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APPLICATION

The camtrapR R package: From data management to interactive ecological analysis of camera trap data

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Abstract

1. Camera trapping has become an indispensable tool in wildlife ecology, generating vast datasets that require efficient and robust analytical workflows. The R package `camtrapR` was originally developed for preparing camera trap data for analysis in external packages and has since become a standard tool for this purpose. The analyses themselves, however, still had to be conducted elsewhere.
2. Here, we present a major update that transforms `camtrapR` into an end-to-end analytical platform that unifies data import, exploration, covariate preparation, activity pattern estimation, occupancy modelling and spatial prediction. All new functionality is available as R functions and through `surveyDashboard()`, a new code-free graphical user interface that guides users through the entire analytical pipeline.
3. Data import supports widely used formats, including exports from the Wildlife Insights platform and datasets conforming to the Camtrap DP data standard. Exploratory tools generate species accumulation curves, maps of species detections and activity patterns for up to two species. Covariates can be extracted at camera trap sites from user-supplied rasters or online sources, providing inputs for model fitting and, as raster layers, for spatial predictions. Users can fit single-species and community occupancy models, some of the most widely adopted analytical frameworks in wildlife ecology, and map predicted occupancy across space.
4. Community occupancy models are fitted in a Bayesian framework using JAGS or NIMBLE. These hierarchical models estimate species- and community-level responses to environmental predictors and improve inference for rare species. The workflow includes convergence diagnostics and posterior predictive checks for model assessment and produces spatial predictions of species occupancy and species richness. The workflow can be implemented both in code and within the dashboard.
5. By combining a code-free interface with advanced modelling capabilities, `camtrapR` now makes robust camera trap data analysis accessible to a wider

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audience of ecologists, wildlife managers and students. This paper accompanies camtrapR version 3 and serves as the reference for its expanded functionality.

KEYWORDS
Bayesian methods, community ecology, modelling (community ecology), modelling (population ecology), population ecology, statistics

1 | INTRODUCTION

Camera trapping has transformed wildlife research and has become an indispensable tool for studying terrestrial wildlife (Wearn & Glover-Kapfer, 2019). The method now supports diverse applications, from species inventories to behavioural studies and from individual species distribution studies to community assessments (Delisle et al., 2021). Yet with widespread adoption has come the challenge of managing and analysing the substantial volumes of data these devices generate (Steenweg et al., 2017).

We first released the R package camtrapR on CRAN in 2015 to address the growing need for standardized data management in camera trap studies (Niedballa et al., 2016). The R package streamlined data organization and preparation for occupancy and spatial capture-recapture analyses. It found broad adoption among researchers, particularly those requiring reproducible data management workflows (Thomson et al., 2018). However, the field has evolved considerably, creating new demands that extend beyond the original package's capabilities.

Several developments in camera trap research now require enhanced analytical tools. The emergence of standardized platforms like Wildlife Insights and Camera Trap Data Package (Camtrap DP) has created new data-sharing frameworks that need support (Ahumada et al., 2020; Bubnicki et al., 2024). There is also increasing focus on community-level analyses, reflecting the need to understand species interactions and community-level responses to environmental variables (Devarajan et al., 2020; Tingley et al., 2020). Additionally, the integration of spatial data in species distribution modelling has become standard practice, requiring more sophisticated tools for handling environmental covariates.

To date, no platform integrates the full workflow from camera trap data management to sophisticated ecological analyses. Existing solutions often address only portions of this workflow: Wildlife Insights and TrapTagger function primarily as data repositories with AI-based species identification while developing analytical capabilities; platforms like Agouti, Camelot and TRAPPER (Bubnicki et al., 2016; Enetwild Consortium et al., 2022; Hendry & Mann, 2018) offer data management with basic analyses; specialized software such as AddaxAI and Sherlock (Penn et al., 2024) focus on AI-based species identification; Camera Trap Data Package (Camtrap DP, Bubnicki et al., 2024) provides a metadata standard without analytical tools; and statistical R packages like unmarked, ubms and spOccupancy (Doser et al., 2022; Kellner et al., 2022, 2023) offer powerful analytical capabilities for single and community models, but lack camera trapping-specific data handling. The updated camtrapR package addresses this fragmentation by offering a complete workflow that connects camera trap data management tools with analytical packages while introducing new features not available elsewhere, particularly a graphical user interface for community occupancy models that allow simultaneous analysis of multiple species while accounting for imperfect detection. See Supporting Table S1 for a comparison of software for working with camera trapping data.

The user base for camera trap data has also expanded beyond academia to include conservation practitioners, wildlife managers and citizen scientists (Willi et al., 2019). This diversification creates a need for more accessible tools that maintain analytical rigour while reducing technical barriers.

In this paper, we present significant updates to camtrapR that address these evolving needs. The package, currently in version 3.1, now features an interactive Shiny dashboard for code-free analysis, enhanced data import capabilities, integrated community occupancy modelling, and streamlined handling of spatial covariates, among other improvements (Niedballa et al., 2026). These developments maintain the package's commitment to standardized ecological workflows while making advanced analytical methods accessible to a broader user base. We demonstrate these new capabilities through a worked example and discuss their implications for future camera trap research.

2 | NEW FUNCTIONALITIES AND IMPROVEMENTS

The updated camtrapR package introduces key enhancements that expand its analytical capabilities while improving accessibility. We focused developments in three main areas: interactive analysis, expanded analytical tools and enhanced data handling.

2.1 | Interactive analysis dashboard

The most significant addition is an interactive dashboard that allows users to analyse camera trap data without writing code. Built using R's Shiny framework (Chang et al., 2025), the dashboard integrates data import, exploration and analysis in a unified interface. It contains help pages for all major components and tooltips for all UI elements to guide users and provides immediate visual feedback as they explore their data, generate summaries

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and build statistical models. We first provide an overview of the dashboard and below are more detailed descriptions of the novel features, which are also available via standalone functions outside the dashboard.

The dashboard comprises several interconnected modules. Users can import their data from various sources (CSV files, WildlifeInsights, Camtrap DP). The summary tab shows key information about surveys and includes interactive maps of the camera trapping grid. Users can filter their data dynamically by site covariates or filter records by species or temporal independence. Users can visualize species activity patterns and species accumulation curves (Hsieh et al., 2016; Meredith & Ridout, 2016). A dedicated covariate extraction module helps users create covariates from spatial rasters and from online elevation databases for use in distribution modelling. It supports the creation of derived terrain metrics and harmonizes all raster data for spatial predictions (Hijmans et al., 2025). Users can further examine relationships and correlation between environmental variables.

The modelling interface guides users through building occupancy models, supporting both frequentist and Bayesian approaches through the `unmarked` and `ubms` packages for single-species analyses. Additionally, the dashboard includes a dedicated interface for building and fitting community occupancy models, allowing users to analyse multiple species simultaneously while accounting for imperfect detection. Advanced features of the occupancy workflows include model comparison, visualization of species responses to environmental variables and creation of spatial predictions.

2.2 | Enhanced data import and standardization

To support emerging data standards, we added dedicated import functions for Wildlife Insights and Camera Trap Data Package (Camtrap DP) formats to both the package and the dashboard (Ahumada et al., 2020; Bubnicki et al., 2024). These functions handle the specific structure and metadata requirements of these platforms automatically.

Besides camera trap photographs, `camtrapR` also supports video data, though extracting metadata from videos remains challenging due to inconsistent standards across camera brands.

2.3 | Expanded analytical capabilities

2.3.1 | Species accumulation curves

To assess sampling completeness, `camtrapR` integrates the rarefaction and extrapolation framework of the `iNEXT` package (Chao et al., 2014; Hsieh et al., 2016). We extend the standard `iNEXT` application by enabling analysis along both spatial and temporal dimensions. The spatial approach, a standard application of `iNEXT`, uses camera trap locations as sampling units to evaluate how species diversity increases with sampling locations. Complementing this, `camtrapR` introduces a novel temporal analysis where survey days (or camera-specific operational days) are treated as sampling units. While the spatial analysis assesses the sufficiency of site coverage, our novel temporal implementation allows researchers to evaluate sampling completeness as a function of survey duration. This dual functionality provides a more robust assessment of survey effort, with confidence intervals to quantify uncertainty in sampling completeness and inform study design.

2.3.2 | Automated spatial covariate handling

The new `createCovariates` function simplifies the integration of spatial data into analyses. It extracts covariate values from local raster files or online elevation databases, manages coordinate system transformations and prepares standardized inputs for both model fitting and prediction. This automation drastically reduces the technical expertise needed to incorporate environmental data while ensuring consistent spatial data handling. Elevation data are obtained from Amazon Web Services (AWS) Terrain Tiles via the `elevatr` package (Hollister et al., 2023). For a selection of data sources for use as environmental covariates, see Supporting Table S2.

2.3.3 | Community occupancy models

A major analytical addition is support for community occupancy models through the `communityModel` function. This implementation handles both standard occupancy models and Royle-Nichols abundance-based occupancy models, allowing users to specify various covariate effects on detection and occupancy probabilities. Models can be fitted using either JAGS or Nimble, with specialized functions for examining results (`summary`), visualizing effects (`plot_effects`) and making spatial predictions (`predict`). The framework incorporates random effects of species and sites, enabling analysis of community responses to environmental conditions while accounting for species-specific variations.

2.4 | Additional improvements

We added several other enhancements to improve the package's utility. For example, the `filterRecordTable` function provides flexible temporal filtering of detection records, useful when importing external data. Camera operation calculations now account for precise timing of camera deployment and retrieval. For situations where image metadata is unavailable, new optical character recognition capabilities can extract date and time information directly from images (Ooms, 2025; Smith, 2007).

While the new dashboard makes our package accessible to users who do not wish to write R code, we also improved the accessibility of `camtrapR` for those who do. Under the hood, key functions of the package—including `recordTable`, `cameraOperation` and

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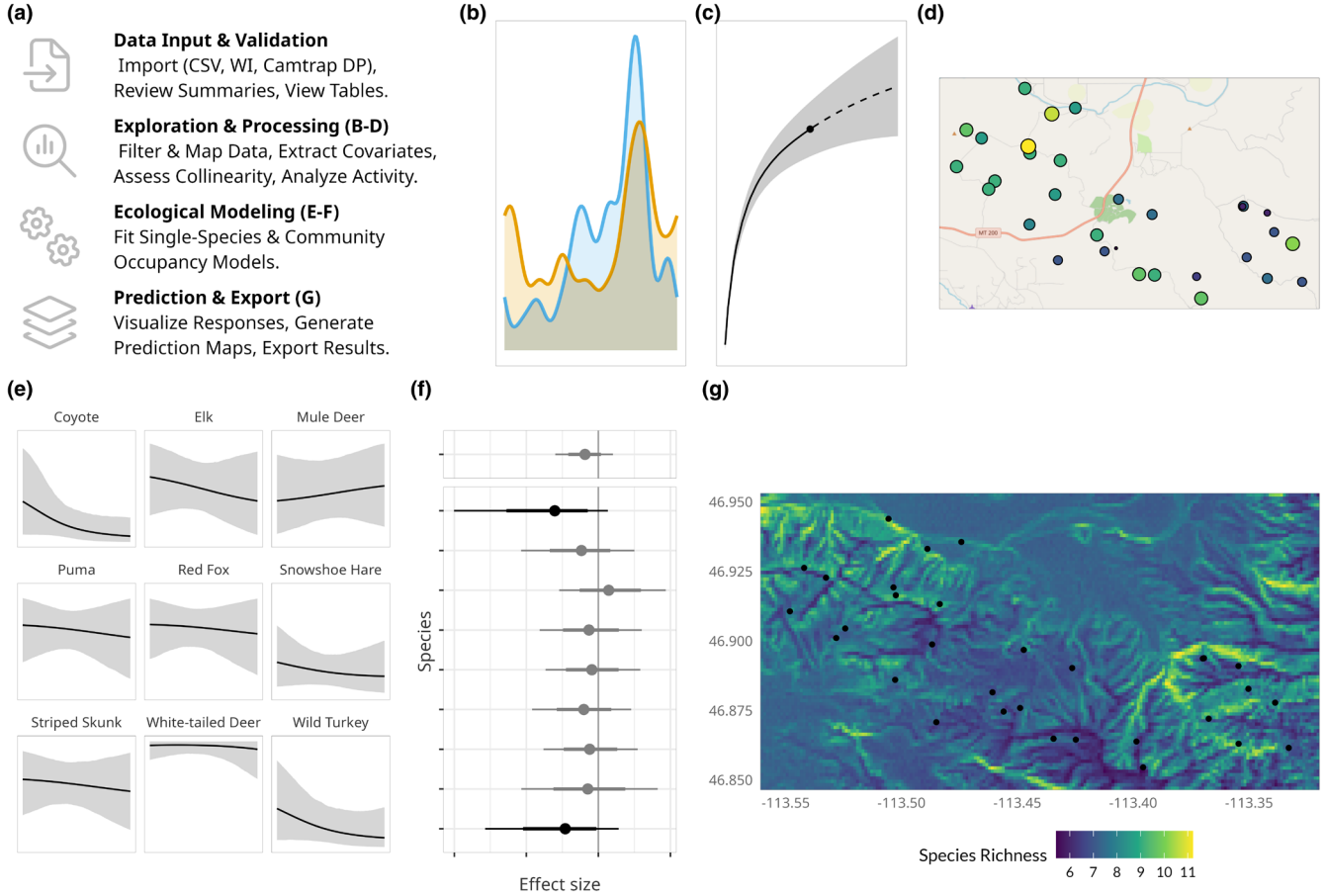

FIGURE 1 A conceptual workflow and example outputs from the `camtrapR` interactive dashboard. (a) The dashboard guides users through four main stages of analysis, from data import to prediction. Key modules are grouped within each stage. Example exploratory outputs include (b) diel activity pattern overlap plots, (c) species accumulation curves and (d) maps of observed species richness. (e) The modelling interface allows users to fit single-species and community occupancy models and visualize model results, such as the relationship between occupancy probability and an environmental covariate and (f) the effect size by species. (g) Final model outputs can be used to generate spatial predictions, such as this map of predicted species richness for a species community (with camera locations overlaid).

`detectionHistory`—now return objects of dedicated S3 classes rather than plain data frames, matrices or lists. This allows for custom `print` and `summary` methods that display these objects far more informatively in the console. It also makes some function calls more intuitive. For example, to generate a plot showing when cameras were operational for each station, it is sufficient to call the function `plot` on an object that has been produced by `cameraOperation`.

3 | WORKED EXAMPLE

To demonstrate `camtrapR`'s new capabilities, we analyse a subdataset of the SNAPSHOT USA data set (Rooney et al., 2025) collected in Lubrecht Experimental Forest, Montana (USA), where 31 locations were surveyed with 57 camera deployments from September to December 2022 to study the effect of hunting on ungulates and pumas. The dataset includes 1602 independent detection events of 24 identifiable wildlife species (excluding humans, domestic animals and species resolved to a coarse taxonomic level).

Our objective here is to examine how species occurrence patterns and community composition vary with elevation and terrain characteristics across the landscape. The manuscript presents a high-level overview, and Supporting Data S1 is an R project containing a Quarto document with a fully worked, executable example.

3.1 | Alternative workflows

Camera trap data can be analysed through two complementary approaches in `camtrapR`. The interactive dashboard supports data exploration, visualization, interactive model development and model predictions. It is particularly valuable during initial analysis phases, yet capable of sophisticated analyses. The code-based workflow facilitates reproducibility and automation, suitable for standardized, reproducible analyses or processing multiple datasets in a consistent way. We demonstrate how to load data, add site covariates from online sources and analyse species habitat associations with a community occupancy model using both approaches to highlight their utility in

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different contexts. Figure 1 gives an overview of the workflow and example outputs.

3.2 | Dashboard-based analysis

After launching the dashboard with: `surveyDashboard()`, or preloading it with specific parameters (to avoid the initial data import), the analysis proceeds through several steps, all of which are implemented on the dashboard interface and accessible without any coding.

1. Data Import and Validation
   - **Import Raw Data: Load** camera trap data from various formats (CSV, Wildlife Insights, Camtrap DP) using the 'Import' module, or by passing parameters directly to `surveyDashboard()`.
   - **Review and Validate: Review** summary statistics, sampling effort and camera operational timelines in the 'Data Summary' module to confirm data integrity. **Verify** correct spatial referencing by examining station maps in the 'Maps' module.
   - **Prepare Covariates: Extract** environmental covariates by combining automatically derived terrain metrics with user-provided local raster files (see Supporting Table S2). **Assess** collinearity using correlation plots and **select** a final set of non-collinear covariates for modelling.
2. Exploratory Data Analysis and Filtering
   - **Visualize Ecological Patterns: Generate** species accumulation curves to assess sampling adequacy. **Map** species detections and observed richness to visualize spatial patterns ('Maps' module). **Visualize** species activity patterns to explore diel activity and temporal overlap ('Species Activity' module).
   - **Filter and Subset: Filter** the dataset by stations, species, or covariate values using the 'Data Filters' module to create subsets for specific analyses.
3. Occupancy Modelling
   - **Define and Fit Models: Select** between single-species (unmarked/ubms) and community (JAGS/NIMBLE) occupancy models. **Define** detection histories and **specify** the model structure by interactively selecting covariates (and random effects for community models) for detection and occupancy parameters. **Run** the model fitting process.
   - **Assess Model Performance: Examine** MCMC convergence diagnostics and **run** posterior predictive checks for goodness-of-fit. **Build** and compare models using a model selection table.
4. Prediction, Visualization and Export
   - **Visualize Model Results: Plot** community- and species-level responses to covariates (marginal effect plots).
   - **Generate Predictions: Create** prediction maps for individual species occupancy and community-level species richness. **Estimate** derived parameters, such as the percentage of area occupied (PAO).
   - **Export: Export** all tables, figures and model objects for reporting and further analysis.

3.3 | Code-based implementation

All functionalities of the graphical user interface are accessible programmatically, enabling reproducible, script-based analyses with greater flexibility. The package's functions are designed to create a logical and intuitive pipeline, mirroring the analytical workflow. Data import is the only source-specific step: camera trap station and record tables can be loaded from csv files with standard R functions, or imported automatically from Wildlife Insights exports and Camtrap DP data packages (Bubnicki et al., 2024) with `readWildlifeInsights()` and `readCamtrapDP()`, respectively. All routes yield camtrapR's standardized input tables, so the downstream workflow is identical regardless of data source.

We illustrate this core pipeline below, noting that each function contains extensive customization options detailed in the package documentation. The code chunks below are illustrative rather than executable; the fully worked, reproducible analysis, which loads the csv files archived on Dryad, is provided in the Supporting Data S1.

First, we load the camera trap station and record tables.

```
cameras <- read.csv("path/to/CTtable.csv")
records <- read.csv("path/to/recordTable.csv")
```

Next, `createCovariates()` prepares the environmental data by combining local raster files and online elevation and terrain data.

```
covs <- createCovariates(CTtable = cameras,
  directory = "/path/to/covariates",
  download_elevation = TRUE,
  terrain_measures = c("slope", "roughness"))
```

Camera operational periods are then summarized with `cameraOperation()`.

```
camop <- cameraOperation(CTtable = cameras)
```

And finally, detection histories are compiled using `detectionHistory()` for selected species and a defined occasion length (in days).

```
detHist_list <- detectionHistory(recordTable =
records,
  camOp = camop,
  species = c("species_1", "species_2"),
  occasionLength=10)
```

Detections, site and observation covariates are then bundled in a single list for use as model input.

```
model_input <- list(ylist = detHist_list$detec-
tion_history,
   siteCovs = covs$CTtable,
   obsCovs = list(effort = detHist_list$effort))
```

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With the data prepared, users can define and fit various community occupancy models. The `communityModel` function integrates detection histories, site covariates and observation covariates into a single data structure, allowing for flexible model specification. The model is then fitted using Markov Chain Monte Carlo (MCMC) simulations.

```
comm_mod <- communityModel(data_list = model_input,
  occuCovs = list(ranef = c("elevation", "slope")),
  detCovsObservation = list(fixed = "effort"))
fit <- fit(comm_mod, n.iter=10000, chains=3)
```

Predictions can be generated from the model output and environmental covariates.

```
pred_richness <- predict(object = comm_mod,
  mcmc.list = fit,
  type = "richness",
  x = covs$predictionRaster)
```

The `predict` function's output format is determined by the `type` argument. It returns spatial rasters for predictions of species richness, occupancy probability, or abundance (from Royle-Nichols models) containing layers for the mean, standard deviation and confidence intervals. Alternatively, it can also calculate Percentage of Area Occupied (PAO), a summary statistic which is returned as a data frame.

3.4 | Key results

As a demonstration of `camtrapR`'s modelling capabilities, we fitted a community occupancy model to the example Snapshot USA dataset. While all model steps, from data preparation to prediction, were successfully executed, the 95% credible intervals of species' responses to environmental covariates like elevation, ruggedness and topographic position did not show evidence for strong positive or negative effects in this particular small dataset and for the presented model structure. Some species showed trends (75% credible intervals not overlapping zero), which are presented solely to illustrate the output format and interpretation of coefficient plots generated by the package. While 75% credible intervals can be useful for highlighting suggestive trends or weaker evidence, they should not be interpreted as providing the same level of support as 95% credible intervals, and users should avoid over-interpreting these patterns as evidence of strong effects.

This example demonstrates how `camtrapR`'s new features integrate to provide a comprehensive analytical workflow, with the option of a visual and interactive dashboard offering robust ecological inference while maintaining accessibility, and traditional, reproducible code-based analysis for users requiring maximum control and reproducibility. Both workflows deliver equivalent results.

4 | DISCUSSION

The enhanced capabilities of `camtrapR` reflect the evolving needs of the camera trap research community. By combining accessible interactive tools with sophisticated analytical methods, the package helps bridge the gap between data collection and robust ecological inference. The integration of standardized data formats, community-level analyses and spatial data handling addresses key challenges in contemporary camera trap research.

The new features respond to distinct needs in the research community. The interactive dashboard lowers technical barriers to statistical analyses while encouraging exploration of ecological patterns. This is particularly valuable during initial data assessment and for users new to occupancy modelling, for whom it can also serve as a learning and teaching tool. The community modelling framework allows researchers to leverage data from all detected species while accounting for imperfect detection and facilitating access to advanced community occupancy models. Automated handling of spatial covariates considerably simplifies the integration of environmental data into analyses without the need for specialist GIS skills.

Beyond its research applications, the package serves as an effective teaching tool. The immediate visual feedback provided by the dashboard helps users develop intuition about occupancy modelling and species–environment relationships. This aspect is particularly valuable for building analytical capacity in regions where camera trapping is increasingly used for biodiversity monitoring, but statistical expertise may be limited (Stephenson, 2020).

While the dashboard makes complex analyses more accessible and provides basic guidance, we emphasize that users should understand the underlying statistical concepts in occupancy modelling before interpreting results for scientific publications or management decisions. We recommend that users unfamiliar with these methods consult statistical experts or relevant literature to ensure appropriate model specification and interpretation.

The current implementation has some limitations that suggest future development priorities. Community occupancy models can be computationally demanding for datasets with many species and sites, or when predicting over large areas and/or at high resolution. Support for video files remains limited by inconsistent metadata standards across camera brands. While `camtrapR`'s outputs are well-suited for standard single-season occupancy and Royle-Nichols models, a key future direction is to unlock the full analytical potential offered by specialized modelling packages. We will develop dedicated coercion functions to provide seamless data handoffs to `unmarked`, `ubms` and `spOccupancy`. This will enable users to easily apply a more diverse suite of advanced models—including multi-season dynamic, multi-species and spatial occupancy frameworks—directly to their `camtrapR`-prepared data. Another potential avenue is the inclusion of or interfacing with machine learning tools to help with species identification, which remains one of the most time-consuming steps in camera trap data management and which is an area of intense development (see, e.g., Vélez et al., 2023; Beery et al., 2019; Norouzzadeh et al., 2017; Leorna & Brinkman, 2022). By providing

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import functionality for data that were processed by machine learning tools, camtrapR makes these data available for analysis in R.

We encourage users to contribute to camtrapR's development through the package's GitHub repository, issue tracker or Google group, which are linked directly in the dashboard. User feedback has shaped the current features and will guide future improvements. As camera trap technology and analytical methods advance, we remain committed to maintaining and enhancing camtrapR's utility for wildlife research and monitoring.

AUTHOR CONTRIBUTIONS

Jürgen Niedballa led software development and manuscript drafting. Rahel Sollmann provided statistical oversight and wrote the goodness-of-fit code. Alexandre Courtiol implemented the S3 classes and methods. Nicolas J. Deere prepared Supporting Table S1 and revised the Supporting Quarto document. Matthew Struebig reviewed the manuscript and offered comments during revision. Andreas Wilting contributed to the conceptualization of both the package and the manuscript. All authors contributed to manuscript writing and revisions.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The camtrapR package is freely available from the Comprehensive R Archive Network (CRAN) at https://CRAN.R-project.org/package=camtrapR (Niedballa et al., 2026). The development version, including the latest features and bug fixes, can be accessed through GitHub (https://github.com/jniedballa/camtrapR). The package includes comprehensive documentation through six detailed vignettes covering image organization, species identification, data extraction, visualization, multi-species occupancy modelling and the use of the dashboard with various sample data. Sample datasets and code demonstrating key functionalities are included in the package. The camtrapR Google group (https://groups.google.com/g/camtrapr) serves as a help and support forum for users.

All code used in the worked example is provided in the Supporting Data S1. The example dataset used in this paper is available via Dryad at https://doi.org/10.5061/dryad.k0p2ngfhn (Rooney et al., 2025).

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SUPPORTING INFORMATION

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

Data S1: R Project for the Example Community Occupancy Workflow in `camtrapR`.

Table S1: Comparison of Features and Capabilities of Software Tools for Working with Camera Trapping Data.

Table S2: Selected Remote Sensing Data Sources for Ecological Covariates.

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