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INTERDISCIPLINARY PERSPECTIVES

Camera-trapping version 3.0: current constraints and future priorities for development

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Abstract

Camera traps are a widely used tool in wildlife research and conservation, but *in situ* factors such as theft, poor performance in extreme environments and damage by wildlife may be hindering the effectiveness of the technology. However, we still know little about how widespread these constraints are and which are the priorities to solve in the short- and mid-term. We present results from a global survey of camera-trappers working across a diversity of institutions and habitats, and using camera traps for a range of purposes. We show that: (1) the major current constraints on effective camera-trapping are cost, theft and sensor performance (with 66%, 50% and 42% of respondents respectively classifying those as important or extremely important barriers for camera-trapping); (2) the most-needed technological developments are related to sensor performance (faster triggering responses and higher sensitivity), resistance to extreme environmental conditions (extreme temperatures and high humidity) and automated filtering of blank images; and (3) there is considerable variation among camera trap manufacturers in user-rated performance, and none of the manufacturer ratings exhibited a trend over time, despite improvements in the technology. Our results serve as valuable market research for both open-source and commercial camera trap developers. On the basis of our survey of camera-trappers, we foresee a transition towards camera-trapping 3.0 in the near-future, consisting of both more effective camera trap units, but also greater use of wireless data transmission, sensor networks, automation of processes using algorithms and better, more collaborative tools for managing and analysing camera trap data. Ultimately, this will increase the capacity of researchers and conservationists to implement coordinated wildlife monitoring at unprecedented scales.

Introduction

Since their emergence over a century ago, camera traps have rapidly become ubiquitous as a tool in wildlife research and conservation (O'Connell et al. 2011; Wearn and Glover-Kapfer 2017). This is due to their versatility, low effort-to-data volume ratio and ability to cost-effectively monitor multiple species and detect rare, cryptic and elusive animals (Burton et al. 2015; Rowcliffe 2017).

However, there are a number of issues that remain with using camera traps *in situ*, including theft and vandalism, poor performance in extreme environments and damage by wildlife (Hossain et al. 2016; Newey et al. 2015; Meek et al. 2016, 2018; Wearn and Glover-Kapfer 2017). These factors may be acting as significant constraints on the effective application of the technology to meet research and survey objectives.

Information on the prevalence of these constraints is scarce, making it difficult to prioritize which need to be solved in the short- and medium-term. Existing peer-reviewed literature has mostly been more narrowly focused, for example on preferred camera trap features or limitations of low-quality cameras (e.g. Meek and Pittet 2012; Meek et al. 2015; Newey et al. 2015), and much of the information on camera-trapping constraints and practical mitigation measures exists outside the peer-reviewed literature in unpublished reports, web-based discussions and private communications among camera trap users. To date, there has been no attempt to capture this wealth of unpublished and anecdotal information.

One potentially important constraint on current camera-trapping is also our incomplete knowledge of the relative performance of different camera traps. Published comparisons have focused on single units of a relatively small set of camera trap models (Swann et al. 2004; Weingarth et al. 2013; Wellington et al. 2014), or multiple units of just a single model (Newey et al. 2015). Previous evidence also suggests high variation in camera trap performance within and among camera trap models and manufacturers (Hughson et al. 2010; Meek et al. 2014; Wellington et al. 2014), but those comparisons were narrowly focused on sound emissions and sensor reliability, limiting their utility for guiding camera trap choices based on other criteria. Although a wide range of cameras have been tested using proprietary methods (e.g. www.trailcampro.com), these tests are difficult to reproduce (as the methods are not documented), and the full results are not shared openly or permanently archived. Most importantly, likely due to costs and logistical constraints, none of these previous comparisons of camera traps have assessed their quality across a diversity of uses, habitats and time periods. A survey of a diversity of camera trap users and their experiences with different camera traps can provide an alternative, less resource-intensive means of acquiring similar information.

In addition to the short- and medium-term constraints on effective camera-trapping, there is also a need to identify priorities for longer-term developments in camera trap technology (i.e. 10–20 years from now) as this information will influence the priorities of camera trap developers. Arguably, we are on the cusp of a new phase in camera-trapping, which we call 'camera-trapping 3.0'. This follows on from previous phases: 1.0, in which camera traps were experimental, film-based and triggered with mechanical or active infrared sensors, and the current phase 2.0, which consists of the dominance of commercial digital camera traps with integrated passive infrared sensors and infrared flashes. It will be important to guide this progression into a new phase of camera-trapping based specifically on the needs of the camera-trapping community, which remain poorly defined to date.

We surveyed the global camera-trapping community to: (1) identify the major constraints affecting current camera-trapping efforts and their existing solutions, (2) provide a ranking of the most-needed technological developments in camera-trapping, (3) compare the performance of camera trap manufacturers across a wide diversity of applications and habitats and (4) generate predictions of what 'camera-trapping 3.0' will consist of.

Materials and Methods

Survey design

The survey consisted of four sections: the first section focused on details about the respondents themselves; the second section was on respondent experiences with specific camera trap models; the third section was on the major camera-trapping constraints (termed 'barriers' in the survey) and desired future developments in camera-trapping; and the fourth section was a horizon scanning question about how camera-trapping will evolve in the future (Table S1).

For the first section, we included questions about where respondents had deployed camera traps and their country of residence, the type of institution they belonged to, and how they had used camera traps (purposes, taxa, habitats and heights above ground). We also asked respondents to categorize their experience levels across five different aspects of camera trap use: deploying cameras in the field, managing camera trap databases, analysing camera trap data, developing the technology and using camera traps for outreach/education. Experience categories included no experience, <1 year, 1–5 years and >5 years of experience.

We next asked respondents to score camera trap models they had used according to seven criteria: reliability, image quality, video quality, camera sensor quality, usability, customer service and value for money. Scores ranged from 1 to 5, with 1 representing *very poor* performance and 5 representing *exceptional* performance. We also asked respondents to indicate whether overall they would recommend the rated camera trap to other users. Respondents were allowed to score as many models as they wanted. If respondents had no experience for a given criterion (e.g. customer service), they were allowed to leave the rating blank.

We assessed the constraints respondents currently face and their priorities for future developments by asking them to score a list of possible answers in each case. We compiled these lists of possible constraints and future developments through a camera-trapping literature review (e.g. Meek and Pittet 2012; Newey et al. 2015; Wearn and Glover-Kapfer 2017; Meek et al. 2018), discussions in online camera-trapping communities, and conversations with colleagues engaged in camera-trapping. We also included a free text field to allow respondents to add any other important constraints or future developments that we had not listed. The scoring for constraints ranged from 1 to 5, with 1 corresponding with *not at all a barrier* and 5 with *an extremely important barrier*. The scoring for future developments ranged from 1 to 3, that is, *no importance*, *some importance* and *high importance*.

We designed the survey to take approximately 10 min to complete in order to maximize response rate.

Distribution of the survey

We used a non-random sampling scheme primarily targeting camera-trappers who use camera traps as part of their professional work. We created the survey in Google Forms (in English) and distributed it online through a combination of direct email invitations through the authors' professional networks, forums, list-serves and social media (Twitter and Facebook). The most significant platforms used to reach camera-trappers were: (1) Wildlabs.net (with >1300 members), (2) the Yahoo Camera-trapping Information Exchange (>400 members), (3) the Wildlife Camera-trapping Facebook private group (>1200 members), (4) ECOLOG-L (>20 000 members) and (5) the Society for Conservation Biology Bulletin Board. We also asked participants to share the survey with camera-trappers in their professional networks, thus using snowball sampling (Newey et al. 2015).

Analysis

We present summary statistics for the overall survey results. We also explicitly modelled the data to answer if: (1) survey responses vary between broad types of camera-trapper (as identified by the type of institution respondents were based at), (2) survey responses vary according to the experience levels of respondents and (3) camera trap performance has changed over time.

We first modelled variation in the camera trap ratings. As our multivariate response, we used respondent ratings for camera trap reliability, image quality, sensor quality, usability and value for money. We excluded ratings for video quality and customer service due to the large number of non-responses. As explanatory variables, we used camera-trapper experience and institution type. We hypothesized that differing levels of experience and institutional priorities would emphasize different aspects of camera trap performance. We focused on camera trap manufacturer rather than model due to the limited sample sizes available for individual models and the difficulty of matching model names across respondents. Given that there were four experience categories, we calculated the average across categories for each respondent (by treating no experience equal to zero, <1 year of experience equal to 1, 1–5 years of experience equal to 2 and >5 years of experience equal to 3). We re-categorized respondent institution as academic (n = 104), governmental (n = 34) and non-governmental (NGO, n = 75). We excluded a small number of responses that fell into other categories (n = 12) and responses for manufacturers with <10 ratings (n = 60).

We next modelled variation in how important each of the camera-trapping constraints and future developments were for respondents. The importance scores in both cases – constraints or future developments – were taken as multivariate ordinal response variables. The explanatory variables were mean experience level and institution type (as described above).

We used multivariate ordinal generalized linear models (with a probit link) as implemented in the R package 'mvabund' (Version 3.13.1; Wang et al. 2012). This method is typically applied to multivariate abundance data, and by calling the clm() function from the 'ordinal' package (Christensen 2015), allows modelling of multivariate ordinal data. To test for significant effects of explanatory variables, we used likelihood-ratio-tests based on 999 parametric bootstraps. We assessed model fit by visual inspection of residual and quantile–quantile plots.

To examine how camera trap performance has changed over time, we modelled mean ratings for each manufacturer using generalized linear models (gaussian link). The response was the mean rating across the criteria included in analyses. As explanatory variables, we used the reported year of manufacture or purchase. In many cases, respondents indicated multiple years in their responses, so we took the last year assuming that a camera-trapper's most recent experience using a particular camera trap would have the most influence on their ratings. We again assessed model fit by inspection of residual and quantile–quantile plots. All analyses were conducted in R (Version 3.5.0; R Development Core Team 2018).

Results

Survey respondents

Between 10 June 2016 and 1 December 2017, we received 258 responses to the survey. Respondents resided in 52 countries (Fig. 1A), with the largest number of responses coming from the United States (n = 75), followed by the United Kingdom (n = 29), Australia (n = 13) and Italy (n = 10). Fewer than 10 respondents resided in any of the remaining 48 countries. In comparison, respondents deployed camera traps in 99 countries (Fig. 1B). Similar to residency, the United States was home to the largest number of deployments (n = 72), followed by Australia and South Africa (n = 19 in both cases), and the United Kingdom (n = 18).

Respondents reported working across 19 major habitats (ranging from mangroves to polar regions) with a higher prevalence of tropical (n = 224) over temperate habitats (n = 172) and forested (n = 293) over open habitats (n = 241) (Fig. 2).

Most respondents were employed at universities and research institutions (n = 103) and NGOs (n = 75), with the remaining respondents employed at government agencies (n = 34), companies in industry (n = 6), ecological consultancies (n = 6) or 'other' (n = 9) (e.g. independent

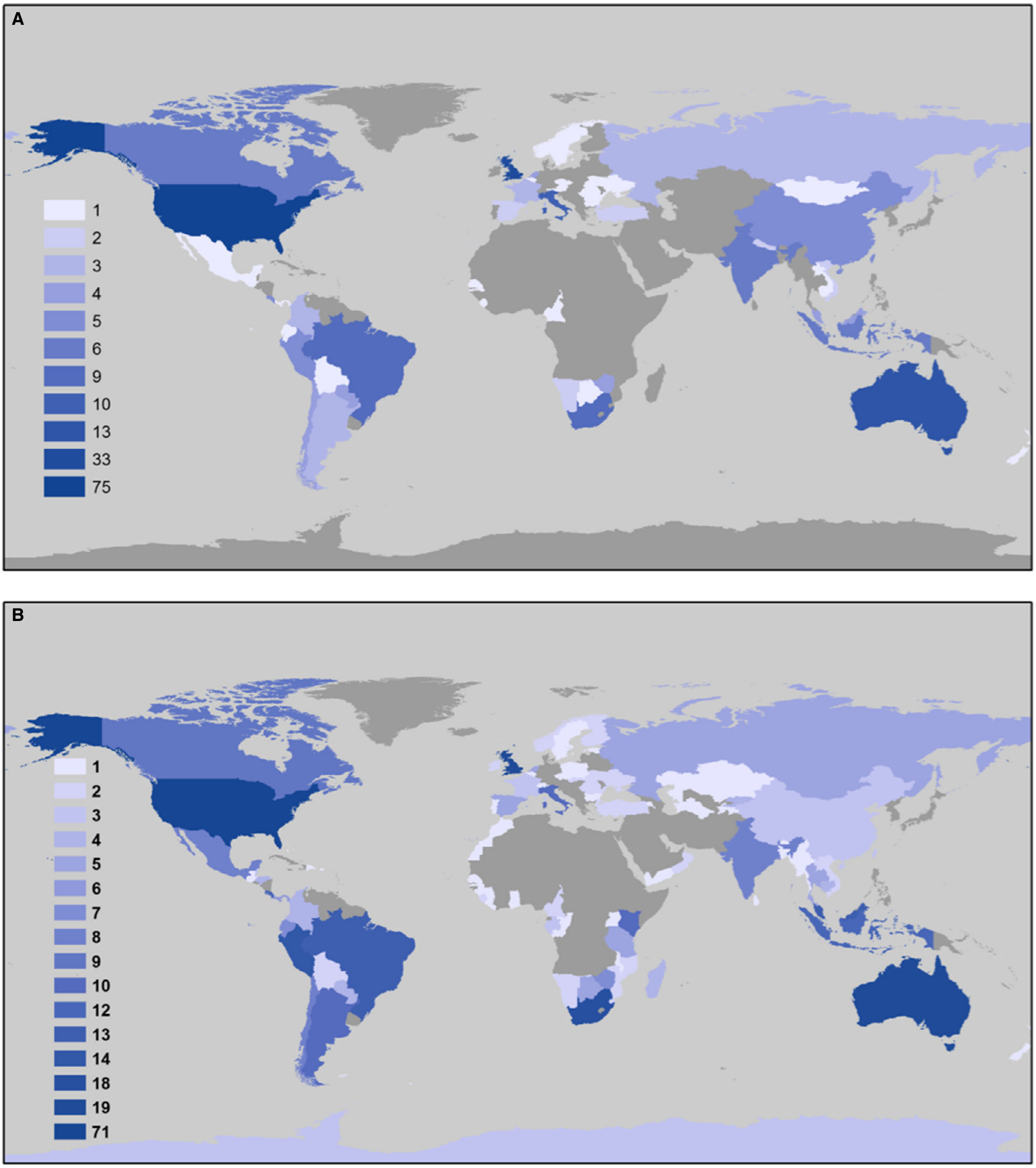

Figure 1. Number of respondents (A) residing and (B) carrying out camera trap deployments in each country.

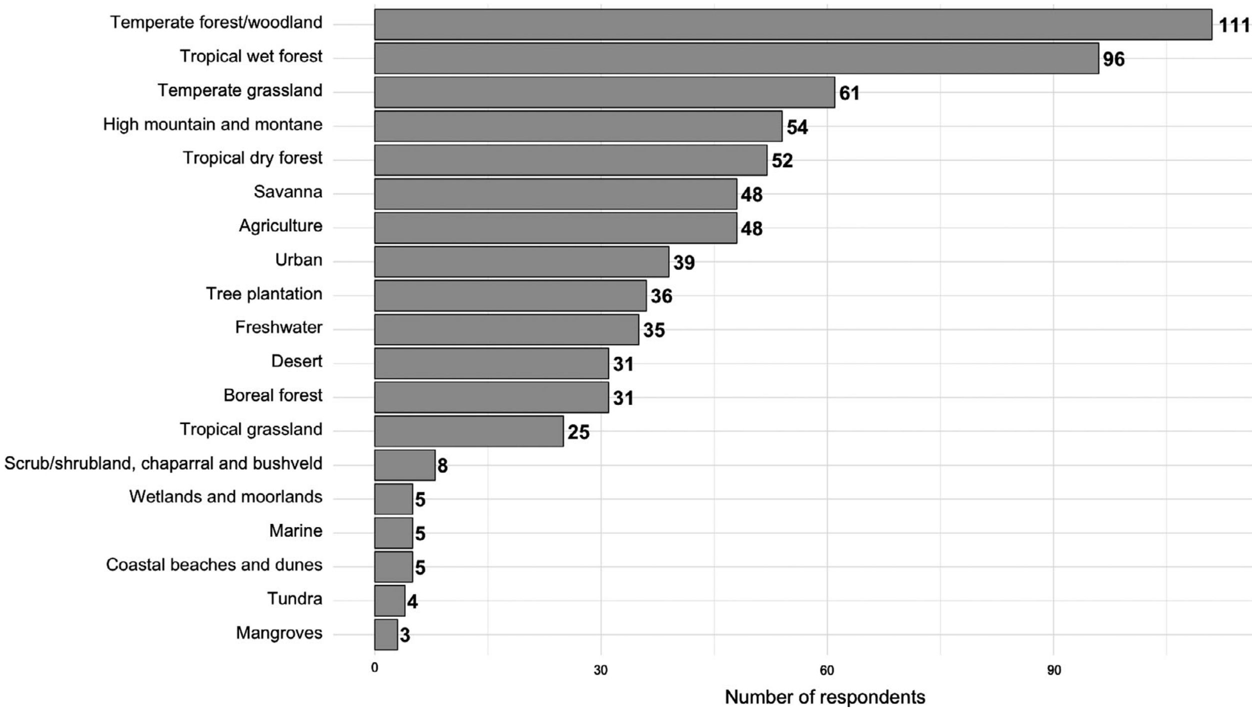

Figure 2. Habitats camera-trapped by survey respondents.

photographers or manufacturer representatives); 25 respondents did not answer the question.

Respondents also indicated that they used camera traps for a wide array of specific activities (Fig. 3), with the majority using them for inventory work (n = 194), and 96% of respondents applying camera traps for multiple activities.

Respondents were most experienced at deploying camera traps and at managing and analysing data, with 50% (n = 124) of the respondents who answered the question (n = 250) having between 1 and 5 years of experience at deploying camera traps and 44% (n = 111) between 1 and 5 years of experience at both managing and analysing data. Respondents were least experienced at developing camera trap technology, with 82% (n = 205) having no experience of this.

Camera-trapping constraints

Respondents identified a wide range of constraints and an even greater diversity of potential solutions that they had employed, including engaging with local communities to mitigate camera trap theft and using citizen science to classify imagery (Table 1).

Survey respondents ranked the cost of camera traps as the most important constraint on achieving their goals (66% ranked cost as an *important* or *extremely important barrier*) (Fig. 4). The next most important constraints were security and theft/vandalism (50% ranked it as *important* or *extremely important*), camera-sensor performance (42%) and battery life (40%).

After removal of incomplete responses, we were left with 198 responses suitable for inclusion in our models of camera trap constraints. Models results indicated that constraints were influenced by camera-trapper type (Λ = 61.63, P = 0.03) but not by their experience (Λ = 10.62, P = 0.65).

Camera trap ratings

Respondents provided a total of 326 ratings of 27 manufacturers. We excluded 100 ratings from further consideration because of missing values or because they were for manufacturers with <5 ratings. The highest mean rating for manufacturers with $\geq$ 5 ratings was for custom-built camera traps, followed by Spartan and Reconyx (Fig. 6). This pattern was also present across criteria, with the same two manufacturers achieving the highest ratings across all seven criteria (Fig. S1). Models indicated that camera trap ratings varied significantly by manufacturer (Λ = 211.29, P < 0.001) and the type of institution the respondent belonged to (Λ = 32.45, P < 0.01), with respondents from NGOs rating camera traps with lower scores for all criteria (Fig. S2). Government respondents rated image quality and sensor quality as having lower importance compared to academics, whilst NGO

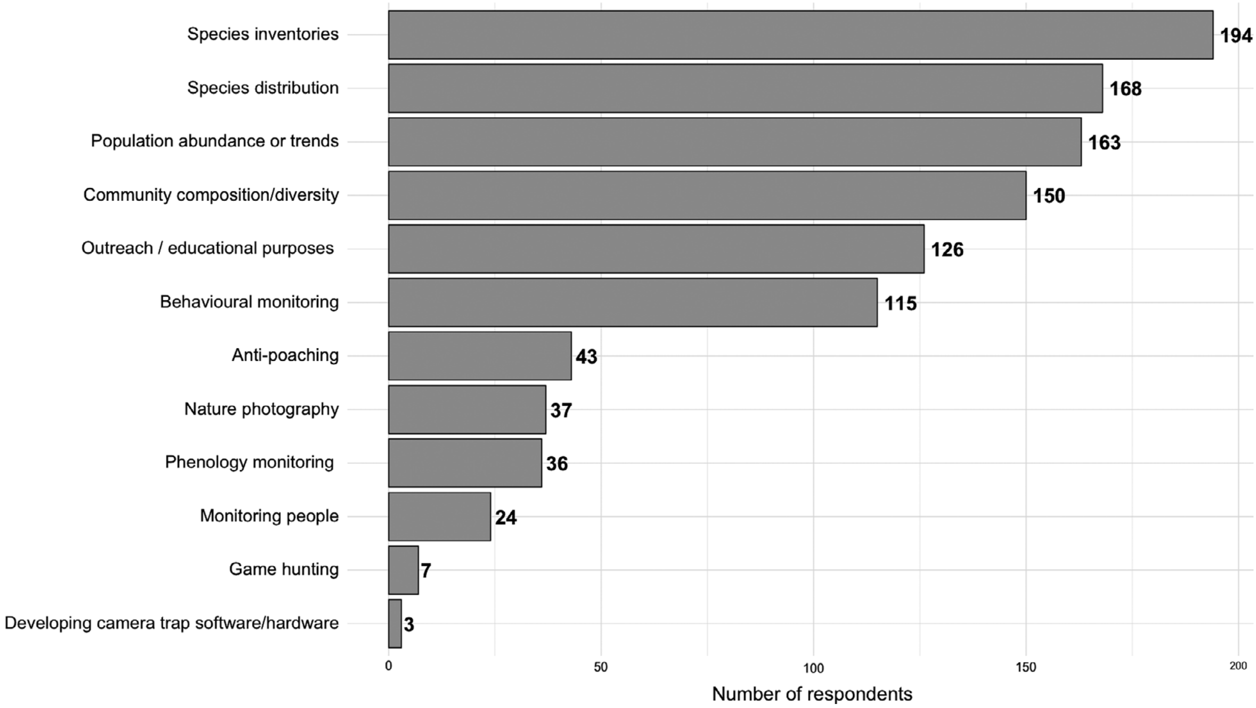

Figure 3. Activities survey respondents used camera traps for.

respondents rated image quality and useability as having lower importance compared to academics (Fig. S2). Camera trap ratings did not vary significantly by experience levels of respondents ($\Lambda = 8.68$, $P = 0.13$).

Although ≥3 years of ratings are arguably sufficient to detect a trend, we opted for a more conservative approach because of the inherent subjectivity of the manufacturer ratings. We limited our analysis of temporal trends in the mean ratings of camera trap manufacturers to those of manufacturers with ≥5 ratings across ≥5 years. Reconyx, Cuddeback, Moultrie, Scoutguard and Bushnell met this minimum, but none exhibited a temporal trend in ratings (all $P > 0.36$), suggesting that user-ratings of camera trap performance have not exhibited a consistent trend over time.

Priorities and predictions for camera trap development

According to respondents, the top priorities (classified as *high importance*) for the next generation of camera traps are the development of faster trigger speeds (66%), followed by humidity resistance (56%), automatic filtering of false positives (54%) and temperature resistance (53%) (Fig. 5). Removal of incomplete responses left 172 that were suitable for modelling development priorities. Results indicated that neither camera-trapper experience ($\Lambda = 29.87$, $P = 0.15$), nor institution ($\Lambda = 34.98$, $P = 0.74$) influenced the development priorities of respondents.

When asked the direction that camera-trapping would take over the next 10–20 years some of the respondents anticipated the integration of camera traps with drones or with other sensors, such as Passive Integrated Transponder detectors (Table 2). Other respondents predicted more immediately feasible possibilities such as an increase in large-scale projects (e.g. country-level monitoring) and more widespread use of citizen scientists to classify imagery. Most respondents predicted that the future of camera-trapping will include major improvements, either through automation of image classification and analyses ($n = 54$), wireless connectivity that would allow remote access to imagery ($n = 36$), more robust survey design and analytical methods ($n = 24$), or improvements in battery life ($n = 20$).

Discussion

By conducting a global survey of camera-trappers we have identified that: (1) the major current constraints to effective camera-trapping are cost, theft and sensor performance, (2) the most-needed technological developments are related to sensor performance (trigger speed and sensitivity), environmental resistance (temperature and humidity) and automated filtering of blank images and (3) there is considerable variation among camera trap

Table 1. Camera-trapping challenges and solutions as identified by survey respondents. Solutions provided by respondents were coded into broader categories. The number of issues and corresponding solutions may not be equal because some issues were identified with solutions, and multiple solutions were sometimes identified for some issues. Numbers in parentheses indicate frequency of response.

Challenges	Solutions
Image classification (25)	Used dedicated software (7); citizen science (e.g. Penguin Watch, Snapshot Serengeti, MammalWeb) (5); eMammal (3); Camera Base (2); Agouti (2); Colorado Parks and Wildlife Photo Warehouse software (2); Google TensorFlow; TEAM software; Scouting Assistant software; EXIF extractor software.
Theft (18)	Commercial or custom security cases (10); locks (8); camouflage (2); information attached to camera trap explaining their purpose (2); use of black flash; held conversations explaining work with local residents; placement of camera traps on private land; modified antenna to make less conspicuous; deployed at times when theft less likely.
Data storage and management (17)	Custom database (9); use of eMammal software (3); use of Agouti software (2); custom hard drive.
Animal interference (15)	Used secure commercial or custom boxes or cases (7); designed holes/covered access points with steel wool to exclude insects (2); reinforced plastic IR sensor cover with wire mesh; fastened securely to immoveable objects; used black flash; wrapped trees with chicken wire near beavers; used pesticide tab to deter insects; secured batteries to ensure they were not disconnected.
Environmental (12)	Replaced camera and Fresnel lenses damaged by the sun and windblown sand; used black glue to exclude water; placement of camera traps high up to avoid flooding; placed tampons inside cameras to absorb humidity; duct-taped seams; developed rain covers made from zinc to reduce moisture penetration; dried camera traps with dehumidifier and lights between deployments (2); inserted silica gel into camera (3).
False positives/negatives (11)	Use of branches to keep cows away from camera traps; bring laptop or other device to test field of view and trigger sensitivity; training of assistants to better place traps; placement of camera trap to avoid direct sunlight (pointing east or west) and shadows; placement at correct distance from target species path; clearing vegetation in field of view; developed custom method for calculating effective detection distances; developed accessory lens to adjust focus depth to 20–100; used auto sensitivity feature; custom modifications.
Camera trap placement (10)	Use of shims, branches, or stones to aim camera trap (3); development of cost-effective tree attachment (5; e.g. straps); custom stakes or poles for mounting in treeless areas (3); custom floating platform.
Data analysis (8)	Developed custom analyses (2); developed *ex situ* method for extracting REM parameters; use of eMammal; use of Camera Base software; increased camera speed to aid behavioural and density analyses.
Battery life (5)	Utilized longer time delay between photographs; modified power system through use of alternative batteries (e.g. 12-volt batteries) or addition of solar panels (3).
Cost (2)	Purchased spare lenses and repaired cameras themselves.
Image quality (2)	Covered portion of flash to reduce light intensity (2).
Memory card corruption (1)	Formatted cards before use.
Access to best practices (1)	Authored best practices.

manufacturers in user-rated performance, and none of the manufacturer ratings exhibited a trend over time.

Constraints on camera-trapping effectiveness globally

Although camera trap prices have gradually declined over the last two decades (especially with the emergence of mass-produced units manufactured in Asia), our results indicate that costs remain an important barrier to camera-trapping efficacy. Previous work also identified cost as one of the main drivers of decision-making in relation to camera trap purchase (Meek and Pittet 2012; Newey et al. 2015). Researchers are faced with two broad strategies: buy a large number of low-cost 'budget' camera traps or a smaller number of high-end camera traps. In order to cover a larger sampling area and more camera trap locations, researchers have tended to favour the former approach, and in the process might be forfeiting camera trap (and data) quality for quantity (Wearn and Glover-Kapfer 2017). Purchasing cheap and potentially poorly performing cameras in bulk might be a *false economy* if a smaller set of high-quality units would actually be more effective in addressing the aims of the survey. We could not directly test for this in our study but in support of the notion that false economies might be in operation, the cheaper camera trap manufacturers (e.g. Scoutguard) were typically rated lower than the more expensive manufacturers (e.g. Reconyx). Further work testing the cost-benefit ratio of high-end and 'budget' camera traps would be beneficial.

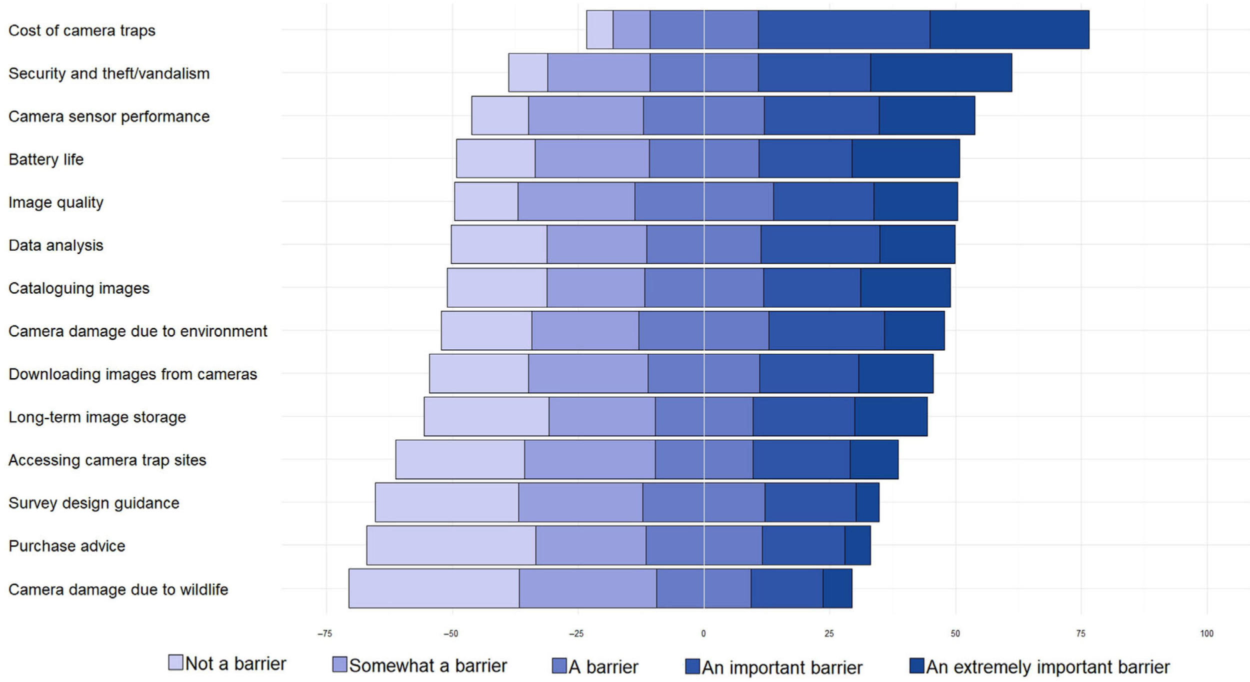

Figure 4. Relative importance of camera-trapping constraints encountered by survey respondents.

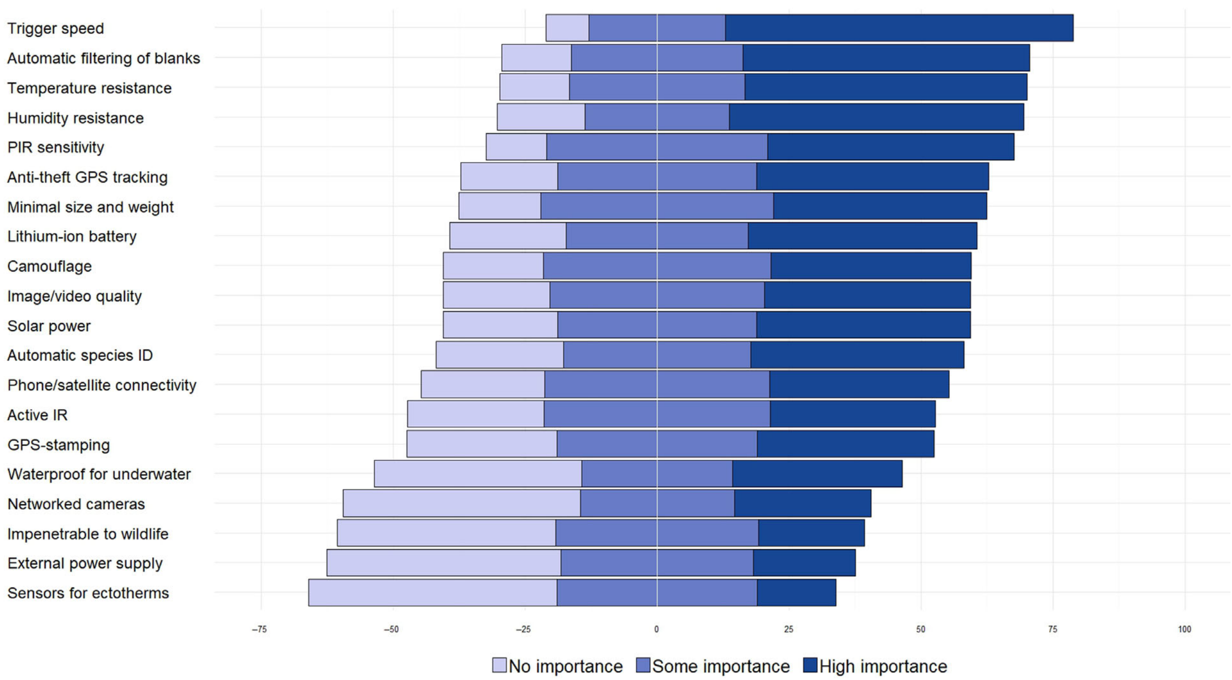

Figure 5. Development priorities for the next generation of camera traps according to survey respondents.

Table 2. Survey responses to the question: What direction do you see camera-trapping potentially going in over the next 10–20 years?

Number of responses	Direction
54	Automation: software that automates the process of determining objects captured in photographs. This includes the automated identification of false positives, species, individuals, and other parameters of interest, e.g. speed and size of objects.
36	Wireless: ability to access camera trap imagery remotely, e.g. via satellite or cellular networks.
24	Methodological: improvement in the quality and accessibility of camera-trapping survey methods and analytical tools.
23	Wider use: an increase in the general use of camera traps (e.g. for behavioural research), the size of camera-trapping projects, the environments in which they can be used, e.g. underwater.
21	Cost: reduced cost. Consistently grouped with improved quality by respondents.
20	Energy: improvements in battery technology or supplementation via solar panels, facilitating longer deployment times and decreasing maintenance frequency.
17	Image quality: improvement in the quality of camera trap imagery.
13	Technology integration: the addition of sensors for monitoring additional environmental variables or other technologies that are not currently included with camera traps, either on-board the camera trap or as part of an integrated, yet physically separate system. Examples include the integration of acoustic sensors, radio frequency identification readers, or temperature sensors, or the use of drones to wirelessly collect camera trap data, or camera traps to automatically collect tracking tag or collar data.
13	Quality: general improvement in reliability. Consistently grouped with reduced cost by respondents.
11	Real-time: ability to receive imagery when the camera trap captures it. Real-time is often included with Auto-identification and Wireless advances to send real-time alerts when particular species or poachers are photographed.
11	Collaboration: greater coordination among camera-trappers to facilitate larger scale analyses using camera-trapping data and increase sharing of information and expertise. Also includes open sourcing of camera trap technology.
11	Citizen science: increase in the use of citizen scientists for image classification and other facets of camera-trapping projects.
11	Sensor: improved ability of sensors to detect small species, species at greater distances, or replacement of current sensors with other methods for detecting species, or other unspecified improvements.
11	Size: decreased size.
8	Database: improved database software.
6	Anti-theft: camera traps that include anti-theft features, including deletion of memory, real-time alerts when moved, or which transmit signals indicating their location.
6	Video quality: improvements to the quality of videos.
5	Two-way: ability to remotely communicate with camera traps in order to change settings or check status.
4	Trigger: increased trigger speed or improved functionality.
4	Data storage: greater memory/storage capacity.
5	Network: frequency with which camera traps are networked. Differs from wireless in that data remain in camera traps.
3	GPS: on-board GPS capabilities for camera traps.
3	Anti-poaching: greater use of camera traps for anti-poaching purposes.
2	Stereo camera: use of ≥2 lenses in order to judge distance from camera trap to photographed objects or estimate size of objects.
2	Animal invisibility: changes to the flash, lens, or internal machinery of camera traps to effectively make them invisible to animals.
2	Weight: decreased weight.
3	Humidity: improved resistance to humidity.
2	Outreach: greater use of camera traps for public engagement and education.
2	Modularity: ability to customize camera trap functionality.
2	Analysis issues: increases in issues associated with data calibration and disagreement over analytical methods.
2	Temperature: improved resistance to temperature.
1	Ethics: an increase in ethical issues arising from the use of camera traps.

Many respondents predicted that camera trap costs would continue to decline in the future. Price-setting and market dynamics are complex for any product, not least for electronic goods. Nonetheless, a crowd-sourced review platform for camera traps would likely improve knowledge of camera-trappers and could drive improvements in camera quality and possibly costs. Our results on ratings for different manufacturers give preliminary insights into the value of such a platform. Costs would also potentially come down with increased market size, allowing companies to benefit from economies of scale, although ultimately the ability of research and conservation organizations to drive price may be limited given the market dominance of hunters in North America (Meek and Pittet 2012). Additionally, the high price of electronic sensors in wildlife research has likely been an important driver towards the recent proliferation of open-source technologies, such as Audiomoth (Hill et al. 2018) and Solo (Whytock and Christie 2017). Camera-trapping could also benefit from this approach, but only with a concerted push from researchers, conservationists and technologists (Berger-Tal and Lahoz-Monfort 2018).

Theft/vandalism was the second most important current constraint on camera-trapping effectiveness. Camera trap vandalism and theft are serious problems that have likely resulted in financial losses running into the millions of dollars (e.g. Meek et al. 2018). In common with these results, we found that theft and vandalism are common across a wide variety of study contexts and locations. Commonly reported solutions to reduce risk included using commercial or custom security cases, cable locks, camouflaging (e.g. natural features such as logs) or camera traps with no-glow (black) infrared flash. Many camera trap manufacturers sell security cases for specific camera trap models which, when used in combination with permanently installed metal posts and-or camouflaging, putatively provide some security. How effective these protective measures ultimately are is unknown (Meek et al. 2018) and a ripe area for further investigation. A commonly suggested effective preventive strategy was engaging with local communities and involving members of the community as volunteer citizen scientists or field technicians. Other studies have reported that in situations when engagement may not be effective (e.g. when dealing with illegal activities), methods focussing on a fear factor (e.g. a false antenna on cameras with a warning sign saying they can be tracked) may make people question the risk before they attempt to steal devices. Developments in anti-theft technology for camera traps similar to those developed for smartphones (e.g. 'Find My iPhone' on Apple devices and 'Find My Device' on Android devices) could also prove effective in the future.

Camera-sensor performance was the third most common constraint experienced by camera-trappers. Poor camera sensor performance can increase false positives (i.e. empty images) and negatives (i.e. missed detections). False positives caused by vegetation, the sun, or dappled shade can be a considerable drain on resources (battery life, memory and time spent reviewing images), and are a common occurrence in open environments (such as grasslands and coastal habitats) with dense ground-level vegetation. False negatives can occur if trigger times are too slow or if the effective range of a sensor, which can be influenced by vegetation density, temperature, relative humidity and the body size of target animals (Kelly and Holub 2008; Rowcliffe et al. 2011), is too short for a given species. Higher temperatures will usually mean a lower differential between the surface temperature of the background and the target species, and as a result animals have to be closer to the sensor in order to trigger the camera. Camera trap sensors also commonly miss species that produce either a weak thermal signal (i.e. small mammals and birds, but see De Bondi et al. 2010), or no signal at all (i.e. amphibians, reptiles and invertebrates, but see Welbourne 2013).

The most common type of camera trap sensor is the passive infrared sensor (PIR) and, whilst trigger times have improved in recent years, it is unlikely that many of the other causes of false positives and negatives can be overcome using this technology. Poor sensor performance might be mitigated by combining multiple PIR sensors or using active infrared sensors that trigger when an infrared beam is crossed (Meek and Pittet 2012). However, these solutions will likely be associated with an increase in cost (Wearn and Glover-Kapfer 2017). Respondents also highlighted several ad-hoc solutions, including on-site testing of field of view and trigger sensitivity, improved training on camera trap setup in the field, modification of the thermal background (e.g. Welbourne 2013) or development of methods for calculating effective detection distances to correct for differences in capture rate (e.g. Hofmeester et al. 2017).

False triggering also reduces battery life, which after costs, theft/vandalism and sensor performance was identified as one the biggest constraints on camera-trapping (Figure 4). Respondents predicted that solar-powered camera traps and integrated lithium-ion batteries (as used in mobile phones and laptops) would lead to improvements in the technology. To a limited extent, some of these functionalities are already available. For example, some camera traps are already compatible with solar panels. Also, some manufacturers (e.g. Spypoint) offer rechargeable lithium-ion battery packs for their camera traps.

Managing data efficiently, particularly in terms of image classification, was also identified among the top five camera-trapping constraints by survey respondents. To date many of our respondents identified the use of dedicated software as a potential solution to this. Dedicated software ensures that data are well-organized (e.g. adhering to metadata standards) and that workflows are efficient (e.g. when cataloging large numbers of images quickly). However, no single software package has emerged as a favourite for processing camera trap data efficiently (Scotson et al. 2017; Wearn and Glover-Kapfer 2017; Young et al. 2018). A number of large-scale camera trap projects have also demonstrated the collective power of citizen scientists for cataloguing camera trap data (e.g. Snapshot Serengeti, eMammal, Mammal Web, Wildlife Spotter, Instant Wild and various projects on Zooniverse.org), achieving in some cases more than 96% accuracy when compared to expert identifications (Swanson et al. 2016). Humans are exceptionally good at visually classifying objects, but computers are fast catching up. Filtering of blank images and automatic identification of species are the most widely useful camera-trapping task that could be achieved using computers. A number of efforts are currently underway to test and refine automatic identification of species through state-of-the-art machine learning algorithms, for example with deep convolutional neural networks (e.g. Nguyen et al. 2017;

Villa et al. 2017; Norouzzadeh et al. 2018; Tabak et al. 2018). Fundamental to this will be an increased availability of open-access camera trap datasets (e.g. Snapshot Serengeti, Wildlife Insights) across the widest range of species and habitats to serve as training data for the algorithms.

As this survey was administered online, was only available in English and was circulated more widely within our professional networks than elsewhere, respondents likely tended to be English-speaking, desk-based, and located somewhere with a good internet connection. Also, our results show a clear prevalence towards North American camera-trappers, with most respondents and most camera trap deployments occurring in the United States. This likely reflects broader biases in where camera-trapping is done (McCallum 2013; Burton et al. 2015). Future surveys of the camera-trapping community may benefit from more equal representation across countries, including a larger number of respondents from Africa and Central-South America. This would enable us to dissect geographic differences in the constraints faced by camera-trappers.

Camera trap ratings

We found large differences in the relative quality of camera traps (Fig. 6), mirroring findings in the few field tests that have compared camera traps to date (e.g. Hughson et al. 2010; Wellington et al. 2014). Mean ratings for camera trap manufacturers are probably more-or-less consistent with current consensus among experienced camera-trappers; however, the variation in ratings presents additional information useful for experienced as well as novice camera-trappers. First, the large variation in mean ratings for some manufacturers suggests that quality control may be an issue. Second, because many manufacturers produce multiple models that provide different functionalities and come at a range of prices, users need to be aware that the performance of models will likely vary even if produced by the same manufacturer. Unfortunately, we were unable to model mean ratings by manufacturer and model, and as such cannot disentangle the relative effects of quality control and variability in model performance. However, it is likely that both contribute to the observed variation in camera trap manufacturer ratings, and should factor into decisions of which camera traps practitioners select.

Intriguingly, there was no discernible positive or negative trend in camera trap manufacturer ratings, despite improvements in the technology (e.g. faster trigger speed) in recent years. Because our analysis was limited to ratings of manufacturers, it is possible that the variation in the quality of camera traps models produced by a single manufacturer obscured real trends. Additionally, user-

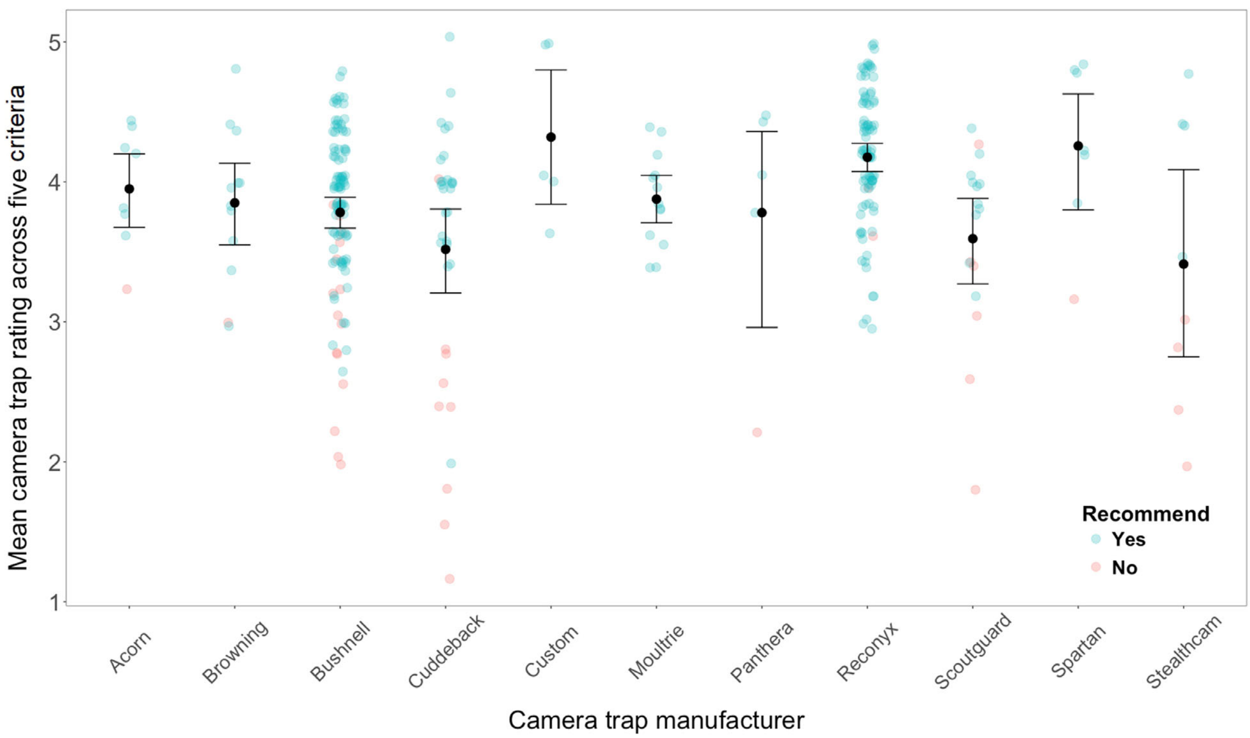

Figure 6. Mean rating and bootstrapped confidence intervals for camera trap manufacturers across five criteria – reliability, image quality, sensor quality, usability and value for money – and whether respondents overall would recommend the camera trap to others.

ratings are a measure of perceived camera trap performance, which is a relative measure (presumably, in reference to the 'ideal' camera trap in the minds of camera-trappers) not an objective absolute measure. Regardless, the fact that manufacturer ratings did not exhibit a consistent trend through time remains telling and could serve as a challenge to camera trap manufacturers.

On the horizon: camera-trapping version 3.0

Faster trigger speed was identified by respondents as the top priority for future development. There has already been a marked improvement in trigger speeds in the last 5 years and most commercial camera traps now have a trigger speed of <1 s (according to testing done by Trailcampro.com). However, we suggest that trigger speeds of <300 ms are desirable for a research-grade camera trap. This trigger delay corresponds to a displacement of <50 cm for a fast-moving animal walking at 1.4 m s^{-1} (using human walking speed as a benchmark).

Survey respondents highlighted increased trigger sensitivity as a development priority for camera traps, which would increase the probability of detecting small animals or distant individuals, without resulting in a high ratio of false triggers. For the PIR sensors typical of most modern camera traps, the distance of an animal from the sensor, and its body mass, determines the magnitude of infrared radiation, which affects the ability of the PIR sensor to trigger an image. The development of sensors capable of detecting small species <100 g at a distance of 5–10 m are likely to be a valuable innovation, especially if animals with a similar temperature to the background are accommodated (i.e. ectothermic species and species living in hot environments). Hobbs and Brehme (2017) proposed a proprietary active infrared system for specifically targeting small animals (small mammals, amphibians, reptiles and large invertebrate species), but it is unsuitable for medium- and large-sized animals. Camera trap systems that separate the camera from the triggering mechanism might also be a promising approach for small-bodied species (e.g. Rico-Guevara and Mickley 2017). Ultimately, however, on-board detection algorithms will likely represent the break-through technology that revolutionises camera trap triggering. Rudimentary pixel change algorithms already exist (Swinnen et al. 2014), as do deep learning algorithms for identifying animals that are small enough in size to fit on a camera trap (Thomassen 2017). These algorithms for triggering camera traps could be based on low-powered continuous video (meaning they could work in hot environments, underwater and for ectothermic species), on low-cost and power-efficient thermopile array sensors (WWF 2018), or in future could even take advantage of bio-inspired photosensitivity enhancers for low-light conditions (Liu et al. 2016).

The development of tools to catalogue camera trap images is crucial for time- and cost-effective camera trap data management and analysis. There is a trend towards closer integration between dedicated camera trap data management software and analytical software (e.g. Camelot and R, via the camtrapR package), and this will likely continue to be enhanced into the future. Automation of species recognition may become seamlessly integrated into camera trap software in the future (Bubnicki et al. 2016; McShea et al. 2016), and possibly even into camera traps or base-stations in the field (e.g. Rosales-Elias et al. 2017; Thomassen 2017).

The collective opinions of a global camera-trapping community define a vision for camera-trapping 3.0 over the next 10–20 years, consisting of camera traps with excellent detection circuitry (trigger speed and sensitivity) and resistance to extreme environments, as well as on-board algorithms for automatic filtering of blank images. Camera-trapping 3.0 will also involve wireless transmission of data, networks of connected sensors, increased automation of processes (including image filtering, species ID, movement tracking, speed estimation and body size estimation) and better, more collaborative tools for managing and analysing camera trap data. These trends reflect broader patterns that have been identified in the rise of *technoecology* (Allan et al. 2018).

Our results serve as valuable market research for both open-source and commercial camera trap developers. Developments in camera trap functionality have been primarily driven by the market dominance of hunters to date (Meek and Pittet 2012), but the demand from researchers and conservationists is likely a growing subsection of total demand. This is important because the priorities of hunters in terms of camera trap functionality do not necessarily align with the needs of the research and conservation community. Demand from researchers and conservationists is only set to increase, in particular with the trend towards large-scale monitoring using camera traps (Steenweg et al. 2017). This is exemplified by the All-India Tiger Estimation, possibly the world's largest coordinated wildlife survey effort to date, which will use 15 000 camera traps to estimate tiger numbers across India (Government of India, 2018).

Technological developments are increasingly moving camera-trapping into the realm of *big data* by creating new opportunities for data collection, storage and access. There is also an increasing expectation within research communities for open data sharing. We see these developments as driving a move away from a reliance on project-specific, non-collaborative solutions, towards greater investment in integrated online platforms for hosting, sharing, classifying and even analysing camera trap data (likely using powerful cloud-computing approaches).

Although proper safeguards have to be put in place to ensure open data are not used for malicious purposes (Lindenmayer and Scheele 2017) and lead to perverse outcomes, coordination among conservation and research communities to scale-up and implement large-scale projects with networks of remote sensors (Steenweg et al. 2017) will, we believe, lead to substantially more effective wildlife monitoring in future.

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Supporting Information

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

Figure S1. Camera-trap ratings and confidence intervals for camera trap manufacturers across reliability, image quality, sensor quality, usability and value for money criteria. Panthera camera traps are not available to buy so ratings on value for money are missing.
Figure S2. Camera trap ratings from NGO, government and academic respondents for reliability, image quality, sensor quality, usability and value for money.
Table S1. Questions used to survey the international camera-trapping community on current constraints to effective camera-trapping, the relative quality of camera-trap models and priorities for future technological developments.

