

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

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## Global biodiversity monitoring with remote cameras

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28 camera, remote sensing.

### 29 **Abstract**

30 Countries committed to implementing the Convention on Biological Diversity's 2011-2020 strategic  
31 plan need effective tools to monitor global trends in biodiversity. Remote cameras are a rapidly  
32 growing technology that has great potential to transform global biodiversity monitoring and  
33 contribute to the call for measuring Essential Biodiversity Variables. Recent advances in camera  
34 technology and methods enable researchers to estimate changes in abundance and distribution for  
35 entire communities of animals, and identify global drivers of biodiversity trends. We suggest that  
36 interconnected networks of remote cameras will soon monitor biodiversity at a global scale and guide  
37 conservation policy. This global network will require greater collaboration among camera studies and  
38 citizen scientists, including standardized metadata, shared protocols, and security measures to protect  
39 the records of sensitive species. With modest investment in infrastructure and continued innovation,  
40 we envision a global network of remote cameras that will provide real-time biodiversity data while  
41 connecting people with nature.

### 42 **In a nutshell:**

- 43 • Global biodiversity conservation needs a global standardized sensor system to monitor trends  
44 and drivers of biodiversity change to help achieve the needs of the Convention on Biological  
45 Diversity and the Intergovernmental Platform on Biodiversity and Ecosystem Services
- 46 • The rapid growth of remote-camera technology has the potential to provide this sensor  
47 network to effectively monitor biodiversity at global scales, akin to the global meteorological  
48 sensor network
- 49 • A growing number of case studies demonstrate the feasibility of large-scale camera networks  
50 to monitor biodiversity trends across 1000's of km<sup>2</sup> of diverse habitats, including tropical  
51 forests, alpine ecosystems, and beyond
- 52 • Modest investment in infrastructure combined with on-going collaborative efforts to  
53 standardize metadata, field protocols, and databases could harness the incredible power of  
54 remote camera technology
- 55 • Scientists alone need not bear the burden; there are many examples of viable ways to integrate  
56 the burgeoning interest of citizen scientists in remote camera monitoring

### 57 **Introduction**

58 Declining biodiversity is a reality of the Anthropocene, and society is lagging to meet international  
59 biodiversity targets (Butchart *et al.*, 2010; Secretariat of the Convention on Biological Diversity,  
60 2014). From Carnivora to Coleoptera, biodiversity is declining across the globe due to human  
61 activities (Butchart *et al.* 2010). Rare species are becoming rarer, geographic ranges are constricting,  
62 and species are going extinct (Dirzo *et al.*, 2014). Monitoring these changes to biodiversity is a  
63 global priority required by international treaties (Secretariat of the Convention on Biological  
64 Diversity, 2014) and coordinated by international networks like the Group on Earth Observations  
65 Biodiversity Observation Network (GEO BON; [earthobservations.org/geobon.shtml](http://earthobservations.org/geobon.shtml)) which has made  
66 a global call for the measurement of Essential Biodiversity Variables (EBVs; Pereira *et al.*, 2013).  
67 With growing concern and funding for maintaining the health of our planet (Tittensor *et al.*, 2014),  
68 real-time biodiversity monitoring is key to identifying and addressing large-scale ecological threats.

69 The Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) was created in  
70 2012 with the unambiguous goal of strengthening the interface between science and policy to  
71 improve biodiversity conservation outcomes, emulating the successful issue-specific policy focus of  
72 the Intergovernmental Panel on Climate Change (IPCC; Mooney and Tallis, 2014). An important  
73 distinction between IPBES and the IPCC, however, is that the latter has a global network of  
74 standardized weather sensors to track changes and inform predictions about future climate.

75 Conversely, biodiversity data are typically collected to serve local objectives, and may not be  
76 suitably standardized to provide effective measures of global change. An international biodiversity  
77 network remains a major gap, and filling this gap is imperative to improve our understanding of  
78 ecological patterns and processes at adequate spatial scales, and to quantify how human activities  
79 affect them (Schmeller *et al.*, 2015).

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

91 Autonomously triggered cameras (also known as remote cameras, or camera traps) are effective  
92 at sampling communities of medium and large sized birds and mammals, and we suggest that they  
93 can help biodiversity monitoring initiatives expand to the necessary scales and meet these global  
94 challenges. With recent advances in camera technology, reduction in cost, and increased interest in  
95 wildlife images as an outreach and education tool, the use of remote cameras has grown  
96 exponentially for the past 10-15 years, doubling every 2.9 years (Burton *et al.*, 2015). Figure 1  
97 scratches the surface of the magnitude of current camera trapping efforts, demonstrating the broad  
98 geographic distribution, taxonomic diversity, and breadth of conservation issues addressed with  
99 remote cameras. In this haphazard sample of global camera studies (only those conducted by  
100 coauthors of this paper) there are on average 78 cameras deployed per study, totaling over 8,000  
101 camera sites (WebTable 1). We estimate that this represents, at most, 5% of current global efforts and  
102 Burton *et al.*'s (2015) 10-year review included 20,000 camera locations — meaning that tens of  
103 thousands of cameras are already deployed across the planet.

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

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

### 128 **Current applications of remote cameras to biodiversity conservation**

129 Given the pressing need for biodiversity monitoring, an increasing number of remote camera studies  
130 are now focusing on multiple species (Figure 1). Studies now extend beyond the nuts and bolts  
131 mensuration of biodiversity components (abundance, distribution, species richness) to applications  
132 that address underlying causes of biodiversity change. For example, remote cameras are an ideal tool  
133 to measure the effectiveness of highway crossing structures to improve multi-species landscape  
134 connectivity (Barrueto *et al.*, 2014), test corridor models (McShea *et al.*, 2015), and evaluate the  
135 effects of forest fragmentation on tropical species diversity and dominance (Ahumada *et al.*, 2011).  
136 Camera surveys can also highlight how different life-history stages respond differently to  
137 disturbances; for example, cameras have identified key habitats linked to higher female grizzly bear  
138 reproductive success (Fisher *et al.*, 2014). Remote cameras are also increasingly used to address  
139 complex ecological interactions between animal behavior and climate change. For example, cameras  
140 were used to assess the impacts of climate change and trophic interactions on elk (Brodie *et al.*,  
141 2014), to measure plant phenology and climate (Morissette *et al.*, 2008), and to determine how large-  
142 mammal food webs respond to forest fragmentation (Brodie *et al.*, 2015). Furthermore, cameras can  
143 measure the success of conservation actions (Dajun *et al.*, 2006), including protected area  
144 effectiveness (Burton *et al.*, 2011), such that cameras are highlighted as tools to monitor local or  
145 regional biodiversity (Tobler *et al.*, 2015). For example, a camera-specific diversity metric, the  
146 Wildlife Picture Index (WPI; O'Brien *et al.*, 2010), has been used to measure trends in large-mammal  
147 communities of Mongolia (Townsend *et al.*, 2014), Costa Rica (Ahumada *et al.*, 2013) and most  
148 recently, on a entire network of forested tropical protected areas (Beaudrot *et al.*, 2016).

149 Remote camera projects usually target ground-dwelling vertebrates (mostly mammals),  
150 although there are examples focused on arboreal mammals (Gregory *et al.*, 2014), and “phenocams”  
151 are an emerging technology for monitoring phenology, snow cover, and disturbance events (Brown

152 *et al.*, 2016). Species commonly documented in remote camera surveys represent a critically  
153 important group for biodiversity maintenance, including large carnivores and herbivores (Ripple *et*  
154 *al.*, 2014, 2015). Even small changes in vertebrate community composition can have large cascading  
155 effects throughout lower trophic levels in food webs, including rates of primary productivity and  
156 decomposition (Hooper *et al.*, 2012). Early detection and mitigation of population declines may be  
157 crucial to conservation. Moreover, actively engaging decision makers and citizen scientists in  
158 conservation is enhanced by photographs of these charismatic mega-fauna, which can act as effective  
159 conservation surrogates for large-scale conservation across taxa (Di Minin and Moilanen, 2014).

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

166 As with museum specimens, the core data collected by remote cameras are spatiotemporally  
167 referenced 'voucher' specimens documenting the occurrence of a species *in situ*. The Smithsonian  
168 Institution has started archiving remote camera data similar to museum collections (McShea *et al.*  
169 2015; eMammal, [emammal.org](http://emammal.org)) and the Global Biodiversity Information Facility (GBIF;  
170 [www.gbif.org](http://www.gbif.org)) provides international open-access infrastructure to collect such data on all species,  
171 including remote camera data. The digital specimen is a non-invasive documentation of an animal *in*  
172 *situ*, in its habitat, with associated spatiotemporal data on behavior, temporal activity, heterospecifics,  
173 and environmental covariates.

174 The public interest in remote camera imagery continues to grow, with coffee-table books now  
175 featuring remote camera photography (Kays, 2016). A frequent ancillary goal of remote camera



176 projects is the production of imagery for use in science communication and building support for  
177 biodiversity conservation. Many studies have harnessed the keen interest of citizen scientists to help  
178 maintain cameras (e.g., replacing batteries, memory cards; Barrueto *et al.*, 2014; McShea *et al.* 2015),  
179 and to classify camera images (see below). Thus remote cameras significantly contribute to the first  
180 goal of the Aichi biodiversity target of the Convention on Biological Diversity (CBD)'s 2011-2020  
181 Strategic Plan: "Address the underlying causes of biodiversity loss by mainstreaming biodiversity  
182 across government and society" (Secretariat of the Convention on Biological Diversity, 2014).

### 183 **Future vision: moving from local to global scales**

184 Global policy frameworks, like the CBD and IPBES, require equally ambitious and large-scale  
185 monitoring tools to ensure progress toward meeting their goals. To meet this need, ecological  
186 monitoring networks are striving to match the capacity of global weather monitoring through  
187 deploying ecological sensors, building data infrastructures, and refining statistical models for  
188 prediction (Keller *et al.*, 2008). The first step towards an equivalent standardized global network for  
189 biodiversity is to link current *in situ* data streams with global-scale data, for example, satellite-based  
190 remote sensing (Turner, 2014; Figure 2). Linking together and expanding current local remote  
191 camera projects into nationally or internationally coordinated efforts, permits continental and global-  
192 scale questions to be asked from locally point-sampled data (Figure 2). This scaling up from local to  
193 global requires not only the usual fuel of human endeavors—time and money—but also innovation  
194 and cooperation. Obstacles to the formation of a truly global remote camera network are common to  
195 many forms of large-scale monitoring; these include standardization of field protocols and metadata,  
196 coordination among regional and international partners, and long-term funding for field and data  
197 management (Lindenmayer and Likens, 2009). But with the number of existing networks growing as  
198 reported below, the barriers to a truly global biodiversity network are falling away. By pulling from

199 100+ years of combined remote camera experience among the authors, we supply some lessons in  
200 overcoming these obstacles when starting regional-scale camera networks.

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

202 Often, a perceived (or real) impediment to starting an individual camera study is the initial cost  
203 associated with camera purchase. Improvements in camera technology continues to reduce their cost  
204 (as low as \$100 US) giving this technology a low cost per unit of sampled area and per species.  
205 Further, with proper protocols, relatively inexpensive local wildlife guides, park rangers, anti-  
206 poaching patrollers or volunteer citizen scientists can be trained to service cameras, further reducing  
207 costs per sample, and thus facilitating larger sample sizes. For example, the eMammal project enlists  
208 more than 400 volunteers to run cameras in over 2000 locations across six US states (McShea *et al.*,  
209 2015), and the Snapshot Wisconsin project makes effective use of citizen scientists to maintain  
210 cameras across the state ([www.snapshotwisconsin.org](http://www.snapshotwisconsin.org)). Financial and logistical barriers for running  
211 cameras at large scales, therefore, are becoming smaller and smaller.

212 Experimental design should be dictated by research objectives (Figure 3; Meek *et al.* 2014). Once  
213 a design is chosen, metadata reporting is critical for compiling image data for larger-scale analyses  
214 (Meek *et al.* 2014, Burton *et al.* 2015). For example, project metadata should include camera model  
215 and settings, number of cameras sites, length of deployment, sampling design and protocol, and site  
216 metadata including GPS location, vegetative community, and environmental conditions (Meek *et al.*  
217 2014). The Tropical Ecology Assessment and Monitoring Network (TEAM; [www.teamnetwork.org/](http://www.teamnetwork.org/))  
218 is the world's largest remote camera network with 17 large camera arrays (~60 sampling points  
219 each), distributed across 15 countries (WebTable 1). Each site follows an identical standardized  
220 protocol to collect data on multiple vertebrate species, ensuring coordinated collection of metadata,  
221 and other projects could follow this cohesive example. Similarly, Parks Canada provides an  
222 archetypal example of how local networks can scale up in spatial extent. With cameras emerging as a

223 new tool to monitor biodiversity in the early 2000s, individual national parks began experimenting  
224 with cameras for park-wide monitoring. With increased deployment came increased coordination and  
225 collaboration. Now, ten years later, 7 national parks covering ~23,000 km<sup>2</sup> are using standardized  
226 methods to systematically distribute 350 cameras for year-round multi-species monitoring (Steenweg  
227 *et al.*, 2016); the list of similarly coordinated networks grows (WebTable 1). Continuing towards  
228 agreement on collecting matching metadata across camera studies is needed for global integration of  
229 camera networks. Standards for metadata descriptions for camera studies are now available (Meek *et*  
230 *al.* 2014; [www.wildlifeinsights.org](http://www.wildlifeinsights.org)).

### 231 **Statistical analyses and scaling up image classification**

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

247 Now there is a growing number of statistical approaches available to estimate abundance,  
248 distribution (occupancy), or species diversity from camera data (Figure 3). A major milestone in the  
249 development and application of camera data was the use of capture-recapture methodology to  
250 estimate density and other demographic parameters of tigers (Karanth 1995). This advancement  
251 contributed to the rapid and widespread adoption of remote cameras in population studies of species  
252 with uniquely-identifiable individuals and has fueled the growth of spatially explicit capture-  
253 recapture methods (Royle et al. 2014). For all camera data, one key challenge is accounting for  
254 occasions when species were present but not detected at a sampling site (Royle and Dorazio, 2008).  
255 One approach applied to camera data is to discretize the continuous sample to mimic a repeated site  
256 visit framework of abundance or occupancy estimation (Figure 3), though other methods using  
257 continuous detection probabilities can be more appropriate (Guillera-Arroita *et al.*, 2011). Using raw  
258 detection rates as a measure of abundance is generally not recommended because it confounds true  
259 absence and undetected presence, ignoring detection issues (Sollmann *et al.*, 2013). Nonetheless, use  
260 of these uncorrected relative abundance indices continues (Burton *et al.*, 2015), perhaps because  
261 more sophisticated approaches require the collection of ancillary movement data to estimate animal  
262 density (e.g. Random Encounter Model; Rowcliffe *et al.*, 2008) or the use of complicated hierarchical  
263 models. Hierarchical models are ideal for camera data analyses because they model biological and  
264 imperfect observation processes that lead to observed data, nested within a model of the ecological  
265 process of interest (e.g. how abundance changes over space; Figure 3). Hierarchical models have  
266 been used to scale up regional estimates of species occupancy and relative abundance to large-scale  
267 assessments of factors affecting species richness (Tobler *et al.* 2015, Sutherland *et al.*, 2016). These  
268 models are now becoming more available with the release of recent books (e.g. Kery and Royle,  
269 2016), open source software (e.g. Fiske and Chandler, 2015; White and Burnham, 1999) and active

270 web forums for quick and friendly help (e.g. [groups.google.com/forum/#!forum/unmarked](https://groups.google.com/forum/#!forum/unmarked) and  
271 [groups.google.com/forum/?hl=en#!forum/hmecology](https://groups.google.com/forum/?hl=en#!forum/hmecology)).

272 One challenge with camera data is communicating how the distribution and abundance of  
273 multiple species change across numerous regions, over time. One proposed solution is the wildlife  
274 picture index (WPI; Figure 3; O'Brien *et al.*, 2010) a conceptually simple metric developed by  
275 TEAM that summarizes the average proportional change in occupancy among species. Mechanisms  
276 of change in WPI can be examined at multiple scales of interest to understand scale-specific causes  
277 of decline. WPI is one of the indicators for CBD's Target 12 (preventing species extinctions),  
278 fulfilling a critical need in tropical terrestrial biodiversity trend monitoring, but many logical  
279 improvements in methodology are possible. For example, it is now possible to jointly model species  
280 richness across study areas to share detection information (Sutherland *et al.*, 2016) and some  
281 diversity studies with cameras account for species that were never detected during the entire study  
282 (Rovero *et al.* 2014). WPI is based on occupancy estimation from detection/non-detection data, but  
283 recent work has estimated abundance from such data (Chandler and Royle, 2013) and thus, may  
284 provide an avenue for moving beyond detection-corrected species richness to more sophisticated  
285 abundance-based diversity measures (Chao *et al.*, 2014).

### 286 **Dealing with data: management, storage, sharing and access**

287 A final challenge to scaling up remote camera data collection is improving data storage and  
288 management, especially given the large storage requirements for images. Regional or global  
289 biodiversity databases are needed that are tailored to camera data in an easy-to-use, accessible and  
290 open-source format. Database platforms are already developed that host and facilitate the  
291 management of large quantities of other types of shared ecological data. MOVEBANK  
292 ([www.movebank.org](http://www.movebank.org)), for example, archives the ever-growing amount of animal movement data  
293 (Kays *et al.*, 2015). A promising platform for camera data management, based upon the experience of

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294 eMammal, the TEAM network, Smithsonian Institution, Wildlife Conservation Society and the North  
295 Carolina Museum of Natural History, is the federated Wildlife Insights project ([wildlifeinsights.org](http://wildlifeinsights.org)).  
296 This latter database was developed to streamline data management and integrate camera data with  
297 other *in situ* data streams such as forest carbon, gaseous flux, and other environmental monitoring  
298 (McShea et al. 2015). This integration will allow scientists to better connect patterns in biodiversity  
299 change with the ultimate causes of declines in biodiversity. If camera data descriptions begin to  
300 follow biodiversity information standards for multimedia data (e.g. proposed by Meek *et al.* 2014;  
301 Wildlife Insights) these data could make an important contribution to wider global networks of  
302 biodiversity databanks such as GBIF, IUCN's Red list, and Map of Life (<https://mol.org/>).

303 A final consideration when combining data from globally disparate studies is addressing  
304 intellectual property rights and privacy needs. Individual studies may be reluctant to contribute data  
305 without such reassurances. For example, for privacy reasons, Parks Canada will never release image  
306 data until it is certain it contains no images of any visitors to the parks. Similarly, some studies may  
307 not want to release geographical locations of particular endangered species for fear of increasing  
308 poaching; or researchers may want to maintain publishing rights to their data. MOVEBANK has a  
309 tested model, offering several user-controlled levels of data security to collaborators wishing to store  
310 data on the server. These options range from completely open access to completely invisible, where  
311 the user controls who can see, use, access, or request collaboration on data contributed to the  
312 database. Such flexibility provides a means to meet every user's intellectual property rights and  
313 privacy needs, while still striving towards an open data philosophy.

### 314 **Conclusions**

315 There is a pressing need for increased coordination of remote camera surveys to achieve effective  
316 global biodiversity monitoring. The non-invasive nature of remote cameras and their decreasing costs  
317 continues to hasten their adoption at every scale. Using concrete examples, we have demonstrated

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318 how barriers to camera servicing, data classification, storage and management have been overcome to  
319 achieve synthesized coordinated regional networks. We suggest these efforts can be scaled up to  
320 create a global network of remote cameras that would provide a unique picture of our planet to  
321 complement other remote biodiversity sensing methods critical to documenting and mitigating the  
322 current biodiversity crisis.

323         Given these advancements in remote camera science, we have three recommendations for  
324 further integration of camera data into biodiversity monitoring. First, we reiterate the need for  
325 standardizing metadata collection and data storage. Agreeing to a global industry standard will  
326 greatly facilitate the usefulness of the plethora of data being collected (Meek *et al.*, 2014). Second,  
327 greater support is required to provide a global infrastructure to improve collaborations among  
328 existing projects and increase local buy-in for new camera projects that can be more explicitly linked  
329 to regional and global camera networks. To do so, it would be important to tap into extant  
330 collaborative networks to facilitate regional collaboration (e.g. TEAM, eMammal, Parks Canada).  
331 With broad cross-institutional support, tremendous opportunities could be gained when capitalizing  
332 on this framework for global biodiversity monitoring. Lastly, institutions like GEO BON and GBIF  
333 could benefit from increasing their rate of adoption of camera data as one of the most standardizable  
334 and expandable data types for biodiversity monitoring, as they can contribute to the generation of  
335 Essential Biodiversity Variables (Pereira *et al.*, 2013) for terrestrial vertebrates and complement other  
336 indices like the Living Planet Index ([livingplanetindex.org](http://livingplanetindex.org)). The public appeal of remote camera  
337 images and citizen-scientist participation will continue to scale-up biodiversity monitoring and excite  
338 public support to ultimately help make successes in global conservation possible.

339

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348

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509 **Figure 1.** Snapshot of recent global remote camera studies. All study area locations where authors  
510 have used cameras to ask large-scale ecological questions are located on map (on average, 78  
511 cameras at each point; range 11-600), providing a glimpse of the ubiquity and diversity of current  
512 efforts around the world to collect ecological data using remote cameras. Cameras studies used in  
513 eMammal and TEAM projects are included. (A) grizzly bear (*Ursus arctos*) (B) tragopan (*Tragopan*  
514 *blythii*) (C) wolverine (*Gulo gulo*) (D) mule deer (*Odocoileus hemionus*) (E) coyote (*Canis latrans*)  
515 (F) giant anteater (*Myrmecophaga tridactyla*) (G) African bush elephant (*Loxodonta africana*) (H)  
516 clouded leopard (*Neofelis nebulosa*). See WebTable 1 for more details of each study included on  
517 map.

518  
519 **Figure 2.** How scaling up data collected from local *in situ* camera sites to higher levels of  
520 organization results in changes in the interpretation of the data, the ecological and conservation  
521 questions that can be asked, and the explanatory covariates required to answer these questions. The  
522 spatial scale of interest determines the meaning of data collected, availability of analyses, and the  
523 needed explanatory variables, therefore, guiding the application of camera data. The smallest scale is  
524 the local *in situ* camera site that can be combined with other point data such as carbon metrics. Next,  
525 cameras are often deployed relative to an idealized camera trap grid. These grids can be coordinated  
526 across a network such as the Canadian mountain parks network, which have the potential to be  
527 integrated across the globe with ever-increasing satellite data.

528  
529 **Figure 3.** Common groups of statistical analyses performed on camera data. Data collected from the  
530 same local camera grid can be easily analyzed to answer many different types of questions including  
531 temporal and spatial behaviour patterns (subfigure modified from Rowcliffe *et al.*, 2014); spatially  
532 explicit abundance (Gopaldaswamy *et al.*, 2012; reproduced by permission of John Wiley and Sons);  
533 occupancy (Ahumada *et al.*, 2013); and species richness (Ahumada *et al.*, 2011; reproduced by  
534 permission of the Royal Society).