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INTERDISCIPLINARY PERSPECTIVE

Camtrap DP: an open standard for the FAIR exchange and archiving of camera trap data

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Abstract

Camera trapping has revolutionized wildlife ecology and conservation by providing automated data acquisition, leading to the accumulation of massive amounts of camera trap data worldwide. Although management and processing of camera trap-derived Big Data are becoming increasingly solvable with the help of scalable cyber-infrastructures, harmonization and exchange of the data remain limited, hindering its full potential. There is currently no widely

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accepted standard for exchanging camera trap data. The only existing proposal, "Camera Trap Metadata Standard" (CTMS), has several technical shortcomings and limited adoption. We present a new data exchange format, the Camera Trap Data Package (Camtrap DP), designed to allow users to easily exchange, harmonize and archive camera trap data at local to global scales. Camtrap DP structures camera trap data in a simple yet flexible data model consisting of three tables (Deployments, Media and Observations) that supports a wide range of camera deployment designs, classification techniques (*e.g.*, human and AI, media-based and event-based) and analytical use cases, from compiling species occurrence data through distribution, occupancy and activity modeling to density estimation. The format further achieves interoperability by building upon existing standards, Frictionless Data Package in particular, which is supported by a suite of open software tools to read and validate data. Camtrap DP is the consensus of a long, in-depth, consultation and outreach process with standard and software developers, the main existing camera trap data management platforms, major players in the field of camera trapping and the Global Biodiversity Information Facility (GBIF). Under the umbrella of the Biodiversity Information Standards (TDWG), Camtrap DP has been developed openly, collaboratively and with version control from the start. We encourage camera trapping users and developers to join the discussion and contribute to the further development and adoption of this standard.

Introduction

Populations of many species across the globe are undergoing dramatic alterations in their abundance and distribution, due to a combination of climate-driven and anthropogenic impacts that can either favor or negatively affect species persistence in certain ecosystems (Dornelas et al., 2019). On the one hand, many species are rapidly declining due to anthropogenic stressors acting at different spatio-temporal scales (Bar-On et al., 2018; Dirzo et al., 2014; Ripple et al., 2017; Venter et al., 2016). Terrestrial large mammals are at high risk of extinction and this has caused widespread trophic downgrading, that is, the removal of apex predators and primary consumers (*i.e.*, large carnivores and herbivores) from a majority of Earth's ecosystems (Estes et al., 2011). Indeed, as much as 60% of large herbivore species worldwide are threatened with extinction (Ripple et al., 2015). As a consequence, a great loss of food web links has been recorded (Fricke et al., 2022), putting important ecological interactions and functions at risk (Dirzo et al., 2014; IPBES, 2018). For example, the impact of defaunation on tropical forests (*i.e.*, the "empty forest" syndrome; Redford, 1992) has compromised key functional relations such as seed consumption, herbivory, pollination and seed dispersal (Benítez-López et al., 2019; Bogoni et al., 2023).

On the other hand, extensive areas are experiencing strong increases in some wildlife populations due to land-use change such as forest recovery after land abandonment but also increasing food availability due to forestry and agricultural practices (Perpiña et al., 2018) and successful conservation policies (*e.g.*, US Endangered Species Act 1973; Habitat Directive EU Commission 1997). As a result, several medium-to-large-sized herbivores and carnivores have increased in number and distribution range (from beaver *Castor fiber* to red deer *Cervus elaphus* and white-tailed deer *Odocoileus virgianus* to wild boar *Sus scrofa*, otter *Lutra lutra* and wolves *Canis lupus*; Chapron et al., 2014; Cimatti et al., 2021). Typically, populations of smaller, functionally generalist and ecologically plastic species increase in human-modified landscapes. However, the return of the lost ecological functionality of larger animals is re-establishing more complex ecosystems in some areas (*i.e.*, trophic up-grading). At the same time, it also increases the likelihood of conflicts, such as crop damage, depredation on livestock, browsing impact on natural tree regeneration, damage to tree plantations and disease transmission and traffic accidents at the human–wildlife interface (Apollonio et al., 2017; Côté et al., 2004; Gibb et al., 2020; Martin et al., 2018; Rodríguez-Morales et al., 2013).

These opposing trends, where wildlife populations are either strongly declining or increasing, highlight that the conservation of wildlife and the mitigation of human–wildlife conflicts are strongly intertwined. To understand and manage these relations at different spatio-temporal scales requires big data obtained through extensive networks and standardized monitoring protocols (Buxton et al., 2021; Sutherland et al., 2004).

One well-established method for monitoring wildlife, and especially medium-to-large mammals, is camera trapping, a non-invasive tool to collect field data on animal abundance, distribution, behavior and temporal activity across varying spatial scales (Burton et al., 2015; Delisle et al., 2021; Rovero & Zimmermann, 2016; Wearn & Glover-Kapfer, 2019). Camera traps are autonomous devices that, either automatically triggered by the passage of animals or as time-lapse (see Welbourne et al., 2016), capture images or videos of a wide range of animals and are particularly effective in collecting rich data simultaneously for many species. In addition, they can capture "by-catch data" on non-target species, species traits or background environmental conditions (Hofmeester et al., 2019; Scotson et al., 2017), making the collected data useful beyond the scope of the focal species monitoring. Camera traps are used by both professional and citizen scientists (Fraisl et al., 2022; Lasky et al., 2021; Parsons et al., 2018) with the unique property of producing records of multiple species occurrences that are verifiable as opposed to direct visual observations.

The automated data acquisition provided by camera trapping has moved wildlife ecology and conservation into the Big-Data era (Farley et al., 2018; Hampton et al., 2013; Michener & Jones, 2012). The massive accumulation of camera trap data worldwide (over 100 million confirmed digital animal observations; Steenweg et al., 2016; Kays et al., 2020; Delisle et al., 2021) potentially allows for large-scale interdisciplinary research and low-cost monitoring of wildlife. However, the exploitation of the full potential of camera trap-derived Big Data requires effective and scalable (*i.e.*, from local landscapes to the entire planet) cyber-infrastructures and tools for collaborative data collection, management, processing, harmonization and exchange (Farley et al., 2018; González Talaván et al., 2014; Hampton et al., 2013; Sequeira et al., 2021; Steenweg et al., 2016). Beyond the initial technical development, these tools need the establishment of a network of users and a direct involvement of the entire community to boost their implementation (Urbano et al., 2021).

In recent years, the global camera trapping community has made significant progress toward building data management tools for camera trapping on a wide array of platforms (González Talaván et al., 2014; Scotson et al., 2017; Young et al., 2018) including desktop software (*e.g.*, Wild.ID, Camelot, Camera Base; Hendry & Mann, 2018; Tobler, 2022), web applications (*e.g.*, eMammal, Agouti, Wildlife Insights, TRAPPER; Bubnicki et al., 2016; Ahumada et al., 2019; Casaer et al., 2019; Kays et al., 2020) and analytical packages (*e.g.*, camtrapR, camtraptor; Niedballa et al., 2016; Oldoni et al., 2023). Progress has also been made in the use of artificial intelligence (AI) to automate camera trap image processing. Computer vision can be used to efficiently filter out blank images (*i.e.*, with no animal pictured on it), as well as humans (to be filtered out for privacy reasons) and identify animal species and individuals with high accuracy (Kellenberger et al., 2020; Norouzzadeh et al., 2018; Tabak et al., 2018; Vidal et al., 2021). If the pace of innovation continues in this field, most recorded material will be (semi-)automatically classified in the near future.

User communities have formed around centralized camera trap data repositories (*e.g.*, Wildlife Insights, Agouti, Snapshot Safari, EuroCaM), which allow them to address big questions in wildlife conservation (Ahumada et al., 2019; Kays et al., 2020; Pardo et al., 2021). These initiatives are important as they provide essential tools to many research groups, NGOs or individual researchers and conservationists to improve image acquisition, streamline image processing, facilitate data sharing, and guide and enhance data analysis (Ahumada et al., 2019; Delisle et al., 2021). Despite these important advances, arguably the largest portion of the global inventory of camera trap data remains isolated within individual data producers. Furthermore, the existing data management platforms and infrastructures remain relatively disconnected, with the risk of duplicated effort and missed opportunity for data integration. To connect existing data management platforms, we urgently need a common exchange format between the existing systems to maximize the potential of data sharing to address large-scale questions (Farley et al., 2018; Rowcliffe, 2017; Steenweg et al., 2016). In other words, there is a strong need to assure the FAIRness (Wilkinson et al., 2016; Findable ("F"), Accessible ("A"), Interoperable ("I"), and Reusable ("R")) of the global circulation and harmonization of camera trap datasets in a format which is both machine- and human-readable.

However, despite its relevance for the community of ecologists and wildlife practitioners, there is presently no accepted and used standard for the exchange of camera trap data. The "Camera Trap Metadata Standard" (CTMS) published by Forrester et al. (2016) represents an important step towards this, but has failed to reach widespread adoption. In this paper, we describe a new data exchange format for camera trap data, the Camera Trap Data Package (Camtrap DP). It builds upon CTMS and aims to overcome its shortcomings such as the lack of maintenance, versioning and widespread promotion, a limited number of fields to describe deployments, media and observations, no support for sub-media observations (*e.g.*, part of video or bounding box on image), and no built-in mechanism for automatic validation. Camtrap DP solves these issues and is designed to allow users to easily exchange, harmonize and archive camera trap data at local to global scales. Importantly, Camtrap DP is the consensus of a long, in-depth, consultation process among the main existing camera trap data management platforms as well as some of the major global players in the field of camera trapping (see author list).

Guiding Principles

We developed Camtrap DP with two guiding principles: (1) it should allow easy and interoperable data exchange, and (2) it should be developed openly and collaboratively.

Interoperable data exchange was achieved in several ways. Camtrap DP structures camera trap data in a simple data model that supports a wide range of camera deployment designs (*e.g.*, simple or systematic random, clustered, experimental, feature-targeted), classification techniques (*e.g.*, human and AI, media-based and event-based) and analytical use cases (from compiling species occurrence data through distribution, occupancy and activity modeling to density estimation using different protocols like Random Encounter Model, spatial capture-recapture, or distance-sampling). Data can be exchanged among systems by transforming to and from this model. Where possible, we used terms from existing standards, such as Darwin Core (Wieczorek et al., 2012), Audiovisual Core (Audiovisual Core Maintenance Group, 2023), Dublin Core, DataCite Metadata Schema (DataCite Metadata Working Group, 2021) and vocabularies suggested by Forrester et al. (2016). We decided to adopt Frictionless Standards (https://specs.frictionlessdata.io), a collection of open specifications developed by the Frictionless Data project (Fowler et al., 2018) that offer a standardized way to describe datasets, data files and tabular data. Their main specification, Data Package (Walsh & Pollock, 2007), is a simple container format to package and describe a collection of files. Frictionless Standards are expressed as Javascript Object Notation (JSON) schemas—vocabularies that allow one to annotate and validate JSON documents—making them machine-readable and extensible. The machine-readability has led to the development of a suite of open source software tools (*e.g.*, Frictionless Framework; Open Knowledge Foundation, 2022) in multiple programming languages to create and validate data: tools that are available for Camtrap DP users out-of-the-box. The inherent extensibility of JSON schemas allows communities to expand upon the generic Data Package requirements with domain-specific metadata and requirements. By using Frictionless Standards, Camtrap DP is both domain-specific and highly interoperable.

Camtrap DP has been developed entirely openly, collaboratively, and version-controlled, as is typical for open source software development. It is licensed under the permissive MIT license (https://choosealicense.com/licenses/mit/), allowing anyone to use it. Suggestions for changes to the standard were, and continue to be, proposed and discussed in a public issue tracker (https://github.com/tdwg/camtrap-dp/issues) to which anyone can subscribe and contribute. During the development of the standard, suggestions were reviewed, tested and implemented by a team of software developers and researchers in coding sprints. Major changes were only implemented after reaching broad consensus. Useful feedback and new use cases were received from a wider audience through conference presentations (*e.g.*, Desmet et al., 2021), a webinar (GBIF Secretariat, 2022) and by inviting co-authors to this manuscript. Once a number of changes were adopted, a new version of the standard was released using semantic versioning. This allows Camtrap DP to continue to evolve over time, while making sure that software and datasets referring to older versions of the standard are still valid. The standard itself is maintained as JSON Schemas, which are versioned using GitHub and presented as human-readable documentation at https://camtrap-dp.tdwg.org.

Description of the Standard

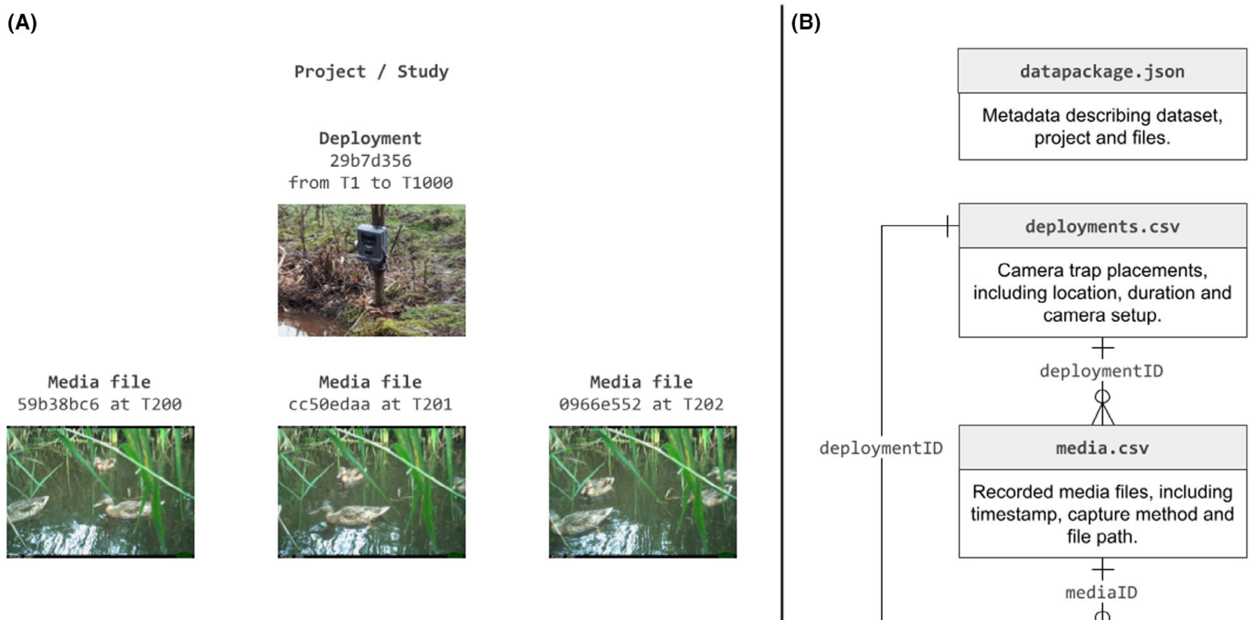
Following the Frictionless Data Package specification, a Camtrap DP dataset contains two types of files: (1) a JSON descriptor file named datapackage.json with dataset **metadata,** and (2) three CSV (comma-separated values) files with tabular **data**. The descriptor file also includes the location and technical description of the data files (called “Resources”) and thus serves as an entry point to the dataset. Resources are described with the Data Resource specification (Walsh & Pollock, 2016), defining their name, path, encoding and CSV dialect, while the tabular data itself is described with Table Schema (Walsh & Pollock, 2012), defining field names, data types, required formats, constraints, missing values, primary keys and foreign keys.

The Camtrap DP standard (version 1.0, see Desmet et al., 2023, https://github.com/tdwg/camtrap-dp/releases/tag/1.0 and Data S1) extends the Data Package specification in two ways. First, it defines a Profile (camtrap-dp-profile.json) to capture the essential metadata of a camera trap study. This Profile makes a number of existing Data Package properties required (contributors and created date) and adds new ones (*e.g.*, project information, spatial, temporal and taxonomic scope). It purposely limits the scope of a dataset/package to a single study/project, which facilitates describing dataset-level properties. Secondly, it specifies the Resources to capture the data collected by the study. The fields and relationships of these Resources are described in three Table Schemas (-table-schema.json). For each property in the Profile and field in the Table Schemas, the data type and format are defined, whether it is required or optional, and whether values should be unique or follow a controlled vocabulary. The three resources collectively represent a data model to exchange camera trap data (Fig. 1).

Deployments is a table with information on the camera trap placements (deployments). It includes the location (locationID, locationName, latitude, longitude, coordinateUncertainty), duration (deploymentStart, deploymentEnd) and camera settings (*e.g.*, cameraModel, cameraDelay, cameraHeight). It also allows to record bait use, feature type, habitat and comments, and to organize deployments in groups (deploymentGroups).

Media is a table with information on the media files (images/videos) recorded during deployments (deploymentID). It includes the recorded timestamp, capture method (motion detection or time lapse) and file information (*e.g.*, filePath, filePublic, fileMediatype). No assumptions are made regarding the location of the media files themselves: they can be referenced with a local path or URL.

Observations is a table with information on the observations (also called classifications) derived from the media files. It contains information about the classification process (*e.g.*, classificationMethod, classificationProbability) and a high-level type (observationType) to separate animal observations from (typically unwanted) other observations (blank, human, vehicle, unknown and unclassified). Animal observations can further specify the scientific name, count, life stage, sex, behavior and identifier of the observed individual(s). Fields required for distance-sampling analyses and random encounter modeling (Howe et al., 2017; Rowcliffe et al., 2008) are available as well (individualPositionRadius, individualPositionAngle, individualSpeed).



observation ID	observation Level	media ID	event Start	event End	scientificName	count
obs1	media	59b38bc6	T200	T200	Anas platyrhynchos	3
obs2	media	cc50edaa	T201	T201	Anas platyrhynchos	4
obs3	media	0966e552	T202	T202	Anas platyrhynchos	4
obs4	event		T200	T202	Anas platyrhynchos	5

Figure 1. (A) Schematic representation of a camera trap project: camera traps are deployed at a location for a period (T1-T1000), recording media files (59b38bc6, cc50edaa, 0966e552). These can be classified into observations at media-level (obs1, obs2, obs3) or event-level (obs4). The total count of observed individuals for an event can be larger than what can be seen in a single media file. (B) Schema representing the structure of a Camtrap DP dataset: it contains one metadata file (datapackage.json) and three tabular data files (deployments.csv, media.csv, observations.csv). Media files can be included in the dataset (not shown) or stored remotely. The relationships between the files are indicated with lines using entity relationship diagram notation. The line ends represents the cardinality of the relationship, with 0< zero to many, |< one to many and || exactly one. A deployment for example has zero to many media, while a media belongs to exactly one deployment.

The table supports two common classification approaches: media-based and event-based (observationLevel). Media-based observations use a single media file as their source (mediaID). These are especially useful for machine learning and do not need to be mutually exclusive (*e.g.*, multiple classifications of the same file are allowed). Event-based observations consider an event with a specified duration (eventStart, eventEnd) as their source and can comprise a collection of media files. These are especially useful for ecological research and analysis (Meek et al., 2014) and should be mutually exclusive, so that their count can be summed. In such ecological analysis, important parameters of many species abundance and density models (*e.g.*, animal group size) can be reliably assessed (*i.e.*, preventing under- and over-counts) by taking into account the context information of an entire sequence of consecutive camera trap records constituting an ecological event (*sensu* Meek et al., 2014). Note that media-based observations can be automatically aggregated into events using statistical functions or custom algorithms, but might under- or overestimate total group count (see Fig. 1).

Media-based observations can further refer to a specific region of interest (ROI) of a media file where an animal or human was observed. A spatial ROI is expressed as a bounding box (bboxX, bboxY, bboxWidth, bboxHeight), specifying the x and y coordinates of the top-left corner of the bounding box and its width and height, respectively. All values are relative to the absolute width and height of the media file. A temporal ROI is expressed as two timestamps (eventStart, eventEnd), specifying the start and end times in a video file. These sub-media spatio-temporal ROIs can be used for machine learning applications (Beery et al., 2019), object tracking and behavior recognition.

To demonstrate the use of Camtrap DP, we included an example dataset (Desmet et al., 2022 and Data S2), versioned with the standard. Like any Camtrap DP dataset, its datapackage.json file references the version of Camtrap DP it should comply with. This allows the standard to evolve to new versions, archived datasets to remain valid and software implementations to understand how to interpret the data. Since the datapackage.json references the data files, it also allows to directly load remote data into a programming environment (Desmet & Oldoni, 2022; Oldoni et al., 2023). Camtrap DP datasets can be transformed to species occurrence data expressed as Darwin Core Archives (Darwin Core Maintenance Group, 2021), as demonstrated by the write_csv() function in the "camtraptor" R package (https://inbo.github.io/camtraptor/reference/write_dwc.html; Oldoni et al., 2023). Since Darwin Core is designed as a cross-domain biodiversity information standard (Wieczorek et al., 2012), this transformation loses some information by design, both in width (excluding camera-trap-specific terms) and length (excluding non-animal observations, such as blank sequences).

Discussion

The increase in camera trap data and its availability offers not only exciting opportunities but also important challenges to overcome. Thus far, camera trapping has not achieved its full potential for standardization, reuse and scaling-up from local to global spatial domains (Steenweg et al., 2016). We think that facilitating the exchange of camera trap data can stimulate the creation of information that is critically needed to address relevant challenges in wildlife conservation and management. Through this publication, we provide a missing piece for the global camera trap data infrastructure, Camtrap DP, which we propose as a standard for exchanging camera trap data in a FAIR, open and both machine- and human-readable way. This data exchange standard enables the camera trapping community to take the next steps towards more collaborative and open research, using specialized software, big data, sophisticated image recognition algorithms and large cyber-infrastructures (Farley et al., 2018).

The role of Camtrap DP

Camtrap DP will facilitate interoperable and robust data flow between all relevant global camera trap cyber-infrastructure components, offline databases and individual participants (Hanke et al., 2021). In this way, the possibility of frictionless harmonization of camera trap data produced by a globally distributed network of researchers and conservationists will help with "harnessing its collective power" (Hampton et al., 2013) and addressing major environmental problems related to wildlife conservation and management.

One of the fundamental principles of Camtrap DP is its simplicity. This does not preclude its robustness in organizing tabular data and providing rich metadata content. This has been shown by several other data-intensive scientific communities where similar solutions (*i.e.*, based on the Frictionless Data specification) have been developed and adopted in diverse scientific domains, for example, electricity system modeling (Wiese et al., 2019), experimental life sciences (Jacob et al., 2020), marine microbiology (Ponsero et al., 2020) or the monitoring of a COVID-19 outbreak in India using a citizen science approach (Ulahannan et al., 2020).

Since the Camtrap DP standard captures essential metadata about a camera trap study, it can also be used as a format to archive data in line with FAIR principles. FAIR publishing or archiving data on research repositories (*e.g.*, Zenodo, DataOne, Dataverse, Figshare, OSF or Dryad) prevents data loss and facilitates reuse, and is increasingly demanded by funders and journals. We recommend archiving/publishing data through the Global Biodiversity Information Facility (GBIF) (see section Facilitating adoption of Camtrap DP). Sensitive data can be restricted or generalized if necessary (see Chapman, 2020; Lennox et al., 2020). For example, access to images of threatened species can be restricted, deployment coordinates can be generalized or roughly indicated, and people names can be replaced with anonymous identifiers.

Camtrap DP can also stimulate the development of standardized camera trap data processing pipelines, including those focused on the application of Artificial Intelligence/Machine Learning methods for automatic image recognition (Kellenberger et al., 2020; Tabak et al., 2018) and the automation of camera trap data analysis using already well-established statistical frameworks for modeling, for example, species distribution, species richness, activity patterns, occupancy and abundance (Rovero & Zimmermann, 2016; Wearn & Glover-Kapfer, 2017). Apart from one valuable initiative, https://lila.science, most of the publicly available camera trap datasets that could be used to train AI models remain fragmented, difficult to find and have low accessibility. Camtrap DP will facilitate creating and publishing open, harmonized, findable and easily accessible datasets of annotated images and videos of wildlife species recorded in different ecosystems worldwide. The findability and interoperability will enable camera trap data to be harvested from public or private API endpoints (*e.g.*, from GBIF, Zenodo or camera trap data management systems) and processed in high-performance cloud computing environments.

How does Camtrap DP extend the Camera Trap Metadata Standard (CTMS)?

The Camtrap DP development has been based upon an open, collaborative and community-oriented approach, which should reduce the risk of becoming outdated with no maintenance and versioning, as is unfortunately occurring for CTMS (Forrester et al., 2016). Similar to Darwin Core (Wieczorek et al., 2012), we envision Camtrap DP as a community-driven and evolving standard. This flexibility seems to be especially important given rapid development in ecological and conservation technology, with camera trapping not being an exception.

Camtrap DP builds upon the first effort to standardize camera trap data (CTMS) in important ways. It structures the data in a simple yet flexible data model, contains equivalents of all CTMS fields for which use cases were found, adds new fields to capture more information about deployments, media (*e.g.*, their file location) and observed species (*e.g.*, sex and life stage). It supports the expression of observations at the level of (ecological) events (Meek et al., 2014; sequence in CTMS), media and sub-media (*e.g.*, detected objects encompassed by bounding boxes). This approach better enables the development and training of AI models (media-level) as well as ecological analysis (event-level). Animal observations include fields for animal sex, life stage, behavior, individual identifier and more. Rather than a single file (JSON or XML in CTMS), data are organized in a descriptor file (JSON) for dataset/project-level metadata and tables for deployments, media and observations. We recommend the use of CSV files, but any other serialization format supported by Table Schema (including JSON) is valid. Data tables are linked together via foreign keys, thus mimicking the structure of relational database system (Fowler et al., 2018).

Camtrap DP is based on a well-established framework and it comes with a suite of open source software tools in multiple programming languages to create, validate and read camera trap data packages. The JSON Schemas enable validation of dataset metadata, structure, required fields and compliance of values with controlled vocabularies, another important improvement over CTMS.

Is Camtrap DP FAIR?

As Camtrap DP is directly derived from the Frictionless Data specification it automatically inherits most of the basic principles of FAIRness (Wilkinson et al., 2016), https://www.go-fair.org/fair-principles). For example, principles supported out-of-the-box include the possibility to assign a globally unique and persistent identifier to the dataset and each data record (Findability: fair principle "F1"), Profile and Table Schemas describing all (meta) data properties with rich metadata (Findability: "F2", "F3"; Reusability: "R1"), access to all elements of the dataset over http (Accessibility: "A1"), and the possibility to clearly define a dataset license (Reusability: "R1.1"). The Interoperability principles are supported by the package descriptor concept, which uses an accessible, shared, broadly applicable and machine-readable format (JSON) and vocabularies (JSON schemas) to describe package metadata and its specification. The latter has a great potential for new extensions. Moreover, the CSV format is a well-established, simple, compact and machine-readable standard for storing and exchanging tabular data. Camtrap DP extends the base support for the FAIRness principles provided by the Frictionless Data specification in the following manner:

• Findability ("F") and Reusability ("R"). We include three dataset-level terms to indicate spatial, temporal and taxonomic coverage. The latter is especially useful since camera trapping datasets often contain a large amount of so-called by-catch data (Scotson et al., 2017).

• Accessibility ("A"). Allowing data to be shared with or without the access to original media files provides more granular levels of accessibility.

• Interoperability ("I"). Term equivalents from other standardized vocabularies (Darwin Core, Dublin Core, Audiovisual Core, DataCite Metadata Schema) are indicated whenever applicable using Simple Knowledge Organization System (SKOS) identifiers such as skos:exactMatch.

• Reusability ("R"). Reusability is further bolstered by proposing Camtrap DP as a domain-relevant community standard ("R1.3") for camera trap data and by including package-level metadata such as project ownership, published references and sampling methodology ("R1.2").

Extending Camtrap DP

Through open collaborative development and version tracking, Camtrap DP can be easily improved or extended in response to feedback from the camera trapping community, following the methodology described in the Guiding Principles. An example of a potential extension of Camtrap DP is the integration of a separate table for animals that can be identified at the individual level using physical features such as distinct fur, feather or skin patterns or even using facial recognition algorithms (Vidal et al., 2021). Similarly, an extra table with detailed descriptions of animal behavior captured by camera trap videos could be considered in future releases and incorporated into the core Camtrap DP structure when agreed by the community.

However, Camtrap DP also comes with a built-in extension mechanism that allows users to add additional information to the core structure of a data package themselves and remain compliant with the standard. This can be achieved by defining new Resources in a data package descriptor file, adding the corresponding data files to the data folder, and defining a JSON schema for each new resource. For example, adding an extra attribute describing the health condition of observed animals would involve creating a table health.csv, adding it as a new resource to datapackage.json and defining a new schema with the first column being a foreign key to the observations.csv table and the second providing categorical or numerical information about the health status of the observed individual. This new table would then be automatically validated by Camtrap DP along with the core tables.

Moreover, we also believe that Camtrap DP provides a solid basis for further application in (semi-)automated media capture by sensors that are not fixed in one location (*e.g.*, mounted on drones, autonomous underwater vehicles, etc.). Camtrap DP could potentially also be extended to other types of remote sensing data, such as observations from PhenoCams (Richardson et al., 2018), which are used to monitor vegetation phenology and other environmental variables, including snow cover onset (Kosmala et al., 2018). The same extension mechanisms as described above could be used. This would broaden the scope of Camtrap DP beyond wildlife camera trapping and make it more attractive to a multidisciplinary audience.

Facilitating adoption of Camtrap DP

Community-wide adoption of a data standard requires implementation by existing systems and applications. Many authors of this paper are maintainers of software tools used by the camera trapping community, which should facilitate the adoption of Camtrap DP. On the production side, it is critically important that camera trap data management systems add support for Camtrap DP as an export format. Agouti and Trapper have already done so, and Wildlife Insights, eMammal and the R package "camtrapR" all officially support the development and release of Camtrap DP, with plans to incorporate seamless conversion between Camtrap DP and their native data formats. The R package "camtraptor" (Oldoni et al., 2023) was developed to facilitate the consumption of Camtrap DP. It provides functionality to read, explore, filter, transform and visualize Camtrap DP datasets, and aims to support the conversion of datasets to the latest version of Camtrap DP, combining datasets for cross-study analyses and closer integration with "camtrapR". The publication of Camtrap DP datasets is supported by GBIF (Reyserhove et al., 2023) and has been implemented as a data publication format in the forthcoming version 3 release of their Integrated Publishing Toolkit (IPT; Robertson et al., 2014; GBIF Secretariat, 2023). Using the IPT, researchers can upload their camera trap data, transform it to the standard, document it with metadata using a graphical user interface, publish the dataset and register it with GBIF for harvesting and increased findability. The demonstrated ability to transform Camtrap DP to Darwin Core allows GBIF to integrate these data with other species occurrence data.

Equally important to software implementation, is building trust within a community toward a proposed solution (Urbano et al., 2021). This can be achieved by an open, collaborative and community-oriented development process (Wieczorek et al., 2012) and active promotion within the existing networks of camera trap data producers (Urbano et al., 2021). The support from trusted and well-recognized organizations can also be of critical importance. We hope to facilitate that trust by developing Camtrap DP under the umbrella of the Biodiversity Information Standards (TDWG), a non-profit organization dedicated to developing biodiversity information standards and responsible for maintaining well-known and commonly used standards such as Darwin Core or Audiovisual Core. Through TDWG we can also seek sustainable maintenance, community review and ratification as a standard. Through outreach and collaboration, Camtrap DP is now supported by GBIF and recommended by GigaScience Press as the submission format for camera trap data in their journals GigaScience and GigaByte.

Finally, it is worth noting that by using the Camtrap DP data exchange format, users are by no means forced to make their datasets publicly available. Camtrap DP is designed to facilitate data exchange between researchers and institutions and to ensure that the data can be easily shared and reused in the future. However, the decision to make the data publicly available is entirely up to the data owner. This can be especially important, for example, for long-term camera trap studies and researchers who are open to sharing their datasets with others on request, but are not willing to publish their data in an open access mode (Mills et al., 2015).

A common data model for camera trap data

While Camtrap DP answers the need for a data exchange model and format, it would be good if it was underpinned by a comprehensive data model for the whole camera trapping domain—one that models and defines all domain-relevant concepts, can fully capture datasets without redundancy, ambiguity or partiality, cross-references terms and synonyms and can act as a rosetta stone for users of different management systems, thus facilitating the translation of data to Camtrap DP. Although such a comprehensive Camtrap Data Model (Camtrap DM) is not the subject of this paper, its in-depth analysis and description are planned for future publication.

Conclusions

The rapid generation of large and harmonized camera trap datasets, together with the development of standardized and accessible AI-driven data processing pipelines, will allow ecologists to learn more about wildlife community ecology, including human–wildlife coexistence across large-scale ecological gradients of human pressure and landscape configuration. Conservationists and policy-makers can capitalize on this knowledge to make informed science-based management decisions and encourage cooperation between countries, engaging in dialog with stakeholders (wildlife managers, farmers, NGOs, policy makers) and promoting best practices in wildlife management methods.

As technological innovations in camera trapping continue at a rapid pace, many camera trap research teams face significant challenges when managing, classifying, re-using and sharing datasets that often contain thousands of media files. Using efficient infrastructure and tools at hand, the data from various camera trap projects can be harmonized and integrated to address scientific and conservation goals. As an open, evolving standard for the FAIR exchange and archive of camera trap data, Camtrap DP represents an important step toward a global data sharing workflow with rapid results and thus more timely science-based wildlife management recommendations.

Author Contributions

JWB and PD conceived the initial idea for Camtrap DP (conceptualization) and supervised and coordinated its development (supervision, project-administration); JWB, BN, DO, DS, JC, JN, JW, MR, MT, PAJ, SJB, TDF, TR, TRH, YL and PD contributed to the development of Camtrap DP (methodology, validation); JWB, DO, JN, MR, TR, YL and PD coordinated software development in support of Camtrap DP (software); JWB, TM, and PD acquired funding in support of Camtrap DP (funding-acquisition); PD created the example dataset (data-curation), website and figure (visualization); JWB, BN and PD wrote the initial draft of the manuscript (writing-original-draft). All authors contributed critically to the drafts and gave final approval for publication (writing-review-editing).

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Data Availability Statement

Camtrap DP version 1.0 is deposited on Zenodo (Desmet et al., 2023). See https://github.com/tdwg/camtrap-dp for the current version.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Data S1. Human-readable documentation for Camtrap DP version 1.0. See https://camtrap-dp.tdwg.org for the current version.

Data S2. Example dataset for Camtrap DP version 1.0.