Liang et al. *Zool. Res.* 2026, 47(4): 1097−1105
https://doi.org/10.24272/j.issn.2095-8137.2025.340
https://cstr.cn/32248.14.zr.2025.340

ZR | Zoological Research

Article **Open Access**

Global Camera Trapping Inventory (GCTI) v.1.0: A worldwide inventory of camera-trapping studies for spatial biodiversity analysis

Li-Wen Liang[1,2,3], Azka Fatimah[1,3], Qian Qian[1,3], Tong Zhang[4], Xiao-Yi Wang[1], Feng-Ying Zhang[2], Qi Xiao[1,3], Ze-Guang Guo[1,3], An-Li Jiang[1,3], Xiao-Yong Zhao[1,3], Xiao-Gang Wu[1], Ming-Xi Du[5], Ji-Yuan Yu[6], Huang-Cheng Liu[7], You-Hua Chen[1], Jian-Ping Jiang[1], Zi-Yan Liao[1,*]

[1] *Chengdu Institute of Biology*, *Chinese Academy of Sciences*, *Chengdu*, *Sichuan* 610213, *China*
[2] *Sichuan Provincial Institute of Forestry and Grassland Inventory and Planning*, *Chengdu*, *Sichuan* 610081, *China*
[3] *University of Chinese Academy of Sciences*, *Beijing* 100049, *China*
[4] *Central South Inventory and Planning Institute of National Forestry and Grassland Administration*, *Changsha*, *Hunan* 410014, *China*
[5] *School of Public Policy and Administration*, *Xi'an Jiaotong University*, *Xi'an*, *Shaanxi* 710049, *China*
[6] *Huaneng Lancang River Hydropower Inc.*, *Kunming*, *Yunnan* 650214, *China*
[7] *Powerchina Zhongnan Engineering Corporation Ltd.*, *Changsha*, *Hunan* 410014, *China*

ABSTRACT

Camera traps have significantly advanced biodiversity monitoring by enabling standardized, noninvasive detection of medium- and large-sized wildlife across broad spatial scales. However, the lack of data sharing within the camera-trapping community, particularly during the early development of the field, has restricted the availability of public species-occurrence records and limited the integration of camera-trap evidence into global spatial analyses. Data sensitivity, especially for threatened species, has further constrained open access to study-level geographic records. To address this gap, the Global Camera Trapping Inventory (GCTI) v.1.0 was developed to compile project-level spatial information from 970 camera-trapping studies indexed in the Web of Science (WoS) and China National Knowledge Infrastructure (CNKI) between 1990 and 2023. The database includes an Excel file with 22 fields documenting study design, survey methods, recorded taxa, and associated metadata, together with three shapefile formats that capture geographic information at complementary spatial resolutions. The GCTI database was established to strengthen open, collaborative data sharing in biodiversity monitoring while preserving the spatial structure needed for research synthesis. By providing project-level shapefiles linked to specific regions and species, GCTI offers a spatially explicit resource for biodiversity, conservation, ecology, and biogeography research. Compared with existing platforms such as Wildlife Insights and eMammal, GCTI provides data suitable for meta-analyses, literature reviews, and spatial overlap analyses with global biodiversity resources, such as GBIF and the IUCN Red List. To facilitate data access and application, an interactive web platform was developed to enable online searching, visualization, and download (https://biodiversityoptimization.shinyapps.io/gcti_v1/).

Keywords: Camera trapping; Global inventory; Biodiversity datasets; Spatial data; Open data sharing

INTRODUCTION

Biodiversity loss in the Anthropocene has intensified the need for coordinated systems that can track biodiversity change across national boundaries, a priority emphasized by the Convention on Biological Diversity (CBD) (Schmeller et al., 2015; Steenweg et al., 2017). Camera trapping has become one of the most powerful tools for this task as it provides noninvasive, nonlethal, and repeatable observations of terrestrial wildlife across landscapes and over time (Blount et al., 2021; Cordier et al., 2022; Harley & Eyre, 2024; Rich et al., 2017; Rowcliffe et al., 2014). Large-scale syntheses have demonstrated that camera-trap records can substantially improve inference on global biodiversity patterns and temporal change (Oliver et al., 2023). At the same time, advances in infrared imaging, battery performance, storage capacity, and

Received: 13 October 2025; Accepted: 18 November 2025; Online: 19 November 2025

Foundation items: This work was supported by the National Key Research and Development Program of China (2022YFF1301401), National Natural Science Foundation of China (32571938, 32201424), Sichuan Provincial Natural Science Foundation (2025ZNSFSC1024), and Science and Technology Project of China Huaneng Group Co., Ltd (HNKJ22-H109)

*Corresponding author, E-mail: liaozy@cib.ac.cn

equipment affordability have made camera trapping an increasingly accessible and cost-effective technology for research (Jenks et al., 2011; Liu et al., 2013). Since 2005, rapid growth in camera-trap studies has generated extensive and geographically dispersed data (Delisle et al., 2021; Green et al., 2020; McCallum, 2013). From a macro-biogeographic perspective, the key challenge is to integrate this expanding body of camera-trap data into spatially explicit resources that complement global species-occurrence databases and support efforts to address biodiversity loss.

Effective reuse of camera-trap evidence depends on two core elements: reliable species records and precise geographic information. However, open release of fine-scale locality data can expose populations to poaching or other human pressures, particularly for rare, commercially valuable, or threatened taxa (Lindenmayer & Scheele, 2017). Consequently, restricted access to sensitive information on threatened species has been widely recommended to mitigate potential risks (Lindenmayer & Scheele, 2017; Lindenmayer et al., 2017). As a result, researchers often omit exact camera locations from publications and instead report generalized or spatially obscured coordinates. Although this practice reduces conservation risk, much camera-trap data remains underutilized and difficult to mobilize, compare, or integrate into quantitative analyses. Existing local and global platforms and databases have made progress in encouraging camera-trap data sharing (Ahumada et al., 2020; Camera Data Team for Wildlife Diversity Monitoring, 2013; Forrester et al., 2016), and large-scale initiatives increasingly distribute processed detection records rather than raw images or videos (Burton et al., 2024; Devarajan, 2025). While these efforts have broadened access to camera-trap information, inconsistent data formats and limited analytical tools continue to hinder wider reuse (Bubnicki et al., 2024). A standardized framework is therefore needed to extract and organize camera-trap data from published studies in a form that protects sensitive locality data while maximizing accessibility for biodiversity synthesis, conservation planning, and macroecological analysis.

Integration of camera-trap records into macroecological pipelines has been limited by more than the need to protect sensitive locality data. Until recently, the field lacked a widely adopted exchange standard, which made it difficult to harmonize records across multiple sources. The Camera-Trap Data Package (Camtrap DP), introduced in 2023, aimed to provide a common structure for camera-trap data publication and reuse (Bubnicki et al., 2024). Major biodiversity platforms have also faced technical barriers. For example, the Global Biodiversity Information Facility (GBIF) historically grouped camera-trap records within the broad category of "machine observations", a format that did not adequately capture essential project-level context, including deployment effort and locality information, thereby limiting data discovery and reuse (GBIF, 2022). With the launch of the Integrated Publishing Toolkit (IPT v3+) and support for Camtrap DP, full-fidelity publication of camera-trap datasets has become increasingly feasible (GBIF, 2026). Furthermore, longitudinal surveys indicate that willingness among researchers to share data has increased, although institutional constraints, practical barriers, and confidentiality concerns continue to limit the release of precise locality information, especially for sensitive species (Tenopir et al., 2015). These technical, institutional, and cultural barriers have collectively slowed the integration of camera-trap evidence into broad-scale biodiversity analyses.

Standardized extraction and library construction remain difficult because camera-trap studies vary widely in survey design, layout configuration, sampling effort, and reporting conventions (Ahumada et al., 2011; Burton et al., 2015; Meek et al., 2014). Although several studies have proposed more standardized deployment schemes and data protocols (Foster & Harmsen, 2012; Hofmeester et al., 2019; Mugerwa et al., 2024; Schmeller et al., 2015; Young et al., 2018), these guidelines have not fully resolved how to share and manage sensitive data associated with threatened species. Current global camera-trap platforms, such as Wildlife Insights and eMammal, address this risk by strongly obscuring sensitive localities or restricting access to such data. For large-scale studies, these data management practices can compromise both data integrity and availability, resulting in insufficient georeferenced data for spatial analyses. This limitation is especially important in regions with high extinction risk, where camera-trap research remains uneven and, in some countries, insufficient for biodiversity assessment (Mugerwa et al., 2024). A standardized camera-trap database optimized for spatial analysis is therefore needed to improve data mobilization, enable quantitative synthesis, and support global biodiversity assessment.

To address this data gap, the Global Camera Trapping Inventory (GCTI) was developed as a standardized resource that reconstructs study-level geographic context from published camera-trapping research, including studies that did not report explicit spatial data in machine-readable form. GCTI combines 22 standardized data-extraction fields with georeferenced study-area shapefiles, thereby improving spatial comparability across heterogeneous camera-trap studies. Each record includes a list of target species, linked to the corresponding georeferenced study area, providing detailed ecological context for each site while avoiding disclosure of precise camera or species locations. By integrating dispersed literature records into a searchable spatial database, GCTI also provides a user-friendly web platform for locating species- and region-specific camera-trapping records, supporting both broad macroecological synthesis and focused research queries. GCTI provides three main advances for camera-trap data mobilization. First, it offers a global overview of camera-trapping research from 1990 to 2023, together with standardized geographic information for published studies. Second, it introduces a figure-based geographic information extraction approach that preserves spatial utility without exposing precise species locations. Third, it enables quantitative assessment of global camera-trapping coverage, facilitating the identification of research hotspots, geographic gaps, and priorities for future biodiversity monitoring. Overall, GCTI was designed for broad use by conservation professionals, researchers, field managers, rangers, and community-based monitoring teams. Its georeferenced format and standardized attributes support efficient species- and region-based searches, GIS-based spatial overlap analyses, and large-scale meta-analyses across camera-trapping studies, with broad applications in ecology, biogeography, and biodiversity conservation.

MATERIALS AND METHODS

Inventory construction followed two sequential stages: literature retrieval and screening, followed by data extraction and database construction. The Web of Science (WoS) and China National Knowledge Infrastructure (CNKI) were selected as source databases for their broad disciplinary coverage, consistent formatting, and structured metadata, which facilitated standardized and efficient data extraction.

Scopus and Google Scholar were not included due to differences in indexing criteria, inconsistent metadata formats, and access limitations (Singh et al., 2024).

Literature collection and screening

Literature retrieval and screening followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher et al., 2009). Searches were conducted in WoS and CNKI using the criteria shown in Figure 1. Seven keywords related to camera trapping were used in topic searches to maximize retrieval of eligible studies (Xiao et al., 2022). Additional filters for research area, document type, and publication year were then applied to refine the candidate set. Commonly used publication languages were also included in the search strategy to broaden coverage. A total of 2 534 results were retrieved as of 10 August 2023.

During initial screening, records were evaluated for relevance to "animal camera trapping technology". Papers that were inaccessible or failed to meet the topic criteria were excluded, leaving 1 692 articles for further review.

A second stepwise screening procedure was then applied according to the workflow shown in Figure 2. First, research content and document type were assessed to identify studies containing unique empirical information from camera-trapping surveys. Second, each article was checked for sufficient methodological and spatial information, including details on camera deployment, monitoring design, and either a study-area map, schematic diagram, or geographic coordinates for the camera-trap survey area. Duplicate publications were also assessed, and only nonrepetitive information on target species from the same study was retained. After completion of this screening process, 970 papers were included in the final inventory.

Data extraction and inventory construction

To maintain methodological consistency, the inventory was restricted to studies that used infrared camera traps. Devices activated by auxiliary trigger mechanisms, such as pressure plates, were excluded. The final inventory contained two linked components: a tabular inventory provided as an Excel spreadsheet file and a spatial inventory provided as shapefiles.

Project-level information was extracted from each eligible paper using 22 standardized attributes (Table 1), which define the columns of the tabular inventory. Extraction followed the standardized procedures described in Section 2.3. Each row represents one target-species record from a given camera-trapping study.

The spatial inventory was constructed from maps, schematics, coordinates, and other geographic information reported in the source publications. For studies that provided maps or figures showing camera-deployment areas, these figures were georeferenced in ArcMap v10.8, and buffered polygon shapefiles were generated to represent the corresponding survey areas. These shapefiles denote camera-trap study areas rather than species area-of-occupancy (AOO) estimates. AOO is conventionally estimated from species-occurrence records using a 2×2 km grid, whereas the present workflow did not apply grid-based AOO calculation. Instead, a unified polygon was created by applying a buffer to mask exact camera locations and avoid disclosure of sensitive locality information. The resulting unified layer should therefore be interpreted only as the "research survey area", not as an AOO estimate. For publications that reported only latitude and longitude information, or that provided figures with approximate or spatially imprecise site information, point or multipoint shapefiles were created according to the available geographic data. Each shapefile attribute table contains three fields, "ID", "Sub_ID", and "Title", which correspond to the same fields in the tabular inventory and enable direct linkage between spatial files and extracted study records.

Tabular inventory

The tabular database, "Table database.xlsx", records bibliographic information, survey design, and monitoring results for each camera-trapping publication. The database structure is summarized in Table 1. Key fields are defined as follows: (i) "ID", a unique identifier assigned to each study. Multiple publications may share the same "ID" in cases of duplicate reporting. A small number of records were excluded during georeferencing due to missing geographic information, resulting in nonsequential "ID" values; (ii) "Sub_ID", a location-specific identifier nested under each "ID". A single publication may therefore contain multiple "Sub_ID" entries; (iii) "Spatial scale" classifies the geographic extent of each study into five categories: (a) "Protected area", indicating that the survey was conducted within a single protected area; (b) "Locality", indicating that the survey included multiple protected or nonprotected areas; (c) "Country", indicating that the survey covered an entire country; (d) "International", indicating that the survey crossed national borders but remained within one continent; (e) "Intercontinental", indicating that the survey spanned more than one continent; (iv) "Country" records the country or countries covered by the study. For records classified as "International" or "Intercontinental" under "Spatial scale", multiple country names may be entered in a single cell; (v) "Region" records the subnational region when applicable. For records classified as "Country" under "Spatial scale", this field may be left blank. (ⅵ) "Subject" classifies the main research focus using five categories: (a) "Animal Ecology"; (b) "Animal Ethology"; (c) "Animal Morphology"; (d) "New Record Report"; and (e) "Technology and Methods". Up to two subject categories may be assigned to a single record.

Shapefile inventory

The shapefile inventory contains three spatial data products: polygon shapefiles ("Shp Database"), point shapefiles ("Point Database"), and multipoint shapefiles ("Multipoint Database"). Each dataset includes the associated .shp, .shx, .sbn, .sbx, .prj, .dbf, .cpg, and .shp.xml files. The attribute table of each shapefile contains three columns: "ID", "Sub_ID", and "Title", which correspond to the same fields in the table database and enable direct linkage between spatial records and extracted study information. The spatial distribution of records in the shapefile inventory is shown in Figure 3. All shapefile data represent project-level geographic information rather than observation-level occurrence records, including point and multipoint shapefiles. Polygon and point shapefiles summarize study-area information together with the associated species lists and metadata. Multipoint shapefiles represent two types of source information: multiple reported locations for the same species within a single study area, or multiple approximate monitoring locations reported within one study, which may include records for more than one species.

Technical validation

Several validation procedures were implemented during inventory construction to reduce data uncertainty:

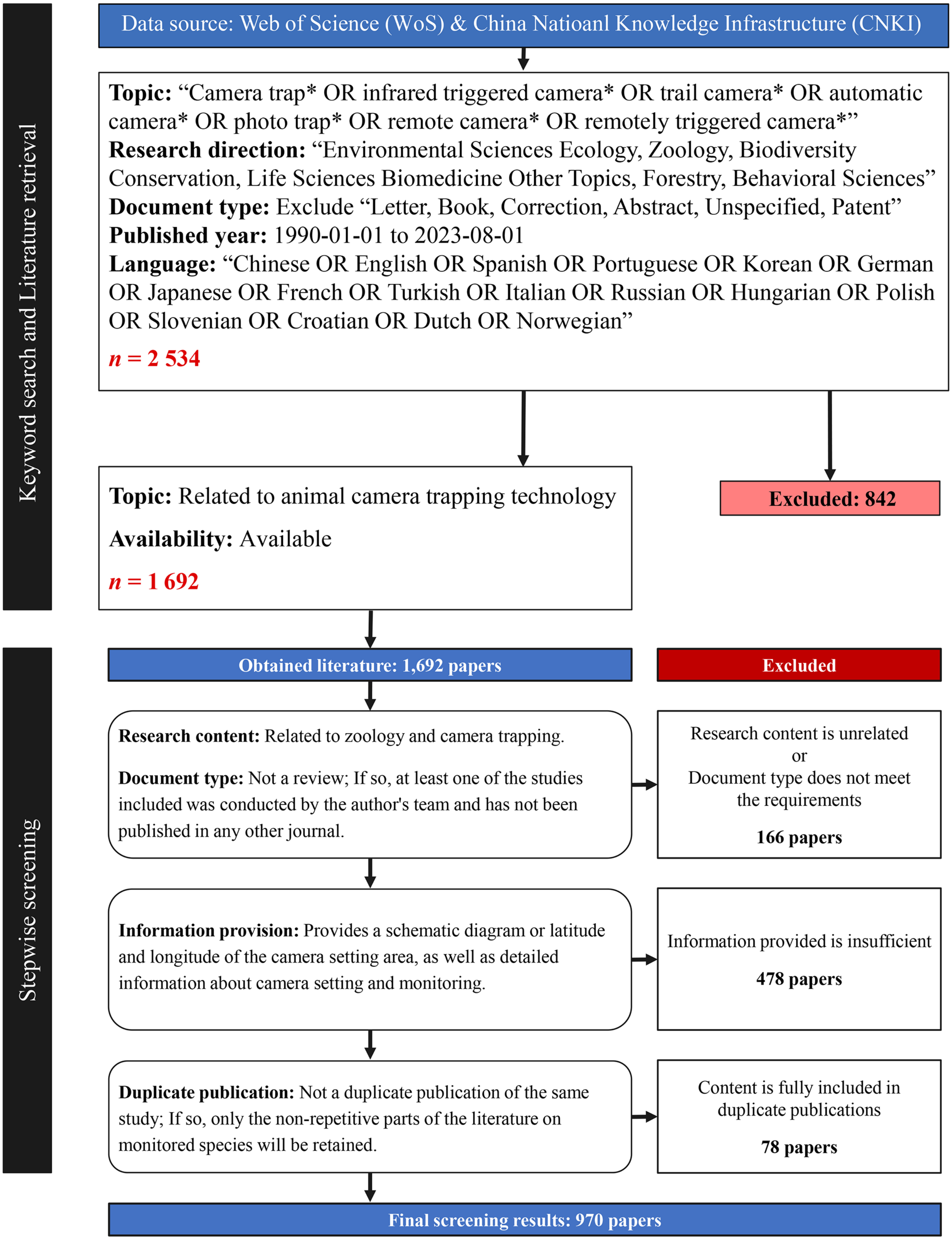

Figure 1 Keyword search strategy and stepwise screening workflow used to compile publicly available scientific literature for the GCTI v.1.0 spatial camera-trap inventory

(i) Camera number. Camera-trap studies often involve camera replacement during sampling or rotational deployment of a limited number of cameras across multiple sampling areas. In these cases, the actual number of cameras deployed during the survey may differ from the number specified in the original sampling design. To standardize this field and reduce extraction error, "Camera number" records the minimum number of cameras required by the initial survey design rather than the cumulative number of cameras used during the study (Table 1).

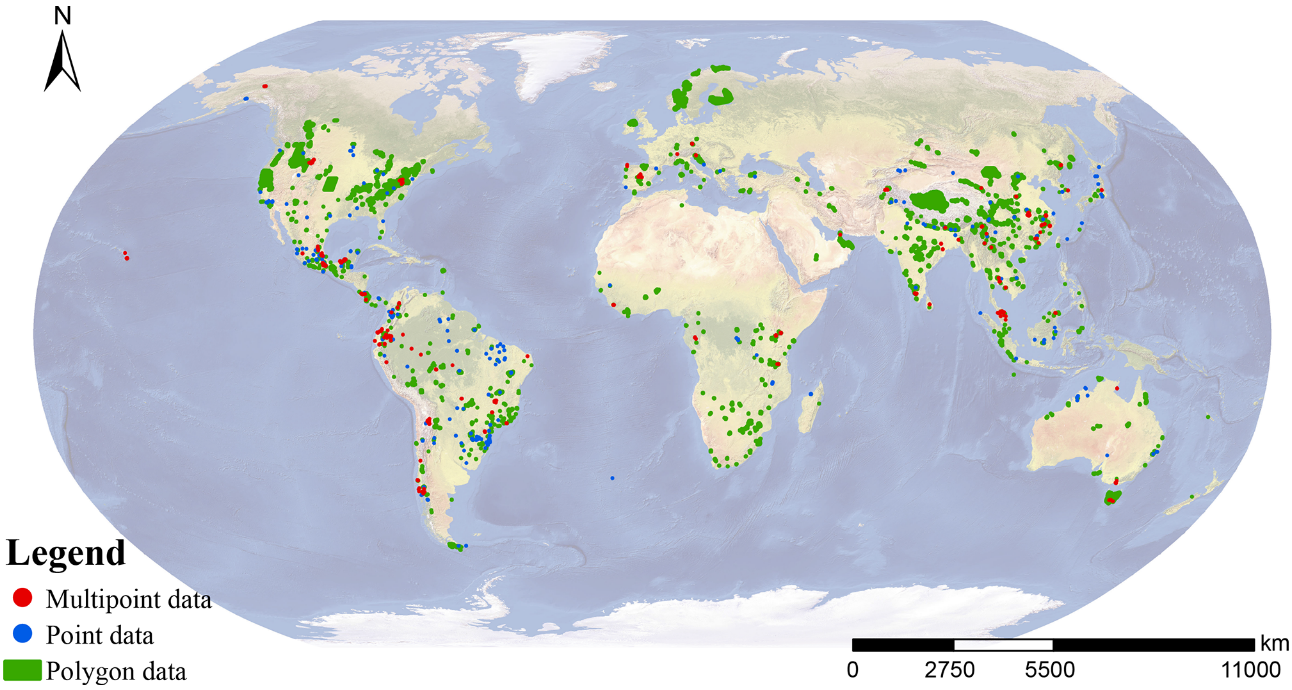

Figure 2 Overview of the GCTI v.1.0 shapefile inventory

Table 1 Description of the 22 attributes included in GCTI

Number	Field name	Description	Field type	Multiple values	Null value
1	ID	Unique identifier for each study	Integer	N/A	N/A
2	Sub_ID	Location-specific identifier nested within each study ID	Character	N/A	N/A
3	Title	Article title	Character	N/A	N/A
4	Journal	Journal name	Character	N/A	N/A
5	DOI	Digital object identifier of the article	Character	N/A	N/A
6	Citation	Full citation of the article	Character	N/A	N/A
7	Language	Publication language	Character	N/A	N/A
8	Continent	Continent in which the study area is located	Character	N/A	N/A
9	Country	Country in which the study area is located	Character	Allowed	N/A
10	Region	Name of study location	Character	N/A	Allowed
11	Longitude	Longitude of the record/study location	Float	N/A	Allowed
12	Latitude	Latitude of the record/study location	Float	N/A	Allowed
13	Spatial scale	Spatial scale of the study	Character	N/A	N/A
14	Starting year	First year of camera-trap monitoring	Integer	N/A	Allowed
15	Ending year	Final year of camera-trap monitoring	Integer	N/A	Allowed
16	Sampling effort	Camera-trap sampling effort, expressed as camera days	Integer	N/A	N/A
17	Subject	Main research focus of the study	Character	Allowed	N/A
18	Species	Target species	Character	N/A	N/A
19	Camera number	Number of cameras required for survey design	Integer	N/A	N/A
20	Camera model	Camera-trap model used in the study	Character	Allowed	N/A
21	Attractants	Use of attractants during monitoring (1=used, 0=not used)	Binary	N/A	N/A
22	Corrected name	Corrected species name based on GBIF Species Matching Tool and manual verification	Character	N/A	N/A

N/A: Not applicable.

(ii) Spatial validation and shapefile construction. Georeferenced figures extracted from source publications were checked and corrected using Google Maps satellite imagery, polygon data for the corresponding protected area, or both, with protected-area boundaries obtained from the World Database of Protected Areas (WDPA, https://www.protectedplanet.net/en). Polygon shapefiles were generated using a standardized approach based on the detection range of infrared cameras and the spatial sampling design reported in each study. Some studies divided the survey area into square sampling units, with side lengths ranging from one to several kilometers, and deployed one or more cameras within each unit according to the study objective and focal taxa. However, many studies did not use an explicit sampling-unit design, partly due to the difficulty in quantifying the effective sampling area of camera traps. For studies without defined sampling units, the mean distance from the outermost cameras to the boundary of the study area was used as the approximate sampling-unit size. A buffer zone was then manually applied to the camera points or core

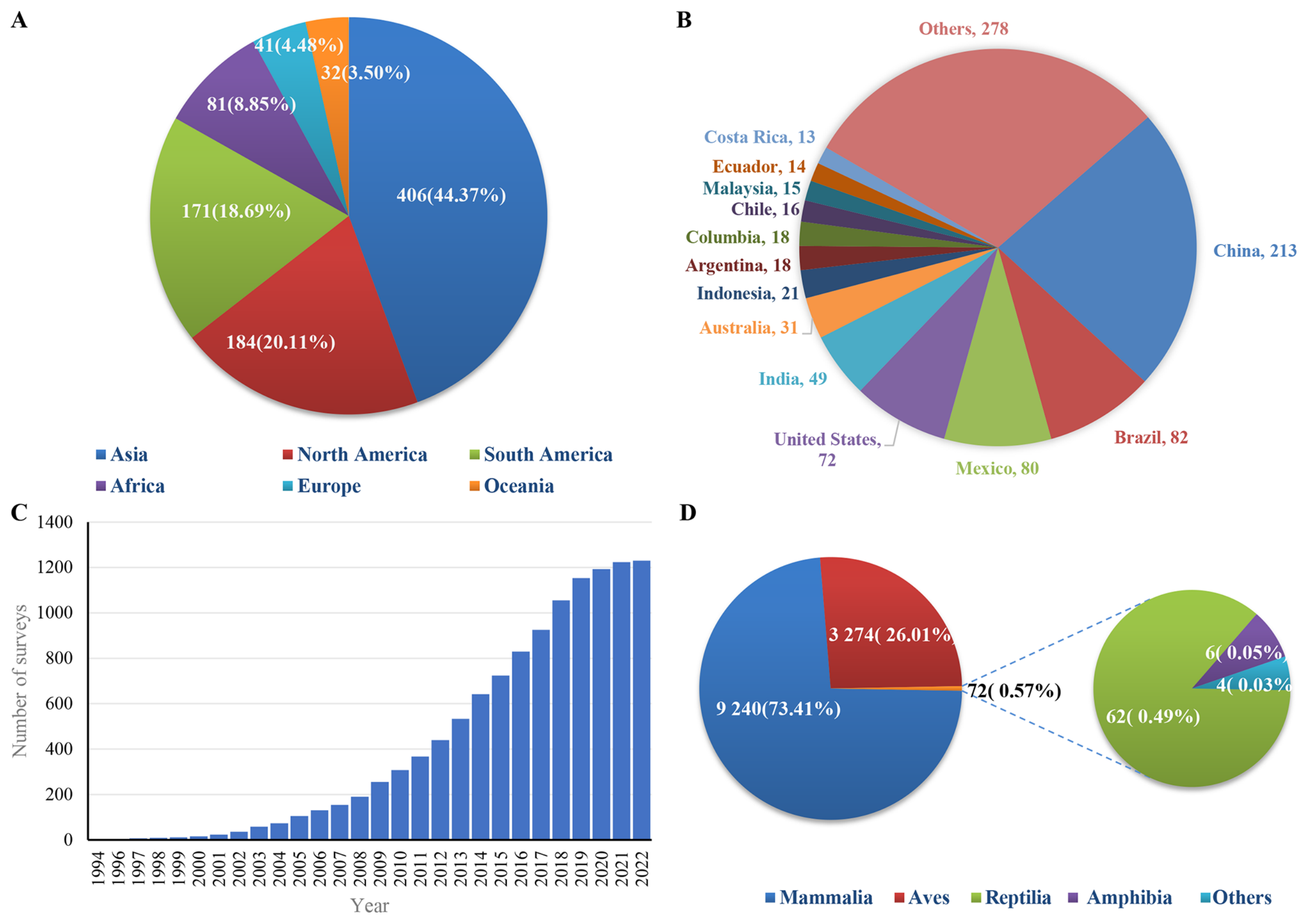

Figure 3 Summary statistics for GCTI v.1.0

A: Number and proportion of camera-trapping studies by continent. B: Number of camera-trapping studies by country. C: Cumulative number of camera-trapping studies by year. D: Number and proportion of monitored animal classes.

survey areas extracted from publication figures, with the buffer distance set to the estimated sampling-unit size. When two survey areas were separated by more than three times the sampling-unit distance, they were treated as independent spatial units and assigned separate polygon shapefiles. As a quality-control measure, all manual georeferencing was cross-verified by at least two operators to minimize subjective bias.

(iii) Species-name validation. Species names were standardized using the GBIF Species Matching Tool (https://www.gbif.org/tools/species-lookup), followed by manual verification. Corrected species names were checked against the International Union for Conservation of Nature (IUCN) database to improve taxonomic consistency. Unidentified taxa, domestic animals, and species that could not be matched to the IUCN database retained the names reported in the original publications. Corrected species names are provided in the “Corrected name” field of the tabular database (Table 1).

To evaluate the spatial reliability of the shapefile inventory, mammal and bird distribution data were downloaded from the IUCN database (https://www.iucnredlist.org/resources/spatial-data-download, accessed 28 October 2024). After excluding unidentified species, domestic animals, and species that could not be matched to the IUCN database, 12 514 mammal and bird shapefile records from the inventory (99.43%) were selected for spatial comparison with the IUCN database. For point and multipoint shapefiles, a 1 km buffer, based on the typical sampling-unit design, was applied during comparison with IUCN distributions to maintain consistency with the polygon shapefiles. Spatial overlap analyses were conducted using the R package “sf” (Pebesma, 2018). Records that did not overlap with IUCN ranges but occurred within 5 km of an IUCN range boundary were classified as boundary records, potentially reflecting marginal habitat, range-edge populations, or recent range expansion. Records with 0% overlap were further examined manually to identify the source of the discrepancy.

Literature retrieval, article screening, inventory construction, and data inspection were independently cross-checked by multiple field surveyors to reduce extraction error and improve the reliability of the final inventory.

RESULTS

Inventory description

GCTI comprises a tabular inventory containing 12 591 records and a spatial inventory containing 873 polygon shapefiles, 271 point shapefiles, and 84 multipoint shapefiles. The inventory covers camera-trapping studies conducted in 94 countries from 1994 to 2023 and includes records for 1 932 species. Summary statistics for the inventory are provided in Table 2 and Figure 3. The dataset is accessible through the GCTI web platform (https://biodiversityoptimization.shinyapps.io/gcti/). In the “Map” window, users can filter records by class, order, family, genus, species, continent, country, and year, visualize the selected records, and download the corresponding data. The “Detailed information per vector” window provides record-level information for each spatial vector, with each record linked to the “Map” layer through “Sub_ID”. Keyword searches can be performed using the search bar in the upper-right

Table 2 Number of GCTI records per species and per study

	Maximum	Minimum	Mean	Standard deviation
Number of records per species	159	1	5.33	13.19
Number of records per study	140	1	7.88	10.99

corner of this window. Data are available in two formats: Excel spreadsheet (.xlsx) and shapefiles.

Effectiveness validation

Each shapefile was spatially compared with the corresponding species distribution range from the IUCN database, and an overlap rate was calculated. Among all evaluated shapefiles, 52.63% showed complete overlap with the corresponding IUCN range, 26.72% had overlap rates between 66.70% and 99.90%, 3.82% had overlap rates between 0.10% and 66.70%, and 16.83% showed no overlap with the corresponding IUCN range (Supplementary Figure S1).

Among records with no spatial overlap, 7.42% occurred within 5 km of the corresponding IUCN range boundary and were therefore considered within the expected spatial uncertainty associated with marginal species distributions. A further 80.37% represented new distribution records outside the mapped IUCN range, 4.40% represented invasive or alien species records, and 7.81% were classified as uncertain records (Supplementary Figure S2).

DISCUSSION

GCTI provides a structured resource for literature synthesis, meta-analysis, and spatial analysis in camera-trapping research. The shapefile inventory supports spatial overlay analyses in geographic information system software, enabling quantitative assessment of where camera-trapping research has been conducted and how its geographic coverage has changed over time. When the spatial inventory is linked with species and survey information in the tabular inventory, GCTI can support analyses of camera-trap performance, survey design, and factors influencing detection, as well as studies of species distributions and broad biodiversity patterns. Integration with existing species distribution databases, such as GBIF and the IUCN Red List, further enables identification of geographic gaps in camera-trapping coverage for endangered and focal species, comparison of detected species records with known distribution ranges, and prioritization of areas where future surveys could strengthen conservation monitoring.

A notable pattern in GCTI is the predominance of mammal records, which account for 73.41% of the database. This taxonomic bias is consistent with the operating principles of infrared camera traps, which are activated by movement and thermal contrast between animals and the surrounding environment (DeWitt & Cocksedge, 2023). Consequently, camera traps are most efficient for medium- and large-bodied mammals with moderate movement speeds (Tan et al., 2022). In contrast, birds are recorded less frequently due to their smaller body size and rapid flight, with the exception of ground-dwelling species such as pheasants. Amphibians and reptiles demonstrate the lowest capture rates, largely because their small body size, low body temperature, and slow movement may fail to activate infrared sensors reliably (Hobbs & Brehme, 2017).

The database has several limitations to mention. First, literature retrieval was restricted to WoS and CNKI, which may have excluded relevant studies indexed elsewhere (Mongeon & Paul-Hus, 2016; Vera-Baceta et al., 2019). These databases were selected because they provide a large corpus of peer-reviewed literature with structured metadata, consistent indexing, and sufficient coverage for constructing a scientifically rigorous and practical infrared camera-trap inventory. WoS provides stronger coverage of the natural sciences and engineering than Scopus, although both major citation indexes show geographic and linguistic biases (Mongeon & Paul-Hus, 2016). To reduce language bias, the search was not restricted to English and included additional publication languages such as Spanish, Portuguese, and Japanese (Figure 1). CNKI was also included to improve coverage of Chinese-language research, adding 223 Chinese studies and expanding the inventory by 29.85%. Nevertheless, residual biases likely persist, particularly for regions and languages that remain underrepresented in major bibliographic databases, including sub-Saharan Africa (Asubiaro et al., 2024).

Second, spatial generalization was applied to reduce the potential risk of misuse of camera-location data. Standard practices for protecting sensitive species data include full access restriction, location masking, and spatial buffering (Tulloch et al., 2018). Although access restriction and masking can protect vulnerable taxa, they also reduce the value of spatial data for ecological modeling, conservation planning, and survey-gap analysis. Buffering was therefore adopted as a compromise between data utility and conservation risk. This approach remains imperfect, and future efforts should adhere to the tiered guidelines provided by GBIF for sensitive species occurrence data (https://docs.gbif.org/sensitive-species-best-practices/master/en/). This framework evaluates sensitivity based on vulnerability to human activities and assigns corresponding levels of spatial generalization, ranging from unrestricted publication for low-sensitivity species to spatial offsets of 0.001°, 0.01°, or 0.1° for species with low-to-medium, medium-to-high, or high sensitivity, respectively. For species of high biological significance under severe threat, all locality data should be withheld.

Finally, records with uncertain spatial correspondence require careful interpretation. Records that did not overlap IUCN range maps but occurred within 5 km of an IUCN range boundary may represent borderline distributions, including marginal habitats, range-edge populations, or range expansions. Conversely, records located beyond this boundary should be treated as potential misidentifications or records requiring verification rather than definitive errors. Confident classification is challenging because discrepancies can arise from taxonomic uncertainty, differences between reported scientific names and accepted IUCN nomenclature, and ambiguous common names that may correspond to multiple taxa in the absence of a definitive scientific identifier. These cases require verification through a review of the published species list, distributional evidence, and, where available, original camera-trap images. In addition, the spatial vectors in GCTI represent the entire monitoring area rather than the exact locations of species detections; therefore, the actual distributional extent of a species within a study may be smaller than the mapped vector. For point and multipoint data, some records represent approximate locality information rather than precise detection points. Spatial buffers and associated positional uncertainty should therefore be considered when using these data for species distribution analyses.

Notwithstanding these limitations, GCTI introduces a practical framework for reconciling two competing needs in camera-trap data sharing: protecting sensitive locality information and preserving sufficient spatial detail for ecological analysis. By assembling project-level geographic vector data from global studies, GCTI provides a structured resource for integrating, reusing, and comparing data across diverse survey designs and regions. This database supports large-scale assessments of camera-trapping research coverage and provides spatial evidence to inform more timely wildlife management decisions. Future applications include monitoring habitat change for threatened species, evaluating the impacts of invasive species on native ecosystems, and investigating distributional shifts across climatic zones, geographical regions, and habitat types.

DATA AVAILABILITY

Data are available from the GCTI website (https://biodiversityoptimization.shinyapps.io/gcti_v1/). The R script used for overlapping and distance calculation is available at https://github.com/Liang2128368/GCTI.

SUPPLEMENTARY DATA

Supplementary data to this article can be found online.

COMPETING INTERESTS

The authors declare that they have no competing interests.

AUTHORS' CONTRIBUTIONS

L.W.L.: Conceptualization, Data curation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. A.F.: Data curation, Methodology, Writing – original draft, Writing – review & editing, Validation. Q.Q.: Data curation, Methodology. T.Z.: Data curation, Methodology. X.Y.W.: Data curation, Methodology. F.Y.Z.: Data curation, Methodology. Q.X.: Data curation, Methodology. Z.G.G.: Data curation, Methodology. A.L.J.: Data curation, Methodology. X.Y.Z.: Data curation, Methodology. X.G.W.: Data curation, Methodology. M.X.D.: Data curation, Methodology. J.Y.Y.: Data curation, Methodology, Funding acquisition, Supervision, Writing – review & editing. H.C.L.: Data curation, Methodology, Funding acquisition, Writing – review & editing. Y.H.C.: Writing – review & editing. J.P.J.: Funding acquisition, Supervision, Writing – review & editing. Z.Y.L.: Conceptualization, Data curation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. All authors read and approved the final version of the manuscript.

REFERENCES

Ahumada JA, Fegraus E, Birch T, et al. 2020. Wildlife insights: a platform to maximize the potential of camera trap and other passive sensor wildlife data for the planet. *Environmental Conservation*, **47**(1): 1–6.

Ahumada JA, Silva CEF, Gajapersad K, et al. 2011. Community structure and diversity of tropical forest mammals: data from a global camera trap network. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **366**(1578): 2703–2711.

Asubiaro T, Onaolapo S, Mills D. 2024. Regional disparities in Web of Science and Scopus journal coverage. *Scientometrics*, **129**(3): 1469–1491.

Blount JD, Chynoweth MW, Green AM, et al. 2021. Review: COVID-19 highlights the importance of camera traps for wildlife conservation research and management. *Biological Conservation*, **256**: 108984.

Bubnicki JW, Norton B, Baskauf SJ, et al. 2024. Camtrap DP: an open standard for the FAIR exchange and archiving of camera trap data. *Remote Sensing in Ecology and Conservation*, **10**(3): 283–295.

Burton AC, Beirne C, Gaynor KM, et al. 2024. Mammal responses to global changes in human activity vary by trophic group and landscape. *Nature Ecology & Evolution*, **8**(5): 924–935.

Burton AC, Neilson E, Moreira D, et al. 2015. REVIEW: wildlife camera trapping: a review and recommendations for linking surveys to ecological processes. *Journal of Applied Ecology*, **52**(3): 675–685.

CameraData Team for Wildlife Diversity Monitoring. 2013. CameraData network of wildlife diversity monitoring: an online database. Beijing: Institute of Zoology.

Cordier CP, Ehlers Smith DA, Ehlers Smith Y, et al. 2022. Camera trap research in Africa: a systematic review to show trends in wildlife monitoring and its value as a research tool. *Global Ecology and Conservation*, **40**: e02326.

Delisle ZJ, Flaherty EA, Nobbe MR, et al. 2021. Next-generation camera trapping: systematic review of historic trends suggests keys to expanded research applications in ecology and conservation. *Frontiers in Ecology and Evolution*, **9**: 617996.

Devarajan K, Fidino M, Farris ZJ, et al. 2025. When the wild things are: defining mammalian diel activity and plasticity. *Science Advances*, **11**(9): eado3843.

DeWitt PD, Cocksedge AG. 2023. A simple framework for maximizing camera trap detections using experimental trials. *Environmental Monitoring and Assessment*, **195**(11): 1381.

Forrester T, O'Brien T, Fegraus E, et al. 2016. An open standard for camera trap data. *Biodiversity Data Journal*, **4**: e10197.

Foster RJ, Harmsen BJ. 2012. A critique of density estimation from camera-trap data. *The Journal of Wildlife Management*, **76**(2): 224–236.

GBIF. 2022(2022-03-30). Basis of record. https://docs.gbif.org/course-data-use/en/basis-of-record.html.

GBIF. 2026 (2026-04-28). Best practices for managing and publishing camera trap data. https://docs.gbif.org/camera-trap-guide/en/.

Green SE, Rees JP, Stephens PA, et al. 2020. Innovations in camera trapping technology and approaches: the integration of citizen science and artificial intelligence. *Animals*, **10**(1): 132.

Harley D, Eyre A. 2024. Ten years of camera trapping for a cryptic and threatened arboreal mammal – a review of applications and limitations. *Wildlife Research*, **51**(2): WR23054.

Hobbs MT, Brehme CS. 2017. An improved camera trap for amphibians, reptiles, small mammals, and large invertebrates. *PLoS One*, **12**(10): e0185026.

Hofmeester TR, Cromsigt JPGM, Odden J, et al. 2019. Framing pictures: a conceptual framework to identify and correct for biases in detection probability of camera traps enabling multi-species comparison. *Ecology and Evolution*, **9**(4): 2320–2336.

Jenks KE, Chanteap P, Kanda D, et al. 2011. Using relative abundance indices from camera-trapping to test wildlife conservation hypotheses – an example from Khao Yai National Park, Thailand. *Tropical Conservation Science*, **4**(2): 113–131.

Lindenmayer D, Ehmke G, Scheele B. 2017. Publish openly but responsibly—response. *Science*, **357**(6347): 142–142.

Lindenmayer D, Scheele B. 2017. Do not publish. *Science*, **356**(6340): 800–801.

Liu XH, Wu PF, Songer M, et al. 2013. Monitoring wildlife abundance and diversity with infra-red camera traps in Guanyinshan nature reserve of Shaanxi Province, China. *Ecological Indicators*, **33**: 121–128.

McCallum J. 2013. Changing use of camera traps in mammalian field research: habitats, taxa and study types. *Mammal Review*, **43**(3): 196–206.

Meek PD, Ballard G, Claridge A, et al. 2014. Recommended guiding principles for reporting on camera trapping research. *Biodiversity and Conservation*, **23**(9): 2321–2343.

Moher D, Liberati A, Tetzlaff J, et al. 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Medicine*, **6**(7): e1000097.

Mongeon P, Paul-Hus A. 2016. The journal coverage of Web of Science and Scopus: a comparative analysis. *Scientometrics*, **106**(1): 213–228.

Mugerwa B, Niedballa J, Planillo A, et al. 2024. Global disparity of camera trap research allocation and defaunation risk of terrestrial mammals. *Remote Sensing in Ecology and Conservation*, **10**(1): 121–136.

Oliver RY, Iannarilli F, Ahumada J, et al. 2023. Camera trapping expands the view into global biodiversity and its change. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **378**(1881): 20220232.

Pebesma E. 2018(2018-05-16). Simple features for R: standardized support for spatial vector data. https://journal.r-project.org/articles/RJ-2018-009/.

Rich LN, Davis CL, Farris ZJ, et al. 2017. Assessing global patterns in mammalian carnivore occupancy and richness by integrating local camera trap surveys. *Global Ecology and Biogeography*, **26**(8): 918–929.

Rowcliffe JM, Kays R, Kranstauber B, et al. 2014. Quantifying levels of animal activity using camera trap data. *Methods in Ecology and Evolution*, **5**(11): 1170–1179.

Schmeller DS, Julliard R, Bellingham PJ, et al. 2015. Towards a global terrestrial species monitoring program. *Journal for Nature Conservation*, **25**: 51–57.

Singh P, Singh VK, Kanaujia A. 2024. Exploring the publication metadata fields in web of science, Scopus and dimensions: possibilities and ease of doing Scientometric Analysis. *Journal of Scientometric Research*, **13**(3): 715–731.

Steenweg R, Hebblewhite M, Kays R, et al. 2017. Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote sensors. *Frontiers in Ecology and the Environment*, **15**(1): 26–34.

Tan MY, Chao WT, Cheng JK, et al. 2022. Animal detection and classification from camera trap images using different mainstream object detection architectures. *Animals*, **12**(15): 1976.

Tenopir C, Dalton ED, Allard S, et al. 2015. Changes in data sharing and data reuse practices and perceptions among scientists worldwide. *PLoS One*, **10**(8): e0134826.

Tulloch AIT, Auerbach N, Avery-Gomm S, et al. 2018. A decision tree for assessing the risks and benefits of publishing biodiversity data. *Nature Ecology & Evolution*, **2**(8): 1209–1217.

Vera-Baceta MA, Thelwall M, Kousha K. 2019. Web of Science and Scopus language coverage. *Scientometrics*, **121**(3): 1803–1813.

Xiao ZS, Xiao WH, Wang TM, et al. 2022. Wildlife monitoring and research using camera-trapping technology across China: the current status and future issues. *Biodiversity Science*, **30**(10): 22451. (in Chinese)

Young S, Rode-Margono J, Amin R. 2018. Software to facilitate and streamline camera trap data management: a review. *Ecology and Evolution*, **8**(19): 9947–9957.