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

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Keywords: applied conservation, big data, biodiversity, citizen science, global, monitoring, remote camera, remote sensing.

Abstract

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 biodiversity monitoring and contribute 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 identify global drivers of biodiversity trends. We suggest that interconnected networks of remote cameras will soon monitor biodiversity at a global scale and guide conservation policy. This global network will require greater collaboration among camera studies and citizen scientists, including standardized metadata, shared protocols, and security measures to protect the records of sensitive species. With modest investment in infrastructure and continued innovation, we envision a global network of remote cameras that will provide real-time biodiversity data while connecting people with nature.

In a nutshell:

- Global biodiversity conservation needs a global standardized sensor system to monitor trends and drivers of biodiversity change to help achieve the needs 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 provide this sensor network to effectively monitor biodiversity at global scales, akin to the global meteorological sensor network
- A growing number of case studies demonstrate the feasibility of large-scale camera networks to monitor biodiversity trends across 1000's of km^2 of diverse habitats, including tropical forests, alpine ecosystems, and beyond
- Modest investment in infrastructure combined with on-going collaborative efforts to standardize metadata, field protocols, and databases could harness the incredible power of remote camera technology
- Scientists alone need not bear the burden; there are many examples of viable ways to integrate the burgeoning interest of citizen scientists in remote camera monitoring

Introduction

Declining biodiversity is a reality of the Anthropocene, and society is lagging to meet international biodiversity targets (Butchart *et al.*, 2010; Secretariat of the Convention on Biological Diversity, 2014). From Carnivora to Coleoptera, biodiversity is declining 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 (Secretariat of the Convention on Biological Diversity, 2014) and coordinated by international networks like the Group on Earth Observations Biodiversity Observation Network (GEO BON; earthobservations.org/geobon.shtml) which has made a global call for the measurement of Essential Biodiversity Variables (EBVs; Pereira *et al.*, 2013). With growing concern and funding for maintaining the health of our 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 unambiguous 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, and filling this gap is imperative to improve our understanding of ecological patterns and processes at adequate spatial scales, and to quantify how human activities affect them (Schmeller *et al.*, 2015).

To meet global challenges in monitoring and conserving biodiversity, we need to 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 needed 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, reduction 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). Figure 1 scratches the surface of the magnitude of current camera trapping efforts, demonstrating the broad geographic distribution, taxonomic diversity, and breadth of conservation issues addressed with remote cameras. In this haphazard sample of global camera studies (only those conducted by coauthors of this paper) there are on average 78 cameras deployed per study, totaling over 8,000 camera sites (WebTable 1). We estimate that this represents, at most, 5% of current 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 of multiple 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 truly global potential of remote cameras as a standardized monitoring platform for terrestrial vertebrate biodiversity. The current emergence of remote cameras and its coordination 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 that 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 its collaborative networks, data intensification, and application (Peters *et al.*, 2008; Reichman *et al.*, 2011). Here, we review the current 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 change 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 now extend beyond the nuts and bolts mensuration of biodiversity components (abundance, distribution, species 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.*, 2015), 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 differently to disturbances; for example, cameras have identified key habitats linked to higher female grizzly bear reproductive success (Fisher *et al.*, 2014). Remote cameras are also increasingly used to address complex ecological interactions between animal behavior and climate change. For example, cameras were used to assess the impacts of climate change and trophic interactions on elk (Brodie *et al.*, 2014), to measure plant phenology and climate (Morisette *et al.*, 2008), and to determine how large-mammal food webs respond to forest fragmentation (Brodie *et al.*, 2015). Furthermore, cameras can measure the success of conservation actions (Dajun *et al.*, 2006), including protected area effectiveness (Burton *et al.*, 2011), such that cameras are highlighted as tools to monitor local or regional biodiversity (Tobler *et al.*, 2015). For example, a camera-specific diversity metric, the Wildlife Picture Index (WPI; O'Brien *et al.*, 2010), has been used to measure trends in large-mammal communities of Mongolia (Townsend *et al.*, 2014), Costa Rica (Ahumada *et al.*, 2013) and most recently, on a entire network of forested tropical protected areas (Beaudrot *et al*., 2016).

Remote camera projects usually target ground-dwelling vertebrates (mostly mammals), although there are examples focused 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 represent a critically important group for biodiversity maintenance, including large carnivores and herbivores (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 rates of primary productivity and decomposition (Hooper *et al.*, 2012). Early detection and mitigation of population declines may be crucial to conservation. Moreover, actively engaging decision makers and citizen scientists in conservation is enhanced by photographs of these charismatic mega-fauna, which can act as effective conservation surrogates for large-scale conservation 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. For example, Moriarty *et al.*, (2009), used cameras to document the first evidence of wolverine expansion in California. Cameras can potentially assess range changes due to climate change. Cameras could also provide 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 similar to museum collections (McShea *et al.* 2015; eMammal, emammal.org) and the Global Biodiversity Information Facility (GBIF; www.gbif.org) provides international open-access infrastructure to collect such data on all species, including remote camera data. The digital specimen is a non-invasive documentation of an animal *in situ*, in its habitat, with associated spatiotemporal data on behavior, temporal activity, heterospecifics, and environmental covariates.

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

Future vision: moving from local to global scales

Global policy frameworks, like the CBD and IPBES, require equally ambitious and large-scale monitoring tools to ensure progress toward meeting their goals. To meet this need, ecological monitoring networks are striving to match the capacity of global weather monitoring through deploying ecological sensors, building data infrastructures, and refining statistical models for prediction (Keller *et al.*, 2008). The first step towards an equivalent standardized global network for biodiversity is to link current *in situ* data streams with global-scale data, for example, satellite-based remote sensing (Turner, 2014; Figure 2). Linking together 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 the usual fuel of human endeavors—time and money—but also innovation and cooperation. Obstacles to the formation of a truly global remote camera network are common to many forms of large-scale monitoring; these include standardization of field protocols and metadata, coordination among regional and international partners, and long-term funding for field and data management (Lindenmayer and Likens, 2009). But with the number of existing networks growing as reported below, the barriers to a truly global biodiversity network are falling away. By pulling from

100+ years of combined remote camera experience among the authors, we supply some lessons in overcoming these obstacles when 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 continues to reduce their cost (as low as $100 US) giving this technology a low cost per unit of sampled area and per species. Further, with proper protocols, relatively inexpensive local wildlife guides, park rangers, anti-poaching patrollers or volunteer citizen scientists can be trained to service cameras, further reducing costs per sample, and thus facilitating larger sample sizes. For example, the eMammal project enlists more than 400 volunteers to run cameras in over 2000 locations across six US states (McShea *et al.*, 2015), and the Snapshot Wisconsin project makes effective use of citizen scientists to maintain cameras across the state (www.snapshotwisconsin.org). Financial and logistical barriers for running cameras at large scales, therefore, 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). For example, project metadata should include camera model and settings, number of cameras sites, length of deployment, sampling design and protocol, and site metadata including GPS location, vegetative community, and environmental conditions (Meek *et al*. 2014). The Tropical Ecology Assessment and Monitoring Network (TEAM; www.teamnetwork.org/) 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, and other projects could follow this cohesive example. Similarly, Parks Canada provides an archetypal 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, individual national parks began experimenting with cameras for park-wide monitoring. With increased deployment came increased coordination and collaboration. Now, ten years later, 7 national parks covering ~23,000 km^2 are using standardized methods to systematically distribute 350 cameras for year-round multi-species monitoring (Steenweg *et al.*, 2016); the list of similarly coordinated networks grows (WebTable 1). Continuing towards agreement on collecting matching metadata across camera studies is needed for global integration of camera networks. Standards for metadata descriptions 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 with 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.*, 2015). The TEAM network uses specialized software (Wild.ID), now available to any remote camera project, to classify images and provides 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; examples including: www.chimpandsee.org, www.chicagowildlifewatch.org, and www.snapshotwisconsin.org. One of the best-known projects is Snapshot Serengeti (www.snapshotserengeti.org), which counts 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 crowd source image processing is also freely available via www.zooniverse.org/lab.

Now there is 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 (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. 2014). 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 discretize the continuous sample to mimic a repeated site visit framework of abundance or occupancy estimation (Figure 3), though 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 the collection of ancillary movement data to estimate animal density (e.g. Random Encounter Model; Rowcliffe *et al.*, 2008) or the use of complicated hierarchical models. Hierarchical models are ideal for camera data analyses because they model biological and imperfect observation processes that lead to observed data, nested within a model of the ecological process of interest (e.g. 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 available with the release of recent books (e.g. Kery and Royle, 2016), open source software (e.g. Fiske and Chandler, 2015; White and Burnham, 1999) and active web forums for quick and friendly help (e.g. 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 wildlife picture index (WPI; Figure 3; O'Brien *et al.*, 2010) a conceptually simple metric developed by TEAM that summarizes the average proportional change in occupancy among species. Mechanisms of change 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 possible. 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 were never detected during the entire 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 large storage requirements for images. Regional or global biodiversity databases are needed that are tailored to camera data in an easy-to-use, accessible and open-source format. Database platforms are already developed that host and facilitate the management of large quantities of other types of shared ecological data. MOVEBANK (www.movebank.org), for example, 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, the TEAM network, Smithsonian Institution, Wildlife Conservation Society and the North Carolina Museum of Natural History, is the federated Wildlife Insights project (wildlifeinsights.org). This latter database was developed to streamline data management and integrate camera data with other *in situ* data streams such as forest carbon, gaseous flux, and other environmental monitoring (McShea et al. 2015). This integration will allow scientists to better connect patterns in biodiversity change with the ultimate causes of declines in biodiversity. If camera data descriptions begin to follow biodiversity information standards for multimedia data (e.g. 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/).

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

Conclusions

There is a pressing need for increased coordination of remote camera surveys to achieve effective global biodiversity monitoring. The non-invasive nature of remote cameras and their decreasing costs continues to hasten their adoption at every scale. Using concrete examples, we have demonstrated how barriers to camera servicing, data classification, storage and management have been overcome to achieve synthesized coordinated regional networks. We suggest these efforts can be scaled up to create a global network of remote cameras that would provide a unique picture of our planet to complement other remote biodiversity 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, greater support is required to provide a global infrastructure to improve collaborations among existing projects and increase local buy-in 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 extant collaborative networks to facilitate regional collaboration (e.g. TEAM, eMammal, Parks Canada). With broad cross-institutional support, tremendous opportunities could be gained when capitalizing on this framework for global biodiversity monitoring. Lastly, institutions like GEO BON and GBIF could benefit from increasing their rate of adoption of camera data as one of the most standardizable and expandable data types for biodiversity monitoring, as they can contribute to the generation of Essential Biodiversity Variables (Pereira *et al.*, 2013) for terrestrial vertebrates and complement other indices like the Living Planet Index (livingplanetindex.org). The public appeal of remote camera images and citizen-scientist participation will continue to scale-up biodiversity monitoring and excite public support to ultimately help make successes in global conservation possible.

Acknowledgements

We thank W Turner, J Nichols and 3 anonymous reviewers for comments on previous drafts. We thank organizers of the 2014 Society for Conservation Biology conference in Missoula, MT for providing a productive venue for this idea-sharing workshop on cameras and conservation. Thanks to C Reynolds for help with figures. Funding was provided by the University of Montana, Parks Canada, NASA grant NNX11AO47G to M Hebblewhite, Alberta Biodiversity Monitoring Institute, Panthera Inc., and Yellowstone to Yukon Conservation Initiative. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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Figure 1. Snapshot of recent global remote camera studies. All study area locations where authors have used cameras to ask large-scale ecological questions are located on map (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. (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*) (H) clouded leopard (*Neofelis nebulosa*). See WebTable 1 for more details of each study included on map.

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, therefore, guiding the application of camera data. The smallest scale is the local *in situ* camera site that 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, which have the potential to be integrated across the globe with ever-increasing satellite data.

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 behaviour patterns (subfigure modifed 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).