodiversity trend monitoring, but many logical improvements in methodology are achievable. For example, it is now possible to jointly model species richness across study areas to share detection information (Sutherland *et al.* 2016), and some diversity studies with cameras account for species that, despite previous evidence that they are present, were not detected during the study (Rovero *et al.* 2014). WPI is based on occupancy estimation from detection/non-detection data, but recent work has estimated abundance from such data (Chandler and Royle 2013) and thus may provide an avenue for moving beyond detection-corrected species richness to more sophisticated abundance-based diversity measures (Chao *et al.* 2014).

Dealing with data: management, storage, sharing, and access

A final challenge to scaling up remote-camera data collection is improving data storage and management, especially given the storage requirements associated with

image files, which can often be large. Regional or global biodiversity databases should be tailored to camera data in an easy-to-use, accessible, and open-source format. Existing database platforms host and facilitate the management of large quantities of other types of shared ecological data. MOVEBANK (www.movebank.org), for instance, archives the ever-growing amount of animal movement data (Kays *et al.* 2015). A promising platform for camera data management – based upon the experience of eMammal, TEAM, Smithsonian Institution, Wildlife Conservation Society, and the North Carolina Museum of Natural History – is the federated Wildlife Insights project (wildlifeinsights.org), which was developed to streamline data management and integrate camera data with other in situ data streams such as that of forest carbon and gaseous flux (McShea *et al.* 2016). This integration will allow scientists to better connect patterns in biodiversity change with the ultimate causes of biodiversity declines. If camera data descriptions begin to follow biodiversity information standards for multimedia data (eg proposed by Meek *et al.* [2014]; Wildlife Insights), these data could make an important contribution to wider global networks of biodiversity databanks such as GBIF, IUCN's Red List, and Map of Life (https://mol.org).

When combining data from disparate studies worldwide, intellectual property rights and privacy needs must also be considered; otherwise, without assurances that such matters will be respected, researchers may be reluctant to contribute their data. For instance, because of privacy concerns, Parks Canada only releases image data verified to exclude any identifiable likenesses of park visitors. Similarly, some researchers may want to withhold information on geographical locations of endangered species to prevent an increase in poaching, while others may wish to maintain publishing rights to their data. MOVEBANK has a tested model, offering several user-controlled levels of data security – ranging from open access to restricted – with regard to viewing, accessing, and storing data on its database. Such flexibility provides a means to meet every user's intellectual property rights and privacy needs, while striving toward an open data philosophy.

Conclusions

There is a pressing need for increased coordination of remote-camera surveys to effectively monitor global biodiversity. The non-invasive nature of remote cameras and their decreasing costs continue to hasten their adoption at multiple scales. Using concrete examples, we have demonstrated how issues associated with camera servicing – as well as with data classification, storage, and management – have been overcome to synthesize and coordinate regional networks. We suggest these efforts can be scaled up to create a global network of remote cameras, which would provide a unique picture of the Earth to complement other remote-sensing methods critical to documenting and mitigating the current biodiversity crisis.

Given these advancements in remote-camera science, we have three recommendations for further integration of camera data into biodiversity monitoring. First, we reiterate the need for standardizing metadata collection and data storage. Agreeing to a global industry standard will greatly facilitate the usefulness of the plethora of data being collected (Meek *et al.* 2014). Second, additional support is required to provide a global infrastructure to facilitate building partnerships among existing projects and increase local support for new camera projects that can be more explicitly linked to regional and global camera networks. To do so, it would be important to tap into existing collaborative networks (eg TEAM, eMammal, Parks Canada) to facilitate regional collaboration. With broad cross-institutional support, such a framework would offer important opportunities in monitoring biodiversity worldwide. Finally, institutions such as GEO BON and GBIF could benefit from increasing their rate of adoption of camera data, which not only have great capacity to be standardized and expanded for the purposes of biodiversity monitoring, but can also contribute to the generation of EBVs (Pereira *et al.* 2013) for terrestrial vertebrates, and complement other indices (eg the Living Planet Index; livingplanetindex.org). The public appeal of remote-camera images and citizen-scientist participation will continue to facilitate biodiversity monitoring at larger scales and help to ensure effective conservation outcomes.

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