

## REVIEW

# Best practices and software for the management and sharing of camera trap data for small and large scales studies

Lorraine Scotson<sup>1</sup>, Lisa R. Johnston<sup>2</sup>, Fabiola Iannarilli<sup>1</sup>, Oliver R. Wearn<sup>3</sup>, Jayasilan Mohd-Azlan<sup>4</sup>, Wai Ming Wong<sup>5</sup>, Thomas N. E. Gray<sup>6</sup>, Yoan Dinata<sup>3</sup>, Ai Suzuki<sup>7</sup>, Clarie E. Willard<sup>8</sup>, Jackson Frechette<sup>9</sup>, Brent Loken<sup>10, 11</sup>, Robert Steinmetz<sup>12</sup>, Alexander M. Moßbrucker<sup>13</sup>, Gopaldasamy Reuben Clements<sup>14</sup> & John Fieberg<sup>1</sup>

<sup>1</sup>Department of Fisheries, Wildlife and Conservation Biology, University of Minnesota, 2003 Upper Buford Circle, St. Paul, Minnesota 55108

<sup>2</sup>University of Minnesota Twin Cities Libraries, Minneapolis, Minnesota 55455, USA

<sup>3</sup>Zoological Society of London (ZSL) - Indonesia Programme, Jalan Papandayan No.18, Bogor, West Java, Indonesia

<sup>4</sup>Department of Zoology, Faculty of Resource Science and Technology, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia

<sup>5</sup>Panthera, 8 West 40th Street, Floor 18, New York, New York 10018

<sup>6</sup>Wildlife Alliance, 86, Street 123, Toultompong I, Chamcamon, Phnom Penh, Cambodia, USA

<sup>7</sup>Ecology and Environment, Division of Southeast Asian Studies, Graduate School of Asian and African Area Studies, Kyoto University, Kyoto, Japan

<sup>8</sup>WCS Cambodia Programme, No. 21 Street 21, Sangkat Tonle Bassac, Khan Chamkarmorn, Phnom Penh 12000, Cambodia

<sup>9</sup>Fauna & Flora International, #19 Street 360, Phnom Penh, Cambodia

<sup>10</sup>EAT Initiative, PO Box 1232 Vika, 0110 Oslo, Norway

<sup>11</sup>Stockholm Resilience Centre, Stockholm University, Kräftriket 2B, SE-10691 Stockholm, Sweden

<sup>12</sup>WWF Thailand, 92/2 Soi Phaholyothin 5, Phaholyothin Road, Bangkok 10400, Thailand

<sup>13</sup>Frankfurt Zoological Society (FZS), Jl. A. Chatib No. 60, Jambi 36124, Indonesia

<sup>14</sup>Department of Biological Sciences, Sunway University, No. 5 Jalan Universiti, 47500 Bandar Sunway, Selangor, Malaysia

## Keywords

Bycatch data, data management, macrosystem ecology, metadata, population trends, species identification

## Correspondence

Lorraine Scotson, Department of Fisheries, Wildlife and Conservation Biology, University of Minnesota, 2003 Upper Buford Circle, St. Paul, Minnesota, 55108. Tel: +1 778 833 2594; Fax: +1 612 625 5299; E-mail: scotsonuk@gmail.com

## Funding Information

MAJ was supported by a Ministry of Higher Education (MOHE), Niche Research Grant Scheme: NRGs/1087/2013(01), Iannarilli was funded by the Minnesota Department of Natural Resources, and Scotson was funded by a University of Minnesota Doctoral Dissertation Fellowship and University of Minnesota Conservation Biology Summer Grant while this manuscript was prepared.

Editor: Marcus Rowcliffe

Associate editor: Carlos De Angelo

Received: 4 January 2017; Revised: 6 April 2017; Accepted: 8 May 2017

doi: 10.1002/rse2.54

## Abstract

Camera traps typically generate large amounts of bycatch data of non-target species that are secondary to the study's objectives. Bycatch data pooled from multiple studies can answer secondary research questions; however, variation in field and data management techniques creates problems when pooling data from multiple sources. Multi-collaborator projects that use standardized methods to answer broad-scale research questions are rare and limited in geographical scope. Many small, fixed-term independent camera trap studies operate in poorly represented regions, often using field and data management methods tailored to their own objectives. Inconsistent data management practices lead to loss of bycatch data, or an inability to share it easily. As a case study to illustrate common problems that limit use of bycatch data, we discuss our experiences processing bycatch data obtained by multiple research groups during a range-wide assessment of sun bears *Helarctos malayanus* in Southeast Asia. We found that the most significant barrier to using bycatch data for secondary research was the time required, by the owners of the data and by the secondary researchers (us), to retrieve, interpret and process data into a form suitable for secondary analyses. Furthermore, large quantities of data were lost due to incompleteness and ambiguities in data entry. From our experiences, and from a review of the published literature and online resources, we generated nine recommendations on data management best practices for field site metadata, camera trap deployment metadata, image classification data and derived data products. We cover simple techniques that can be employed without training, special software and Internet access, as well as options for more advanced users, including a review of data management software and platforms. From the range of solutions provided here, researchers can employ those that best suit their needs and capacity. Doing so will enhance the usefulness of their camera trap bycatch data by improving the ease of data sharing, enabling collaborations and expanding the scope of research.

## Introduction

Use of camera traps to obtain self-triggered photographs of wildlife for ecological research is widespread, with a 10% annual growth in scientific publications since the early 1990s (McCallum 2013; Burton et al. 2015). Camera traps typically collect data on a diverse array of terrestrial animals, with a wide range of study objectives (Cutler and Swann 1999; Thorn et al. 2009; Bengsen et al. 2011; Rowcliffe et al. 2014). Camera traps are widely used for small fixed-term surveys in areas of conservation significance to collect baseline data, often with loose or undefined objectives. Parallel to the increase in camera trap studies, the volume of 'bycatch' data (i.e. images collected incidentally, and unrelated to the study's objectives) has increased steadily. When combined over multiple sites, bycatch data can reveal landscape scale macro-ecological patterns across space and time, and can aid in the research of understudied threatened species (Heffernan 2014; McShea et al. 2016).

There is a data gap in global monitoring programs, with fewest data available for areas highest in biodiversity (Collen et al. 2008). Managing species threatened with extinction requires research into species occurrence, population trends and on population responses to changes in the environment, particularly those caused by humans (Balmford et al. 2003; Maxwell et al. 2016). These research topics cannot be addressed by data collected from a single study site, and require combining data from multiple sites across large areas. Such datasets, from small fixed-term studies, are extensive in the tropics and provide considerable, often underutilized, information (e.g. Gray 2012). In the absence of primary data, bycatch data could be key to monitoring progress towards the targets of the Convention on Biological Diversity (CBD, Balmford 2005; Dobson and Nowak 2010; O'Brien 2010). Likewise, bycatch data can inform assessments of mammals considered as threatened with extinction, or data deficient, by the World Conservation Union (IUCN) Red List of Threatened Species, many of which are outside the scope of primary research (Schipper et al. 2008).

To increase use of bycatch data, many challenges need to be overcome. For example, varied study objectives, field methods and data management standards (including data sharing policies and restrictions) of research groups create logistical and statistical challenges in pooling bycatch data over multiple sites (Sanderson and Trolle 2005; Olsen et al. 1999). Large volumes of data can accumulate quickly, and data managers may lack motivation to record and classify all images, due to limited time, funding, staff and other resources. Project resources (e.g. time, money, personnel) are often used for fund raising,

training, field work, reporting and administration, with limited resources allocated to tasks that are perceived as less urgent, such as data management. Furthermore, researchers may under-estimate the expense and time required for effective data management. Bycatch images have been likened to the fisheries bycatch; data are either left unclassified, or are filed away and never used or made publicly available (O'Brien 2010). Identification errors are also widespread within such datasets. Limitations are strongest in small studies working within low-income regions, which have fixed budgets and short time frames (e.g. Non-Government Organizations [NGOs], graduate student projects).

Camera trap studies that are ongoing (i.e. not fixed term) accumulate massive amounts of data over time. Such studies optimize their efficacy by using standardized sampling designs and data management protocols. The Tropical Ecology Assessment and Monitoring Network (TEAM), for example, operates in 17 sites globally, in Africa, Asia and Latin America. Their use of standard methods on a global scale allows combining and analysing data over multiple sites, and enables monitoring of global patterns in ecosystems and biodiversity ([www.teamnet.org](http://www.teamnet.org)). Another ongoing study is The Serengeti Lion project, which maintains a fixed grid of 225 camera traps in the Serengeti National Park, Tanzania, with a strict protocol used to determine camera placement and data processing. These camera traps are used to monitor temporal trends and patterns in wildlife communities within the National Park. The camera traps operate continuously, accumulating massive numbers of primary and bycatch images. The Serengeti Lion project operates an innovative crowdsourced citizen science online platform, Snapshot Serengeti, to quickly classify their ever-growing catalogue of images ([www.snapshotserengeti.org](http://www.snapshotserengeti.org); Swanson et al. 2016).

Data management is an essential, yet often-neglected skill for wildlife ecologists. A survey of 48 American research institutions found that lack of time and teaching resources limited student training on management and preservation of data (Strasser and Hampton 2012). Researchers who are not part of an academic institution, and those from undeveloped regions, may not have access to technology, software, training and materials to facilitate good data management. Skilled data management, however, is critical for camera traps studies; poor data management systems, lack of standardization and failure to use automated management tools, can result in the loss of significant amounts of data, especially bycatch data (Harris et al. 2010). There are multiple resources on data management online, in text books and in the grey and published literature (e.g. McGill 2016; Borer et al. 2009;

Briney 2015), with several peer-reviewed publications focused on the management of camera trap data (e.g. Tobler et al. 2008; Harris et al. 2010; Fegraus et al. 2011; Sundaresan et al. 2011; Sunarto et al. 2013; Meek and Fleming 2014; Burton et al. 2015; Niedballa et al. 2016). We attempted to develop a succinct set of recommendations and to review related resources on data management best practices, ranging from very simple techniques that can be employed with minimal resources (e.g. without need for training, special software and Internet access), to options for more advanced users, including a review of data management software and platforms. By publishing in an open access journal, our guidelines will reach researchers without institutional journal access.

We begin with a case study that reports our experiences assembling and processing bycatch camera trap data from multiple datasets in a study measuring global population trends of sun bears. We use these experiences to identify common data management malpractices that create difficulties in using bycatch data for secondary research. Subsequently, we make recommendations on data management best practices that are focused on enhancing the quality and efficiency of data management, highlighting critical information to include within data and improving the ease of data sharing and preservation, and we identify relevant resources available to help researchers follow our recommendations. We review currently available camera trap management software and platforms for those with more advanced needs, including Wild.ID, Camera Base, CPW Photo Warehouse, eMammal, Aardwolf, CamtrapR and TRAPPER. Finally, we discuss the value of good data management practices for enabling sharing and secondary research.

### Combining camera trap data from multiple sources: a case study

In our case study, like typical data sharing mechanisms reported in the literature (e.g. Kratz and Strasser 2015), we obtained data from external studies via email requests. We combined data from 12 research groups working in 49 field sites. The primary objectives of these studies, which were conducted by NGOs and graduate students (i.e. Clements 2013; Dinata 2008), included species inventories (Mohd-Azlan and Engkamat 2013), occupancy modelling (Wong and Linkie 2013), understanding habitat use and activity patterns (Gray and Phan 2011; Gray 2012), primate terrestrial behaviour (Loken et al. 2013) and investigating response to altered habitats (Wong et al. 2013; Spehar et al. 2015). The data consisted of 43 sets of data in several formats (collectively referred to here as datasets), including raw camera trap images, pdf tables, GIS shapefiles, and (in most cases) single and multi-tab Excel spreadsheets. Data contributors commonly expressed difficulties in locating

and preparing our requests, and communications usually spanned several months. The time it took to process the data was the most significant problem we encountered (Table 1). Manipulating the data into our desired format (i.e. one standardized dataset) often required substantial manual editing and many follow-up questions and requests to contributors. Each dataset took between 2 and 8 h to process. Many data points (i.e. sun bear records) and three entire datasets were discarded due to one or more ambiguities (see Fig. 1 for an exaggerated example of a 'problem' dataset). Missing or ambiguous latitude and longitude data were the most persistent issue leading to loss of data; this problem was encountered in all but one dataset (Table 1). Data were also lost due to missing or ambiguous dates, gaps in trapping effort records and other unclear entries (e.g. Fig. 1). Of 43 datasets, three were unusable (representing data collected from >400 camera traps), and portions of data were lost from 80% of other datasets (Fig. 2).

Contributors to our case study were asked to complete a brief web-based survey of the data management protocols used by their group. Respondents ( $n = 8$ ) expressed that they were mostly satisfied by their data collection methods, but cited problems associated with lack of standard data management protocols and a high turnover in staff responsible for data management. In handling metadata, no group used an industry standard method [e.g. Ecological Metadata Language (EML)]; 75% of respondents created a custom organizational structure, and 25% used a standard developed exclusively for their organization. Data entry and management was the responsibility of a combination of field technicians (88%), administrative staff (25%) and research coordinators (75%). In 50% of cases, data quality was maintained by a process of re-checking by multiple people. In 25% of cases, research groups followed a standard protocol for data entry intended to minimize risk of human error. In 25% of cases, maintaining data entry quality was the responsibility of one person. No respondents reported using automated camera trap data entry software. A repeated sentiment in the survey responses was that data management practices could be improved by increased standardization, and by access to online platforms, which allow storage and sharing of data. Main obstacles to data management were a lack of capacity, high turnover of expatriate and local staff, and a failure to use pre-developed standardized protocols. Specific ideas expressed by data contributors in our case study are incorporated into our list of recommendations below.

### Recommendations for managing camera trap data

We generated nine key recommendations related to data management practices of the four main data types

**Table 1.** Data problems frequently encountered whilst processing 43 datasheets submitted by 12 different research groups.

Data Problem	Examples encountered	Consequence
Datasheet structure in format difficult to manipulate ( <i>n</i> = 9)	Merged and double header rows do not allow easy sorting. Databases with camera trap location and operation information on a separate worksheet than detection data, with no obvious link	Reformatting data for secondary use is time intensive.
Locational information ambiguous, inconsistent or incomplete ( <i>n</i> = 12)	Geographic coordinates missing. Lack of accompanying information on map datum or Universal Transverse Mercator (UTM) zones. Order of X and Y coordinates muddled within a datasheet. Coordinates recorded in a format that cannot be read by GIS software. Coordinates recorded in format that cannot be automatically transformed to another system.	Transforming and projecting points can be time intensive. Data with no location information are usually meaningless.
Date information ambiguous, inconsistent or incomplete ( <i>n</i> = 7)	Dates missing or incomplete (e.g. start date but no end date); date format not specified (e.g. UK or USA); date format used interchangeably within a datasheet.	Data with no date information are usually meaningless.
Number of trap nights averaged across units, unclear or missing ( <i>n</i> = 6)	Manual calculation of trap nights often problematic due to ambiguous date information (see above). Trapping effort sometimes not available for individual units, and instead averaged over all cameras.	Data without trapping effort are usually meaningless. Using average number of trap nights reduces data resolution.
Ambiguous/unintelligible cell entry and formatting ( <i>n</i> = 4)	Ambiguous use of comments and colour coding cells and rows suggests some problem with data	Discard affected data or costly follow-up communication required.
Missing or incomplete metadata ( <i>n</i> = 6*)	No definitions given for co-variables (i.e. land use type, forest cover). No metadata provided.	Undefined covariates are meaningless to secondary researchers.

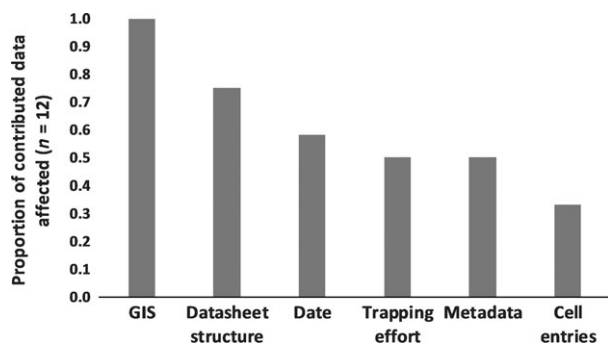
\*Only two contributors provided metadata on an accompanying spreadsheet, a further four provided publications from which metadata could be extracted.

Site ID	Date set <sup>1</sup>	Date end <sup>2</sup>	Trap nights <sup>3</sup>	Latitude <sup>4</sup>	Longitude	Comments <sup>5</sup>
SS_1	01.06.13	15.08.13	23	50°33'4.03"N	127°35'50.84"W	
SS_2 <sup>6</sup>	03.06.13	16.08.13	27	49° 1'31.11"N	122°48'10'67"W	Flooded
SS_3	03.06.13	08.13.14	268	4° 5'14'00"W		
SS_5	06.02.13	16.08.13	29	455 173	2 235 330	Not there
SS_6	02.06.13			636 022	5 897 252	

**Figure 1.** This example problem data sheet includes a collection of errors and ambiguous cell entries that we commonly encountered on data sheets contributed to a global assessment of sun bears. Data system is undefined, and could be in either UK or US system. <sup>1</sup>Dates all similar except for SS\_5; either this unit was set in a different month, or the date is entered incorrectly. <sup>2</sup>End date for SS\_3 is clearly the US date system (mm/dd/yy); system is unclear for all other dates. <sup>3</sup>SS\_3 has an unusually high number of trap nights, and it is unclear if this is an error or real value. <sup>4</sup>Coordinates are inconsistently formatted and switch between Lat/Long and Universal Transverse Mercator (UTM) systems. GIS software cannot read Lat/Longs in this format, and inclusion of symbols prevents easy transformation. UTM coordinates are missing zone and map datum information (i.e. WGS 1984 47N). Longitude for SS\_3 is missing so point cannot be projected. <sup>5</sup>Comments are ambiguous—unclear if row of data should be disregarded or not. <sup>6</sup>Unclear why this row has been highlighted in yellow.

collected by camera trap studies; field site metadata (e.g. forest type, season, weather conditions), camera trap deployment metadata (e.g. date, time, location, camera trap settings, position, trap nights), image classification data (e.g. species identification, behaviour, number of animals), and derived data products (e.g. species

occurrence, count of detections/nondetections per unit/per site, detection rates relative to sampling effort). We incorporated recommended best practices from the scientific literature, field manuals, online forums and blogs, and have embedded links to some of these resources within our recommendations.



**Figure 2.** Proportion of common data entry errors encountered in camera trap datasheets. Multiple datasheets were contributed by 12 research groups to aid in a range-wide assessment of sun bears *Helarctos malayanus* in Southeast Asia; we used this as an example case study to illustrate the common errors that occurred in datasheets that led to loss of data. Data entry errors were combined into six categories, described in Table 1, and occurrence of errors that led to loss of data was calculated as a proportion of the number of research groups.

### 1. Adopt a standardized, non-proprietary and transferrable data storage format to store all camera trap data

In our case study, most of the data contributors used Microsoft Excel to store data. Without requiring significant training in relational database design, this tool is preferred by many researchers (Herold 2015). A major drawback, however, is that Excel is a proprietary, non-transferable format, notoriously unreliable as this tool can invisibly interpret and change entered data (e.g. drop leading “0s and change character strings to Julian dates). Proprietary software, such as Excel and Microsoft Access, may be superseded in the future by incompatible formats, so data stored in these formats could become unusable in the same way that external hard drives, CD-ROMs and DVDs may one day become outdated and unusable, like the floppy disk. If using Excel, Borer et al. (2009) recommend storing all data in non-proprietary software formats, such as comma separated value (.csv) files, which can be viewed and manipulated in Excel. There are several advantages to storing data in open source non-proprietary relational database systems such as PostgreSQL or SQLite, or ecology specific tools such as ECOLOG ([www.ecolog.sourceforge.net/index\\_e.htm](http://www.ecolog.sourceforge.net/index_e.htm)). These formats are available without license fees, are not controlled by developers (e.g. Microsoft), and have wide online communities of users which collectively serve as a crowdsourced online help forum. These formats work across many different operating platforms, are operated with Structured Query Language (SQL), a standard language for relational database management systems, and

store data in a format that is transferable to a new system or software.

### 2. Accompany all spreadsheets with structured metadata

Good management of field and camera trap deployment metadata, regardless of image classification, is crucial for long-term preservation and sharing of data. In our case study, only two research groups included metadata within their datasheets; lack of metadata reduced the interpretability of the datasheets and increased the length of time it took to process the data. Metadata, which give descriptive information about the content, context and structure of data, should accompany all raw data. When possible, use a standard metadata format, such as the EML, a metadata standard, developed by the ecology discipline for the ecology discipline. EML is a pre-designed method that can facilitate efficient data sharing. EML works so that the data created in, for example, the software Morpho, a free program for storing, cataloguing, querying and editing metadata, can be easily ingested into other platforms that are programmed to anticipate the EML data structure (<https://knb.ecoinformatics.org/#tools/morpho>). Forrester et al. (2016) describe a metadata standard specific to camera trap data, which is compatible with EML and other industry standards. At a minimum, researchers should create and provide a ‘ReadMe’ file that describes why the data were collected, including objectives, methodology, database metadata, definitions of all co-variables, codes and acronyms, point of contact, ownership, rules of use and instructions for acknowledgement. A freely available template, developed by the University of Minnesota Libraries, can be found here: <https://z.umn.edu/readme>. For detailed descriptions of desirable metadata refer to Meek et al. (2014), Meek and Fleming (2014), Sunarto et al. (2013) and Michener and Jones (2012). Much of the metadata associated with camera-trap data (e.g., date and time) can be gleaned directly from the image metadata tags if users process their data using camera trap data management software (e.g. eMammal, Wild.ID, Camera Base, Aardwolf; Table 2), but it is important to make sure that labels and formats for GPS coordinates and date and time stamps are consistent across cameras.

### 3. Record data at the highest possible resolution

Researchers should use a structure for raw data that minimizes entry errors and promotes error checking. All raw data and accompanying metadata should be recorded at the highest possible resolution, with other data products derived from these raw data ideally using well-



**Table 2.** A comparison of camera trap data management software in April 2017. The current features of each system were evaluated manually, and by review of user manuals and published literature.

	Wild.ID	Camera Base	CPW Photo Warehouse	eMammal	Aardwolf	CamtrapR	TRAPPER	Agoutt <sup>8</sup>
General features	Desktop	Desktop	Desktop	Desktop plus web-warehouse	Desktop (web browser: Google Chrome suggested)	R software (R Core Team, 2016)	Web-warehouse	Web-warehouse
Platform	Desktop	Desktop	Desktop	Desktop plus web-warehouse	Desktop (web browser: Google Chrome suggested)	R software (R Core Team, 2016)	Web-warehouse	Web-warehouse
Cost (US\$)	Free	Free (GNU General Public License)	Free (CPW Reciprocal Open Source License Agreement)	Project setup cost of \$150, and a monthly per-camera cost of between \$3.87 - \$4.19 for image upload and species id	Free (GNU General Public License 3.0)	Free	Free (GNU General Public License 2.0)	Operating costs shared by users
Data Capacity	100,000's	~2,000,000 <sup>1</sup>	~800,000 (double observer) or ~2,000,000 <sup>1</sup> (single observer); expandable using SQL Server	Unlimited	Unlimited (limited by user's computer memory)	Unlimited	Unlimited	Unlimited
Operating System	Windows, MacOS	Windows	Windows, MacOS <sup>2</sup> , Linux <sup>2</sup>	-	Windows, Ubuntu, Mac OS, Linux	Windows, MacOS, Linux	Windows, Ubuntu	-
Software requirements	Java (free version available)	Microsoft Access 2010 (tested with MS Office XP 2002, 2003, 2007 and 2010; known issues with Office 2013), or free Microsoft Access 2010 Runtime. Windows Media Player, or VLC Player for videos.	Microsoft Access, or free Microsoft Access Runtime (2007 or newer).	-	Freely available: - Node.js, - SQLite; - ImageMagick; - GraphicsMagick; - ExifTool	Freely available: - R; - ExifTool	-	-
Internet access required	No <sup>3</sup> (online registration required)	No <sup>3</sup>	No <sup>3</sup>	Yes (image upload/download)/No <sup>3</sup> (species ID; processed images unloadable later)	No <sup>3</sup>	No <sup>3</sup>	Yes	Yes (possible to run locally, and local system acts as 'server')

(Continued)

Table 2. Continued.

	WildID	Camera Base	CPW Photo Warehouse	eMammal	Aardwolf	CamtrapR	TRAPPER	Agouti <sup>8</sup>
Skill requirements	Low	Medium (requires familiarity with MS Access)	Low/High <sup>4</sup>	Low	Low	Medium (requires familiarity with R)	Low/High <sup>5</sup>	Low
Functionality								
Automatic metadata import	EXIF and camera custom tags	EXIF	EXIF	EXIF	EXIF	EXIF and user-customized tags	EXIF	EXIF
Customize event intervals	Yes	Yes	Yes	No (1-min sequence)	No	Yes	Yes	Yes
Identification at individual level <sup>7</sup>	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Classification by multiple observers	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Visualize/filter images by tag or species	Yes	No	No	Yes	No	Yes	No	No
Verify Taxonomic name	No	Yes	No	No	No	No	Yes	No
Video Output	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Comma separated values (.csv) Summaries <sup>6</sup>	No	Yes	Yes	Yes, as online resources	Yes	Yes	No	No
Data export for occupancy model analysis	No	Yes, MARK, PRESENCE	Yes, MARK, PRESENCE	No	No	Yes, PRESENCE, 'unmarked' R package	No	No
Data export for capture-recapture analysis	No	Yes, CAPTURE, MARK, DENSITY, EstimateS	Yes, MARK, DENSITY, 'secur' R package	No	No	Yes 'secur' R package	No	No

(Continued)

**Table 2.** Continued.

	Wild.ID	Camera Base	CPW Photo Warehouse	eMammal	Aardwolf	CamtrapR	TRAPPER	Agouti <sup>8</sup>
Support and/or data export for activity patterns analysis	No	Yes	Yes, 'overlap' R package	Yes, as online resources	No	Yes, for single-species: histograms of hourly activity, activity kernel density estimations and radial plots; for two-species: activity overlaps	No	Yes
Mapping	No	Yes, exporting to GIS	Yes, spatial queries to view data in Google Earth or ArcMap	Yes, as online resources	No	Yes, in R or export to GIS Shapefile	Yes, online and in GIS	Yes, online
Photo Reports	No	Yes, suggested 30-50 images per report	No	No	No	Yes	No	No
Documentation	<a href="http://wildid.teamnetwork.org/help.jsp">http://wildid.teamnetwork.org/help.jsp</a>	Tobler 2007 <a href="http://www.atrium-biodiversity.org/tools/camerabase/files/CameraBaseDoc1.7.pdf">http://www.atrium-biodiversity.org/tools/camerabase/files/CameraBaseDoc1.7.pdf</a>	Ivan and Newkirk 2016; <a href="http://cpw.state.co.us/Documents/Research/Mammals/Software/CPW-Photo-Warehouse-4.0-User-Guide.pdf">http://cpw.state.co.us/Documents/Research/Mammals/Software/CPW-Photo-Warehouse-4.0-User-Guide.pdf</a>	McShea et al. 2016 <a href="https://emammal.si.edu/participate/science-and-management">https://emammal.si.edu/participate/science-and-management</a>	Krishnappa and Turner 2014; <a href="https://github.com/yathin/aardwolf2/blob/master/README">https://github.com/yathin/aardwolf2/blob/master/README</a>	Niedballa et al. 2016; <a href="https://cran.r-project.org/web/packages/camtrapR/index.html">https://cran.r-project.org/web/packages/camtrapR/index.html</a>	Bubnicki et al. 2016 <a href="https://bitbucket.org/trapper-project/">https://bitbucket.org/trapper-project/</a>	<a href="http://cameratrapplab.org/agouti/">http://cameratrapplab.org/agouti/</a> <a href="https://www.agouti.eu">https://www.agouti.eu</a>

<sup>1</sup>Limited by Microsoft Access (Ivan and Newkirk 2016).

<sup>2</sup>By installing Windows in a virtual machine environment.

<sup>3</sup>After downloading the installer software or package.

<sup>4</sup>Medium (through Access) and high (VBA and SQL code modifications) for advanced user.

<sup>5</sup>Low for basic use; high (python and/or R) for advanced use. Good IT knowledge to be installed (including server configuration) and maintained (e.g. updating the source code).

<sup>6</sup>Includes everything between simple counts of trap-nights per camera, to detection rates, to species-specific detection counts.

<sup>7</sup>Recording of individuals uniquely identifiable by natural or artificial marks.

<sup>8</sup>Based on the information available at the time of writing (May 2017).



documented computer code that facilitates transparency and reproducibility (Sandve et al. 2013). McGill (2016) suggests using an instance-row/variable-column format, in which each measurement has one row, and each column is a different variable or attribute. At minimum, researchers should record the start and end time and date each camera trap was active. This information will allow users to determine camera-specific measures of sampling effort (i.e. number of trap nights), which is preferable to an average measure of effort across all cameras on a site. Ideally, researchers should also provide unique times and dates of individual photos, allowing secondary users to implement their own criteria for what constitutes an independent detection event. Alternatively, it is important to define how data were filtered whenever it is not practical to record individual photographs (e.g. 500 photos of a pig-tailed macaque *Macaca sp.* group are recorded over a 60-minute period). TEAM provide a list of data quality control measures for camera trap data, which includes recommendations on sampling effort (i.e. number of units, trapping periods) and maintaining data quality (access here: [www.teamnetwork.org/files/protocols/terrestrial-vertebrate/TEAM\\_Terrestrial\\_Vertebrates\\_Data\\_Quality\\_Standards.pdf](http://www.teamnetwork.org/files/protocols/terrestrial-vertebrate/TEAM_Terrestrial_Vertebrates_Data_Quality_Standards.pdf)).

#### 4. Use a clearly documented and consistent geographic coordinate system

Providing accurate and identifiable Global Positioning System (GPS) locations with your data is critical. In our case study, missing or ambiguous latitude and longitude data were the most persistent issue leading to loss of data – this problem was encountered in all but one dataset (Table 1). Camera trap deployment metadata should be relatable to an exact geographic location. The large number of geographical and projected coordinate systems available within Global Information Systems (GIS), (i.e. GPS units and mapping software) makes it critical to record the coordinate datum that points are collected in the field (e.g. Indian Thailand Datum). Data collected without an accurate geographic location are of limited use, and may require significant time to process by secondary researchers. A single coordinate system (e.g. Geographic Coordinate WGS 1984) should be used consistently within each stage of collection, entry and processing of data. If changes to the coordinate system are required, they should be carefully documented. Store GPS coordinates in a format easily read and transformed by a GIS (i.e. numbers only; avoid placing letters or symbols within the same cell as geographic coordinates: doing so requires manual editing. See Fig. 1 for an example of this problem). Whatever system is used, also report locations in decimal degrees out to 5 decimal places, placing

the location within 1-metre accuracy and avoiding ambiguities with incomplete Universal Transverse Mercator (UTM) coordinates and studies that straddle more than one UTM zone. Include information on map datums, UTM Zones and geographic coordinate systems within the field metadata. If possible, researchers should label and store each camera trap location in GPS units (keeping hand written locations as a backup), rather than record and transcribe GPS locations from datasheets. Camera trap management software, such as those reviewed below and in Table 2, can import labelled waypoint files from a GPS unit as text or shapefiles, allowing automated data handling and minimizing data entry errors.

#### 5. Maintain a consistent date-time format

In our case study, many data were lost due to missing or ambiguous dates. When dates are missing, trapping effort become ambiguous, or impossible to calculate manually. Researchers should include dates of camera operation (start date, end date), and date and time of individual pictures in the deployment metadata. Regional differences in date-time systems (e.g. UK vs. USA) can lead to confusion in data entry and interpretation. Data managers should choose a date system, specify it clearly in the column heading and/or metadata and stick to it consistently within a dataset. An example of a well-defined date system is 2011-09-14 00:23:33 (YYYY-MM-DD hh:mm:ss). Camera trap management software, such as those reviewed below and in Table 2, can automate handing of time and date data and minimizing errors.

#### 6. Record covariate data that might be used to assess detection probability

An inability to account for differences in detection probability can lower the value of bycatch data. Therefore, researchers should record factors that influence detection probability (e.g. season, habitat type, height of vegetation and tree density) in the field metadata (Rowcliffe and Carbone 2008; Nichols 2010). Likewise, in the deployment metadata, include factors that influence species-specific detection probability (e.g. camera trap model, settings, position, date and time of day). Variables that influence detection probability are useful to both primary and secondary researchers. However, given the multiple factors that can influence detection probability from camera-trap data, it is unlikely that researches using by-catch data, particularly from many small fixed-term studies, will be able to collect sufficient and consistent information for accurately modelling detection

probability. Nevertheless, it is important to clearly state assumptions necessary for drawing valid conclusions from camera-trap data (e.g. constant detection probabilities), particularly when analysing data pooled across multiple studies.

### **7. Plan for the eventual identification of all bycatch data on non-target species and non-animals**

Image classification should ideally include all bycatch data as well as target species. This effort will allow researchers to later ask different questions of their data (e.g. plant phenology, weather patterns, animals' behaviours) and increase opportunities for data sharing and collaborative efforts with other research groups. Classification of all images, however, can be unrealistic when vast quantities of data are collected. As cameras become more affordable, with greater memory capacities and battery life, data processing has become increasingly limited by human processing capacity. At a minimum, researchers can manage field and metadata, and upload images into an online storage system, such as Camera Base ([www.atrium-biodiversity.org/tools/camerabase/](http://www.atrium-biodiversity.org/tools/camerabase/)) so that images can be classified later. Alternatively, engaging citizen scientists to catalogue images is an emerging technique that can significantly increase the amount of information researchers can extract from large datasets (Swanson et al. 2015). Snapshot Serengeti (University of Minnesota Lion Project) and Camera CATalogue (Panthera) are examples of citizen science platforms, both hosted by the Zooniverse ([www.zooniverse.org](http://www.zooniverse.org)). Readers seeking more efficient methods to process raw data are directed to guidelines included in Harris et al. (2010) and Niedballa et al. (2016), and a variety of platforms and software are reviewed below (Table 2).

### **8. Manage data as one authoritative set, which can be acted on by multiple users consistently and simultaneously**

Store a single, raw, unedited and 'read-only' copy of image classification and derived data products in a central location with regulated access. Data replication and confusion can arise when re-editing and renaming multiple file versions (e.g. `Raw_data_FINAL_FINAL_v3`). Multiple downloads by different users can introduce errors or unclear versioning in the data being analysed. Create new copies of edited raw data, with a record of who made edits and why. Free web-based tools like Open Science Framework (<http://osf.io/>) and GitHub (<https://github.com/>) capture and record changes to files, and log and facilitate version control.

### **9. Archive data, and make it available to other researchers with defined conditions for reuse**

This final step allows well-managed data to be discovered and reused by other researchers. Consider sharing data on a project page, with clear terms and conditions for use. The TEAM Network does this (e.g. [www.teamnetwork.org/data/use](http://www.teamnetwork.org/data/use)), and they developed software, Wild.ID, that facilitates data management and long-term storage ([www.teamnetwork.org/solution](http://www.teamnetwork.org/solution)) in the Wildlife Insight web warehouse. Researchers can register on Wildlife Insights (previously The Camera Trap Federation) for open access, citation and preservation of data ([www.wildlifeinsights.org/WMS/#/shareData](http://www.wildlifeinsights.org/WMS/#/shareData)). Alternatively, eMammal provides a paid online platform for project pages ([www.emammal.si.edu/participate/science-and-management](http://www.emammal.si.edu/participate/science-and-management)) with an option for long-term storage on the Smithsonian Data Repository. A researcher's local institutional repository may provide free services for publicly archiving data, including minting Digital Object Identifiers (DOIs), for better citation of the data collection, and preservation of data after the project is complete (e.g. Harvard University's DataVerse or the Data Repository for the University of Minnesota, DRUM). Readers are directed to Whitlock (2011), who outline, a set of data archiving best practices.

### **Camera trap data management platforms**

Our recommendations highlight the steps researchers can take to improve data quality when using non-standardized, custom designed data handling methods. We encourage where possible, however, the use of data management software and/or web-based platforms that are designed specifically for camera trap data management. Use of these programs can reduce data entry errors and data loss, increase efficiency in data management and improve ease of data re-use and sharing. The applications we reviewed include Wild.ID, Camera Base, CPW Photo Warehouse, eMammal, Aardwolf, CamtrapR, TRAPPER and Agouti. These systems range from stand-alone desktop applications, to extensions of Microsoft Access and R Core Team (2016), and web-based platforms. We found a wide range of overlapping general features, summarized in Table 2, and some unique features, described below, all of which users can consider when selecting the system most appropriate for their research needs.

Wild.ID, developed by the TEAM network, is a desktop application designed for protected area managers and wildlife professionals. Described as an 'easy interface' information management platform, Wild.ID can export data to be shared with other Wild.ID users. Users can store data in the Wildlife Insights data repository, a long-

term cloud-based storage system with additional analytic capability (e.g. Wildlife Picture Index; [www.wildlifein sights.org](http://www.wildlifein sights.org)). There is a plug in for TEAM Network members (Wild.ID.TEAMPlugin), and multi-language options including English, Chinese, Spanish and Portuguese.

Camera Base and CPW Photo Warehouse are free desktop extensions of Microsoft Access. Both are limited to handling tens of thousands of images and therefore are suitable for small projects. Unique features of Camera Base include the ability to calculate Mean Maximum Distance Moved (MMDM), and to automatically classify photos as taken during the day, night, dusk or dawn, based on sunrise and sunset calculated for the survey location for each specific date. Camera Base has an interface for direct comparison of images from paired cameras (Tobler 2007). Unique features of CPW Photo Warehouse include: a capacity for multi-observer species identification and user-customized functions via Access query modifications or via VBA and SQL code modifications for advanced user (Ivan and Newkirk 2016).

Aardwolf desktop application and camtrapR R package are both free, open source, extendable, multi-platform systems suitable for projects with large volumes of data (>1 million images). Both systems can handle the complete workflow associated with processing camera trap data, from image organization and annotation, identification of species and individuals, image data extraction, tabulation and visualization of results, and export for other analyses. Aardwolf is designed for small research teams and independent researchers, boasting minimalistic data management, built for use on personal computers and works with SQLite, MySQL and PostgreSQL (Krishnappa and Turner 2014). Aardwolf includes an option to store added metadata (species, etc.) as.XMP files. CamtrapR R package was designed for flexible and efficient management of camera trap data, with a streamlined, reproducible process, including multiple analysis options and the possibility to export data to GIS software (Niedballa et al. 2016). Species and individual identification is performed outside the package, via custom metadata tags assigned in image management software or by moving images into species directories.

TRAPPER and Agouti are both web-based platforms for managing, classifying, sharing and re-use of camera trap data, designed for researchers working alone or within collaborators. TRAPPER handles videos and still images, and features spatial filtering and web-mapping. TRAPPER is open source, allowing flexible data collection protocols and multiple role-based users to facilitate collaborative projects (Bubnicki et al. 2016). TRAPPER has an Application Programming Interface (API), allowing direct access to raw and classified data from a range of software (e.g. QGIS, R, PYTHON, KEPLER or VIS-TRAILS). TRAPPER allows export of metadata in EML

standard. Advanced users can customize functionalities via Python language; Python scripts for some functionalities (e.g., video conversion) are already provided with the software. Agouti, at the time of writing, was available by request to scientists and non-profit organizations, with plans to make it publicly available in the near future (Y. Liefing, Per. Comm. May 2017). Agouti is aimed at structured projects, with projects set up according to user needs on a per-project basis. Project assess is handled per user by a project administration manager. A single user can manage multiple projects, and projects accommodate different user roles within projects (e.g. volunteer, professional). There is a fee for hosting and support costs, although use for academic reasons (e.g. MSc thesis) is typically be free of charge. Agouti supports both photo (most camera trap models and regular cameras) and video (currently .avi, .mov, and .mp4). Agouti will soon include an online data storage solution and follows a metadata protocol compatible with the Smithsonian eMammal and Wildlife Insight repositories.

eMammal is designed for landscape scale projects that use citizen science volunteers to set cameras and collect and upload data. eMammal includes four main components: (1) Leopold, a desktop application for viewing, tagging and uploading camera trap photos, (2) an expert review tool, (3) a curated data repository for archiving approved data, and (4) a web-based platform for managing studies and accessing and analyzing data (McShea et al. 2016). Images are stored for free in the Smithsonian Data Repository, and are publicly available, with options for 1–3-year embargo, or a permanent embargo on data of species of concern and threatened species. Users can tag their favourite pictures and share them on their website and via social media. The desktop app, Leopold, facilitates citizen scientist and multiple researcher participation in species-ID, with a mandatory expert review/quality control process for species-ID through the web-based Expert Review Tool (ERT). Users can decide whether to open the project to the public and take advantage of the citizen scientist option, or to split the images to be identified among a set of researchers. There is a 1-time set up cost for creation of a custom-made home page and project structure, based on information supplied by project managers. There is a per-deployment upload cost, to keep the images in a cloud service during the citizen scientist and expert review process for species identification. The monthly cost is calculated per month of camera activation, and ranges from \$3.87 to \$4.19, depending on number of camera-months (the more you have, the less you pay for each unit; [www.emammal.si.edu/about/FAQ](http://www.emammal.si.edu/about/FAQ)).

For large-scale long-term projects that produce millions of images each year an option is to utilize the recently developed resources provide by the Zooniverse web-

platform ([www.zooniverse.org](http://www.zooniverse.org)). Besides online photo storage, Zooniverse offers researchers the chance to increase public visibility of projects and to take advantage of citizen science. Two of the earliest and widely known camera trap-based Zooniverse projects are Snapshot Serengeti (Serengeti Lion Project; Swanson et al. 2015) and Camera CAtalogue. Camera CAtalogue currently engages more than 8000 volunteers, processing approximately 20,000 images per day. Volunteers are presented with an image and asked to tag the species present, using a predefined list of existing species in the area, and to record the number of individuals, and what side of the animal is visible. Volunteers can confirm the species by comparing it with a pre-existing photograph and species description. Algorithms identify uncertain images that require expert review by selecting those that do not reach a consensus during citizen scientist classification. Accuracy ratings calculated for Camera CAtalogue and Snapshot Serengeti are 96% and 97.9%, respectively (Swanson et al. 2016; R. Pitman pers. comm., 2017). These platforms produce outputs that can be paired with R packages such as CamtrapR to create a holistic camera trap data management and analytical tool.

### The value of sharing data

This paper seeks to convince readers of the benefits of creating a data management plan, maximizing the quality and usability of secondary data, sharing data and preserving it for the long-term. Likewise, we hope that our set of recommendations and resources therein make this considerable task more achievable to researchers at all levels of skill and capacity. Data sharing within the scientific community is widely encouraged (Hampton et al. 2013); according to the Committee on Responsibilities of Authorship in the Biological Sciences, scientists are obligated to make their data available to others in a format that other scientists can use in future research (Council of Science Editors 2014). Some suggest making data sharing a mandatory condition of funders and publishers, and to increase the value of sharing by making datasets publishable and citable (Balmford 2005; Reichman et al. 2011; Whitlock 2011; Goring et al. 2014). Indeed, many journals now require that data are publicly available, including PlosOne, Scientific Reports and all British ecology journals. Some opponents to data sharing are cautious of sharing sensitive data on threatened species, when illegal hunting is a primary threat. Engaging the public in “citizen science” has great potential to raise interest in conservation, while expanding the scope and scale of research (Swanson et al. 2015).

Data are the currency of research and are payoff for all effort invested in planning, fundraising and undertaking research activities. Collection of bycatch data represents a significant portion of that time and effort. Sharing and

combining data over multiple sites harnesses the power of bycatch data, broadens the scope of research, creates multi-collaborator studies and leads to valuable scientific publications. The TEAM network, for example, has published several multi-collaborator research papers on community structure and population trends of threatened tropical species (Ahumada et al. 2011; Beaudrot et al. 2016; Jansen et al. 2014). Likewise, The Serengeti Lion Project has studied the distribution and community interactions of over 30 species across the Serengeti landscape (Swanson et al. 2015), and their bycatch data have led to multiple collaborations (A. Swanson, pers. comm., 2017). Bycatch data pooled across multiple smaller studies have led to publications on regional and range-wide studies of many threatened mammals in Southeast Asia, including Asian tapir *Tapirus indicus*, gaur *Bos gaurus*, sambar *Rusa unicolor*, red muntjac *Muntiacus muntjak*, wild pig *Sus scrofa* (Lynam 2012), small carnivores in Thailand (Chutipong et al. 2014) and almost all the carnivore species occurring on the island of Borneo (Mathai et al. 2016). Bycatch data for the Asian tapir, collected mainly on tiger *Panthera tigris* surveys, led to an extension of the known tapir range in Southeast Asia (Linkie et al. 2013). Collaborations can allow researchers to estimate population densities of hard-to-detect species, such as clouded leopards *Neofelis nebulosa*; data from one site are often of limited use, but it is possible to analyse detections across multiple sites using techniques such as Spatially Explicit Capture Recapture (e.g. Gardner et al. 2010). Open and efficient sharing of camera trap bycatch data has the potential to create endless research opportunities, improving ecological understanding of poorly studied species, from accessing basic information on species distribution and abundance, to allowing the development of complex hypotheses related to habitat preferences, lifecycles, behaviour and response to human disturbance and management interventions.

### Acknowledgements

We are grateful to Ali Swanson, Timothy O’Brien, Francesca Cuthbert and two anonymous reviewers for comments on earlier drafts of this manuscript that led to substantial improvements. I thank David Garshelis for suggesting the initial concept for this paper. MAJ was supported by NRG/1087/2013(01) and Scotson was funded by a University of Minnesota Doctoral Dissertation Fellowship and Conservation Biology summer grant while this manuscript was prepared.

### References

- Ahumada, J. A., C. E. F. Silva, K. Gajapersad, C. Hallam, J. Hurtado, E. Martin, et al. 2011. Community structure and



- diversity of tropical forest mammals: data from a global camera trap network. *Philos. Trans. R Soc. Lon. B: Biol. Sci.* **366**, 2703–2711.
- Balmford, A., et al. 2005. The convention on biological diversity's 2010 target. *Himalayan J. Sci.* **3**, 43–45.
- Balmford, A., R. E. Green, and M. Jenkins. 2003. Measuring the changing state of nature. *Trends Ecol. Evol.* **18**, 326–330.
- Beaudrot, L., J. A. Ahumada, T. O'Brien, P. Alvarez-Loayza, K. Boekee, A. Campos-Arceiz, et al. 2016. Standardized assessment of biodiversity trends in tropical forest protected areas: the end is not in sight. *PLoS Biol.* **14**, e1002357. <https://doi.org/10.1371/journal.pbio.1002357>.
- Bengsen, A. J., L. K. P. Leung, S. J. Lapidge, and I. J. Gordon. 2011. Using a general index approach to analyze camera-trap abundance indices. *J. Wildl. Manage.* **75**, 1222–1227.
- Borer, E. T., E. W. Seabloom, and M. B. Jones. 2009. Some simple guidelines for effective data management data. *Bulletin of the Ecological Society of America*, **90**: 205–214.
- Briney, K. 2015. *Data Management for Researchers: organize, maintain and share your data for research success*. Pelagic Publishing Ltd., Exeter, UK.
- Bubnicki, J. W., M. Churski, and D. P. J. Kuijper. 2016. trapper : an open source web-based application to manage camera trapping projects. *Methods Ecol. Evol.* **7**, 1209–1216.
- Burton, A. C., E. Neilson, D. Moreira, A. Ladle, R. Steenweg, J. T. Fisher, et al. 2015. Review: wildlife camera trapping: a review and recommendations for linking surveys to ecological processes. *J. Appl. Ecol.* **52**, 675–685.
- Chutipong, W., A. J. Lynam, R. Steinmetz, T. Savini, and G. A. Gale. 2014. Sampling mammalian carnivores in western Thailand: issues of rarity and detectability. *Raffles Bull. Zoology* **62**, 521–535.
- Clements, G. R. 2013. The environmental and social impacts of roads in southeast Asia. PhD Thesis, James Cook University. Available from <http://researchonline.jcu.edu.au/31888/>. (accessed 19 December 2016).
- Collen, B., M. Ram, T. Zamin, and L. McRae. 2008. The tropical biodiversity data gap: addressing disparity in global monitoring. *Tropical Conserv. Sci.* **1**, 75–88.
- Council of Science Editors. 2014. Scientific style and format: the CSE manual for authors, editors, and publishers. *Sci. Ed.* **2**, 44–45.
- Cutler, T. L., and D. E. Swann. 1999. Using remote photography in wildlife ecology: a review. *Wildl. Soc. Bull.* **27**, 571–581.
- Dinata, Y. 2008. Assessing the population status and management of tigers in the Batang Hari Landscape, West Sumatra, Indonesia. MSc Thesis, Durrell Institute of Conservation and Ecology, University of Kent, United Kingdom.
- Dobson, A., and K. Nowak. 2010. Does this photo make my range look big? *Anim. Conserv.* **13**, 347–349.
- Fegraus, E. H., K. Lin, J. A. Ahumada, C. Baru, S. Chandra, and C. Youn. 2011. Data acquisition and management software for camera trap data: a case study from the TEAM Network. *Ecol. Inform.* **6**, 345–353.
- Forrester, T., T. O'Brien, E. Fegraus, P. Jansen, J. Palmer, R. Kays, et al. 2016. An open standard for camera trap data. *Biodivers.Data J.* **4**, e10197.
- Gardner, B., J. Reppucci, M. Lucherini, and A. J. Royle. 2010. Spatially explicit inference for open populations: estimating demographic parameters from camera-trap studies. *Ecology* **91**, 3376–3383.
- Goring, S. J., K. C. Weathers, W. K. Dodds, P. A. Soranno, L. C. Sweet, K. S. Cheruvilil, et al. 2014. Improving the culture of interdisciplinary collaboration in ecology by expanding measures of success. *Front. Ecol. Environ.* **12**, 39–47.
- Gray, T. N. E. 2012. Studying large mammals with imperfect detection: status and habitat preferences of wild cattle and large carnivores in Eastern Cambodia. *Biotropica* **44**, 531–536.
- Gray, T. N. E., and C. Phan. 2011. Habitat preferences and activity patterns of the larger mammal community in Phnom Prich Wildlife Sanctuary, Cambodia. *Raffles Bull. Zool.* **59**, 311–318.
- Hampton, S. E., C. A. Strasser, J. J. Tewksbury, W. K. Gram, A. E. Budden, A. L. Batcheller, et al. 2013. Big data and the future of ecology. *Front. Ecol. Environ.* **11**, 156–162.
- Harris, G., R. Thompson, J. L. Childs, and J. G. Sanderson. 2010. Automatic storage and analysis of camera trap data. *Bull. Ecol. Soc. Am.* **91**, 352–360.
- Heffernan, J. B., et al. 2014. Macrosystems ecology: understanding ecological patterns and processes at continental scales. *Front. Ecol. Environ.* **12**, 5–14.
- Herold, P. 2015. Data sharing among ecology, evolution, and natural resources scientists: an analysis of selected publications. *J. Librarianship Sch. Commun.*, **3**, eP1244. <https://doi.org/10.7710/2162-3309.1244>.
- Ivan, J. S., and E. S. Newkirk. 2016. CpW photo warehouse: a custom database to facilitate archiving, identifying, summarizing and managing photo data collected from camera traps. *Methods Ecol. Evol.* **7**, 499–504.
- Jansen, P. A., J. Ahumada, E. Fegraus, and T. G. O'Brien. 2014. TEAM. A standardized camera-trap survey to monitor terrestrial vertebrate communities in tropical forests. Pp. 263–270 In P. Meek, P. Fleming, eds. *Camera Trapping: wildlife Management and Research*. CSIRO Publishing, Collingwood, Victoria, Australia.
- Kratz, J. E., and C. Strasser. 2015. Researcher perspectives on publication and peer review of data. *PLoS ONE* **10**, e0117619.
- Krishnappa, Y. S., and W. C. Turner. 2014. Software for minimalistic data management in large camera trap studies. *Ecol. Inform.* **24**, 11–16.

- Linkie, M., G. Guillera-Aroita, J. Smith, A. Ario, G. Bertagnolio, F. Cheong, et al., et al. 2013. Cryptic mammals caught on camera: assessing the utility of range wide camera trap data for conserving the endangered Asian tapir. *Biol. Cons.* **162**, 107–115.
- Loken, B., S. Spehar, and Y. Rayadin. 2013. Terrestriality in the bornean orangutan (*Pongo pygmaeus morio*) and implications for their ecology and conservation. *Am. J. Primatol.* **75**, 1129–1138.
- Lynam, A. J., et al. 2012. Comparative sensitivity to environmental variation and human disturbance of Asian tapirs (*Tapirus indicus*) and other wild ungulates in Thailand. *Integr. Zool.* **7**, 389–399.
- Mathai, J., J. W. Duckworth, E. Meijaard, G. Fredriksson, J. Hon, A. Sebastian, et al. 2016. Carnivore conservation planning on Borneo: identifying key carnivore landscapes, research priorities and conservation interventions. *Raffles Bull. Zool.* **33**, 186–217.
- Maxwell, S. L., R. A. Fuller, T. M. Brooks, and J. E. M. Watson. 2016. The ravages of guns, nets and bulldozers. *Nature* **536**, 145–146.
- McCallum, J. 2013. Changing use of camera traps in mammalian field research: habitats, taxa and study types: camera trap use and development in field ecology. *Mammal Rev.* **43**, 196–206.
- McGill, B. 2016. Ten Commandments for good data management. Dynamic Ecology Web blog. Access via: <https://dynamicecology.wordpress.com/2016/08/22/ten-commandments-for-good-data-management/> Last accessed 19th December. 2016.
- McShea, W. J., T. Forrester, R. Costello, Z. He, and R. Kays. 2016. Volunteer-run cameras as distributed sensors for macrosystem mammal research. *Landscape Ecol.* **31**, 55–66.
- Meek, P., and P. Fleming, eds. 2014. *Camera Trapping: Wildlife Management and Research*. CSIRO Publishing, Collingwood, Victoria, Australia.
- Meek, P. D., G. Ballard, A. Claridge, R. Kays, K. Moseby, T. O'Brien, et al. 2014. Recommended guiding principles for reporting on camera trapping research. *Biodivers. Conserv.* **23**, <https://doi.org/10.1007/s10531-014-0712-8>.
- Michener, W. K., and M. B. Jones. 2012. Ecoinformatics: supporting ecology as a data-intensive science. *Trends Ecol. Evol.* **27**, 85–93.
- Mohd-Azlan, J., and L. Engkamat. 2013. Camera trapping and conservation in Lanjak Entimau wildlife sanctuary, Sarawak, Borneo. *Raffles Bull. Zool.* **61**, 397–405.
- Nichols, J. D. 2010. The wildlife picture index, monitoring and conservation. *Anim. Conserv.* **13**, 344–346.
- Niedballa, J., R. Sollmann, A. Courtiol, and A. Wilting. 2016. camtrapR : an R package for efficient camera trap data management. *Methods Ecol. Evol.* (early view). <https://doi.org/10.1111/2041-210X.12600>.
- O'Brien, T. G. 2010. Wildlife picture index and biodiversity monitoring: issues and future directions: wildlife picture index and biodiversity monitoring. *Anim. Conserv.* **13**, 350–352.
- Olsen, A. R., J. Sedransk, D. Edwards, C. A. Gotway, W. Liggett, S. Rathbun, et al. 1999. Statistical issues for monitoring ecological and natural resources in the United States. *Environ. Monit. Assess.* **54**, 1–45.
- R Core Team. 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/>.
- Reichman, O. J., M. B. Jones, and M. P. Schildhauer. 2011. Challenges and opportunities of open data in ecology. *Science* **331**, 703–705.
- Rowcliffe, J. M., and C. Carbone. 2008. Surveys using camera traps: are we looking to a brighter future? *Anim. Conserv.* **11**, 185–186.
- Rowcliffe, M. J., R. Kays, B. Kranstauber, C. Carbone, and P. A. Jansen. 2014. Quantifying levels of animal activity using camera trap data. *Methods Ecol. Evol.* **5**, 1170–1179.
- Sanderson, J. G., and M. Trolle. 2005. Monitoring elusive mammals. *Am. Sci.* **93**, 148–155.
- Sandve, G. K., A. Nekrutenko, J. Taylor, and E. Hovig. 2013. Ten simple rules for reproducible computational research. *PLoS Comput. Biol.* **9**(10), e1003285. <https://doi.org/10.1371/journal.pcbi.1003285>.
- Schipper, J., J. S. Chanson, F. Chiozza, N. A. Cox, M. Hoffmann, V. Katariya, et al., et al. 2008. The status of the world's land and marine mammals: diversity, threat, and knowledge. *Science* **322**, 225–230.
- Spehar, S. N., B. Loken, Y. Rayadin, and J. A. Royle. 2015. Comparing spatial capture-recapture modeling and nest count methods to estimate orangutan densities in the Wehea Forest, East Kalimantan, Indonesia. *Biol. Cons.* **191**, 185–193.
- Strasser, C. A., and S. E. Hampton. 2012. The fractured lab notebook: undergraduates and ecological data management training in the United States. *Ecosphere* **3**, 1–18.
- Sunarto, S. R., A. Mohamed, and M. J. Kelly. 2013. Camera trapping for the study and conservation of tropical carnivores. *Raffles Bull. Zool.* Supplement No. 28, 21–42.
- Sundaresan, S. R., C. Riginos, and E. S. Abelson. 2011. Management and Analysis of Camera Trap Data: alternative Approaches (Response to). *Bull. Ecol. Soc. Am.* **92**, 188–195.
- Swanson, A., M. Kosmala, C. Lintott, R. Simpson, A. Smith, and C. Packer. 2015. Snapshot Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an African savanna. *Sci. Data* **2**, 150026.
- Swanson, A., M. Kosmala, C. Lintott, and C. Packer. 2016. A generalized approach for producing, quantifying, and validating citizen science data from wildlife images. *Conserv. Biol.* **30**, 520–531.
- Thorn, M., D. M. Scott, M. Green, P. W. Bateman, and E. Z. Cameron. 2009. Estimating brown hyaena occupancy using baited camera traps. *South African J. Wildlife Res.* **39**, 1–10.



- Tobler, M. 2007. Camera Base. Available at: <http://www.atrium-biodiversity.org/tools/camerabase/> (accessed 06 June 2017)
- Tobler, M. W., S. E. Carrillo-Percestequi, R. Leite Pitman, R. Mares, and G. Powell. 2008. An evaluation of camera traps for inventorying large- and medium-sized terrestrial rainforest mammals. *Anim. Conserv.* **11**, 169–178.
- Whitlock, M. C. 2011. Data archiving in ecology and evolution: best practices. *Trends Ecol. Evol.* **26**, 61–65.
- Wong, W. M., and M. Linkie. 2013. Managing sun bears in a changing tropical landscape. *Divers. Distrib.* **19**, 700–709.
- Wong, W. M., N. Leader-Williams, and M. Linkie. 2013. Quantifying changes in sun bear distribution and their forest habitat in Sumatra. *Anim. Conserv.* **16**, 216–223.