



Charles Darwin University

Accuracy of identifications of mammal species from camera trap images

A northern Australian case study

Potter, Larissa C.; Brady, Christopher J.; Murphy, Brett P.

Published in:
Austral Ecology

DOI:
[10.1111/aec.12681](https://doi.org/10.1111/aec.12681)

Published: 01/05/2019

Document Version
Peer reviewed version

[Link to publication](#)

Citation for published version (APA):

Potter, L. C., Brady, C. J., & Murphy, B. P. (2019). Accuracy of identifications of mammal species from camera trap images: A northern Australian case study. *Austral Ecology*, 44(3), 473-483.
<https://doi.org/10.1111/aec.12681>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

25 *tunneyi*]). There was a positive relationship between accuracy of identifications and body
26 mass. Participant confidence was highest for large and distinctive mammals, but was not
27 related to participant experience level. Identifications made with greater confidence were
28 more likely to be accurate. Unreliability in identifications of mammal species is a significant
29 limitation to camera trap studies, particularly where small mammals are the focus, or where
30 similar-looking species co-occur. Integration of camera traps with conventional survey
31 techniques (e.g. live-trapping), use of a reference library or computer-automated programs
32 are likely to aid positive identifications, while employing a confidence rating system and/or
33 multiple observers may lead to collection of more robust data. Although our study focussed
34 on Australian species, our findings apply to camera trap studies globally.

35

36 **Key words:** camera trap, northern Australia, species identification, small mammal, wildlife
37 survey

38

39 **Introduction**

40 Over the last three decades, the number of camera trap studies for detecting mammals has
41 risen dramatically (Meek *et al.* 2015). This is partly a response to increased availability and
42 affordability of commercial devices (Meek *et al.* 2015; Tobler *et al.* 2008), but also a result of
43 advantages of camera traps over other sampling methods (De Bondi *et al.* 2010). However,
44 like all survey methods, camera traps have inherent limitations, and it is crucial they are
45 understood and acknowledged (Claridge and Paull 2014; Meek *et al.* 2015b; Meek *et al.*
46 2014). Currently, our understanding of the constraints of camera trapping is limited,
47 particularly how these constraints affect our capacity to obtain unbiased and ecologically
48 meaningful data (Burton *et al.* 2015; Meek *et al.* 2015b; Newey *et al.* 2015). This is

49 particularly important given the increasing use of camera traps to aid management and
50 conservation decisions (Burns *et al.* 2018; Comer *et al.* 2018; Jenks *et al.* 2011).

51

52 In a review of the Australian camera trap literature between 1991 and 2003, Meek *et al.*
53 (2015b) found few studies acknowledging or discussing impacts of camera trap limitations
54 on the outcome of results. When mentioned, researchers tend to focus on limitations of
55 cameras themselves, including false triggers, battery life and reliability (Glen *et al.* 2013;
56 Moseby and Read 2014), or experimental design elements like camera orientation (De Bondi
57 *et al.* 2010; Smith and Coulson 2012), detection power (Nelson *et al.* 2014) and comparisons
58 to other sampling methods (Ballard *et al.* 2014; Swan *et al.* 2014b). However, Meek *et al.*
59 (2015b) classified the pitfalls of camera trapping into three broad categories: cameras,
60 animals and observers. While the limitations of camera technology are increasingly
61 recognised, the effect of species' attributes and human ability are still not well understood.
62 Although camera technology is automated, the identification of images is generally done
63 manually, and is strongly influenced by human ability (Ballard *et al.* 2014; Burns *et al.* 2018;
64 Vernes *et al.* 2014). For example, in their examination of misidentification of small rodents
65 in Victoria, Burns *et al.* (2018) found that accuracy in species identifications was species-
66 specific and conditional on image type (white-flash vs. infrared), but the relationship
67 between accuracy and experience was complicated, with the conclusion that species
68 identification appears to be an innate skill.

69

70 Species identification from camera trap images is potentially difficult, introduces inherent
71 error and may be biased by observer skill and experience (Dundas *et al.* 2014; Meek *et al.*
72 2013). Difficulty with species identification may also be affected by the presence of

73 superficially similar, sympatric species (Claridge *et al.* 2010; Meek *et al.* 2013; Oliveira-
74 Santos *et al.* 2010). For example, Meek and Vernes (2016) remarked on the difficulty in
75 discriminating between eight sympatric rodents from the family Muridae, while Claridge *et*
76 *al.* (2010) reported difficulty distinguishing small and superficially similar marsupials from
77 the genus *Antechinus* (family Dasyuridae).

78

79 Due to the growing importance of camera trap survey data for conservation and
80 management, it is imperative to understand factors which may affect accuracy of mammal
81 identifications. The aim of this study was to investigate the effect of two species-level
82 attributes, animal body mass and superficial distinctiveness (i.e. size, body shape, pelage
83 colouration or patterning), and two observer-level attributes, experience and confidence, on
84 accuracy of identification of mammal species from camera trap images. We predicted that
85 accuracy and observer confidence in identifications would be lowest for small, non-
86 distinctive species, in line with personal experience and the literature (Claridge *et al.* 2010;
87 Meek and Vernes 2016). Additionally, we expected that more experienced observers would
88 demonstrate higher accuracy and confidence levels.

89

90 **Materials and methods**

91 ***Collection of camera trap images***

92 Sixty camera trap images of 25 native terrestrial mammal species (Table 1) were collated
93 from six research projects across northern Australia, including coastal regions of the
94 Northern Territory (NT) and the Kimberley region, Western Australia (WA). Individuals were
95 identified to species level by researchers involved in each project (Corey *et al.* 2013; Davies

96 *et al.* 2017; Diете *et al.* 2017) using image sequences, local knowledge, and confirmation
97 from trap records.

98

99 **Survey design**

100 To assess accuracy of mammal identifications by wildlife scientists and enthusiasts, an
101 internet-based survey was developed using the website SurveyMonkey™
102 (www.surveymonkey.com). Respondents were canvassed through Twitter
103 (www.twitter.com), LinkedIn (www.linkedin.com; Australian Ecologists and Environmental
104 Professionals page) and the Facebook (www.facebook.com) groups: Australian Mammal
105 Society, Australian Mammal Identification and Wildlife Camera Trapping. Additionally,
106 colleagues and professional ecologists were emailed directly and asked to distribute the
107 survey through their networks. Due to the public nature of social media, a range of
108 experience levels were obtained. The survey was open between 20 December 2016 and 3
109 March 2017.

110

111 The survey contained 20 questions regarding observer experience, followed by 60 camera
112 trap images to be identified. Experience questions were divided into three sections: live
113 trapping experience ($n=8$), camera trapping experience ($n=6$) and camera trap image
114 identification experience ($n=6$). For image identification, respondents were asked to identify
115 individuals to species, and assign a confidence rating to their identification. Confidence
116 rating was a dropdown menu containing the following categories: >95% (“definite”); 86-94%
117 (“pretty sure”); 66-85% (“probable”); 50-65% (“possible”); 36-49% (“not sure”); and <35%
118 (“no idea”). While a numeric answer was preferable for analysis, words were used in

119 combination to provide respondents with a better indication of what was meant by the
120 confidence rating.

121

122 To mimic general wildlife surveys, a range of image types were used, including day and
123 night, colour (white flash) and monochrome (infrared). All images were non-blurry, from
124 horizontally placed camera traps and contained a single species with >90% of an individual
125 visible within the field of view. Although it would have been preferable to have the full
126 range of image types for each species, this was not possible. Additionally, location
127 descriptions were provided with each image as a practitioner would typically have access to
128 this information to assist in differentiating similar species. No single image was repeated,
129 but multiple images of most species were included (Table 1) to reduce the likelihood that a
130 species was misidentified due to low quality imagery. Respondents were asked to identify
131 the first 24 images as a minimum because these contained one of each species (except
132 Short-beaked echidna [*Tachyglossus aculeatus*] due to survey page design). The remaining
133 36 images were randomised so that if respondents did not complete the survey, the same
134 images were not excluded each time.

135

136 ***Statistical Analysis***

137 All analyses were conducted in the computer program R, version 3.3.2 (R Core Team, 2016).
138 Prior to analysis, it was necessary to standardise comment-type responses and convert
139 length of time answers to a single value. Due to the number of questions used to gauge
140 observer experience ($n=20$), only the three broadest length of time responses were used:
141 i.e. 'years trapping and handling mammals in Australia', 'years using camera traps' and
142 'years identifying wildlife in camera trap images'. Since these responses are not necessarily

143 independent, covariance was examined with the Pearson Correlation Coefficient (Quinn and
144 Keough 2002). All three responses were strongly correlated and thus combined into a single
145 metric of 'experience'. For each respondent, we took the midpoint of 'years trapping' and
146 the largest value of either 'years camera trapping' or 'years of image identification'. This
147 approach to deriving an experience metric had the advantage over other methods (e.g.
148 Principal Component Analysis) of providing a metric with interpretable units (i.e. years of
149 experience).

150

151 To deal with variability in species identifications, responses were converted to binary
152 variables with correct (1), incorrect (0) or non-response (blank) codes. Responses were
153 classed as correct if the correct scientific or common name of the species was provided
154 unambiguously, and incorrect for inappropriate species names, general terms (such as
155 'rodent') or invalid answers. Blank answers were assumed to be a non-attempt and
156 excluded from the analysis.

157

158 Body mass for each species was taken from Van Dyck *et al.* (2013) as either the average
159 value, or the midpoint of the male and female range provided (Table 1). Additionally, each
160 species was assigned a 'distinctiveness' index, based on the number of species within its
161 genus (Table 1) (from Van Dyck *et al.* (2013)). Distinctiveness index was calculated as a
162 percentage: $distinctiveness = ((23 - S)/23) \times 100$, where S is the total number of species in a
163 particular genus and 23 the maximum number of species in the rodent genus *Pseudomys*.
164 The index was rescaled using this maximum, so that larger values indicated greater
165 distinctiveness.

166

167 Binomial generalised linear mixed models (GLMMs) with a logit-link function were
168 developed using the *glmmML* package to examine predictors of accurate identifications.
169 This modelling approach allowed respondent to be included as a random effect. Since
170 predictor variables were measured in different units, and to allow interpretation of the
171 effect size of each, body mass, experience and distinctiveness were centred and
172 standardised, and rows with missing values omitted (Quinn and Keough 2002).

173

174 An information-theoretic approach (Burnham and Anderson 2003) was used to compare a
175 set of candidate models developed for each response variable. Sixteen models were
176 developed, representing all possible combinations of experience, body mass, distinctiveness
177 and confidence.

178

179 Models within a set were ranked using the robust second-order form of Akaike's
180 Information Criteria (AIC_c), and Δ_{AIC_c} (difference between AIC_c of a model and the minimum
181 AIC_c in the candidate set) values calculated (Burnham and Anderson 1998). Additionally,
182 Akaike weights (ω_i) were computed as a measure of the probability of a model being the
183 best in the candidate set. Since AIC-based methods do not present information on the
184 variance explained by a model, D^2 , or the proportion of deviance explained by each model
185 compared to the null model, was calculated (Nakagawa and Schielzeth 2013).

186

187 To examine variables influencing observer confidence, a set of candidate models were
188 developed containing body mass, experience and distinctiveness. Confidence was treated as
189 an ordinal response with 'no idea' < 'not sure' < 'possible' < 'probable' < 'pretty sure' <
190 'definite'. Since this is a multinomial response, models were run as proportional odds

191 logistic regression (command *polr*) in the *MASS* package. Models were ranked using AIC_c ,
192 and Δ_{AIC_c} , ω_i and D^2 were calculated and used for model evaluation.

193

194 **Results**

195 A total 178 respondents answered the experience section and 129 attempted image
196 identification. Of the 129, 83% had trapped and handled mammals in Australia, with
197 experience ranging from 0 to >40 years. However, only 40% had done so in northern
198 Australia. Similarly, 82% of respondents had used camera traps, with 37% deploying them in
199 the study region and 89% had identified mammals from camera trap images. The most
200 experienced respondents had used camera traps for 20 years and spent up to 14 years
201 identifying mammals from their images.

202

203 ***Accuracy of mammal identifications***

204 Accuracy of species identifications was highest for larger mammals, while smaller species,
205 like the rodents, were often misidentified (Table 1). A positive relationship was found
206 between accuracy of responses and a species' body mass (Figure 1), with accuracy
207 increasing from 65% for the smallest mammals (<30 g) to 90% for the largest species (>10
208 kg) ($D^2 = 0.16$; Figure 1).

209

210 A positive relationship was observed between species distinctiveness and accuracy of
211 identifications (Figure 2). A non-distinctive species had a lower predicted accuracy (60%),
212 compared to a greater proportion (75%) of correct responses for a more distinctive species
213 (Figure 2).

214

215 There was no distinct relationship between observer experience and accuracy of mammal
216 identifications (Figure 3). However, the model predictions demonstrate that observers with
217 no experience had an accuracy of 68%, while respondents with the greatest experience (24
218 years) had an accuracy of 80% (Figure 3).

219

220 The above trends in accuracy were supported by the modelling approach. Body mass,
221 distinctiveness, experience and confidence were important factors to accurate
222 identifications. This model explained only 16% of the data, but was the best model in the
223 candidate set ($\omega_i = 1.00$) (Table 2).

224

225 **Confidence**

226 A strong positive relationship was modelled between confidence (as a predictor) and
227 proportion of correct responses (Figure 4). An increase in confidence from 'no idea' (35%) to
228 'definite' (95%) corresponded to a predicted rise in accuracy from 22% to 83% (Figure 4).

229 Model selection showed that body mass, experience and distinctiveness influenced the
230 confidence rating of a respondent, with this model having a high probability of being the
231 best in the candidate set ($\omega_i = 1.00$) (Table 3). However, this model explained only 9% of the
232 deviance. Model predictions demonstrated a strong positive relationship between body
233 mass and confidence, with 25% of responses being 'definite' for small mammals (10 g), to
234 85% 'definite' for the largest mammals (>10 kg) (Figure 5a). Modelled confidence as a
235 function of observer experience showed no obvious relationship, with the proportion of
236 'definite' responses only increasing slightly from 55% to 65% (Figure 5b). Additionally,
237 distinctive animals had a higher probability of a 'definite' rating (75%) compared to a less
238 distinctive species (45%) (Figure 5c).

239

240 **Discussion**

241 Understanding limitations associated with camera traps is essential for obtaining robust
242 data (Burton *et al.* 2015; Meek *et al.* 2015b; Newey *et al.* 2015). Our findings demonstrate
243 that uncertainty in identifying mammals to species level is a genuine limitation of camera
244 trap studies. Correct identifications and corresponding confidence levels were significantly
245 higher for larger, more distinctive species while experience was not a strong predictor of
246 accuracy or confidence. However, respondents who were more confident were more likely
247 to be correct .

248

249 Camera traps are increasingly employed as the sole survey method for small to medium-
250 sized mammals (<5 kg body mass) (Meek and Vernes 2016). However, our results
251 demonstrate that practitioners' capacity to accurately identify such fauna from camera trap
252 images is limited, especially for non-distinctive species. Accuracy for rodents, such as the
253 Pale field-rat (*Rattus tunneyi*), were below 40% (Table 1) and the small dasyurids, Red-
254 cheeked dunnart (*Sminthopsis virginiae*) and Butler's dunnart (*Sminthopsis butleri*), were
255 often confused, 51% and 55% accuracy respectively (Table 1). In comparison, the Dingo
256 (*Canis dingo*) and Short-beaked echidna, both large and distinctive species, were always
257 correctly identified (100%) (Table 1). These results support the observations of Meek and
258 Vernes (2016) and Claridge *et al.* (2010), who reported that distinguishing small rodent and
259 dasyurid species was problematic.

260

261 While our index (based on the number of species in a genus) provided an objective proxy for
262 distinctiveness, another approach would be to characterise distinctiveness based on the

263 presence of conspicuous morphological features, such as spots (e.g. Northern quoll
264 [*Dasyurus hallucatus*]) or an obvious white tail tip (e.g. Black-footed tree-rat
265 [*Mesembriomys gouldi*]). Where obvious features were lacking within a genus (e.g. the
266 Golden bandicoot [*Isoodon auratus*] compared to the sympatric Northern Brown bandicoot
267 [*Isoodon macrourus*]), misidentification occurred (38%) (Table 1). Previous studies have also
268 reported low accuracy in the identification of sympatric species of bandicoots from camera
269 trap images (Claridge *et al.* 2010; Meek *et al.* 2013). The study by Meek *et al.* (2013), is one
270 of the few to investigate the complexities of species identifications from camera trap images
271 and found overall accuracy of small and medium-sized mammal identification to be
272 relatively low (44.5%). In comparison to our study, however, Meek *et al.* (2013) included
273 fewer species, only 30 experts and did not examine experience or confidence levels.
274 Similarity between genera (e.g. the rodents *Pseudomys*, *Melomys* and *Rattus*) and
275 distinctiveness within a genus (e.g. *Macropus*), were not captured by our distinctiveness
276 index. Other approaches, such as an internet poll with camera trap practitioners, or a rating
277 based on personal perspective, may have been more appropriate but are subjective and
278 have their own limitations.

279

280 Difficulty distinguishing small- to medium-sized mammals is likely a result of both
281 morphological and behavioural factors. Diagnostic features such as head-body to tail ratio,
282 pelage colour and body shape are often used to distinguish species (Burns *et al.* 2018;
283 Claridge and Paull 2014; De Bondi *et al.* 2010). For example, when investigating whether the
284 Hastings River mouse (*Pseudomys oralis*) could be differentiated from sympatric small
285 mammals, Meek and Vernes (2016) used a key facial feature, the 'Roman'-shaped nose, for
286 identification. Similarly, Burns *et al.* (2018) demonstrated pelage colouration and

287 morphology were important for distinguishing the smoky mouse (*Pseudomys fumeus*) and
288 New Holland mouse (*Pseudomys novaehollandiae*) from sympatric rodents. However,
289 visibility of such features is highly dependent on image quality and animal size (Burns *et al.*
290 2018). Lighting, camera-to-target distance and animal position, are factors which can mask
291 distinguishing features (Meek *et al.* 2013; Oliveira-Santos *et al.* 2010). Our selected images
292 included a range of lighting conditions - diurnal, nocturnal, white-flash and infrared
293 (Supplementary Table S3). Due to the small number of images and the fact not all conditions
294 were available for each species, we were not able to account for this variable in our models.
295 This is an important limitation of our study as Burns *et al.* (2018) recently found that the
296 effect of image type on accuracy of identifications can be significant. In their investigation,
297 the authors found that white-flash (and hence colour) was crucial for identifying *P. fumeus*,
298 while observers were more accurate identifying *P. novaehollandiae* from infrared images
299 (where morphology was more distinctive). Additionally, small- to medium-sized mammals
300 generally move faster through camera trap detection zones (Glen *et al.* 2013; Swan *et al.*
301 2014b), reducing the number of images, and the likelihood of clear images being obtained.
302 For this survey, we selected only single, high-quality images of each species, but image
303 sequences, rather than a single image, may allow several distinctive features and movement
304 patterns to be observed (Claridge and Paull 2014; Meek *et al.* 2013), thus aiding with
305 accurate identifications.

306

307 While some studies mention difficulty identifying small- to medium-sized mammals from
308 camera trap images, few discuss the implications this may have on results (Meek *et al.*
309 2014). For example, Urlus *et al.* (2014) comment on monochrome images being harder for
310 distinguishing small- to medium-sized mammals, but do not discuss how this may have

311 affected the detectability of five mammal species examined. Similarly, Vernes *et al.* (2014)
312 acknowledged that mammal species were “identified where possible”, but that this was
313 sometimes impossible when individuals were too small, particularly shrews of the genus
314 *Sorex*. Despite including ‘unknown small mammal’, ‘unknown large mammal’ and ‘unknown
315 animal’ in their results section, image identification was not discussed. This highlights that
316 while species identification may not always be an issue, where it is problematic, it requires
317 consideration.

318

319 Our results show that experience was not a strong predictor of accurate mammal
320 identifications from camera trap images . This was unexpected because in many studies,
321 images are sent to experts for verification (Falzon *et al.* 2014; Tobler *et al.* 2008). For
322 example, while inventorying ground-dwelling mammals in southern Australia, Antos and
323 Yuen (2014) captured an image of a rodent resembling a Broad-toothed rat (*Mastacomys*
324 *fuscus*). They reported that the image was “awaiting confirmation from experts”, and
325 follow-up live-trapping was to be carried out. Although we hypothesized that experience
326 would predict accuracy, the contrasting results are understandable. Despite expertise,
327 distinguishing some species can be difficult even when in the hand (Falzon *et al.* 2014; Meek
328 and Vernes 2016). While most respondents had prior experience with Australian mammals,
329 including trapping, camera trapping and image identification (83%, 82% and 89%
330 respectively), fewer respondents had trapped (40%), or employed cameras (37%), in
331 northern Australia. Thus, respondents with a high level of experience may not have
332 encountered the species included in our survey. This may have influenced accurate
333 identifications, as prior experience with local species is likely to improve accuracy of
334 identifications. While indication of morphological characteristics can be obtained from a

335 field guide, seeing an animal up-close is a distinct advantage, because variability between
336 individuals of a species may be high. Furthermore, camera trap practitioners generally work
337 with large numbers of images, often seeing target species repeatedly. Since we only
338 included a few images (in some cases only a single image) of a species, this may be a
339 contributing factor to low accuracy. A greater number of images could have been included,
340 however we felt that the length of the survey would have reduced the number of
341 respondents.

342

343 Type of experience (e.g. consultant or naturalist), or how recently a respondent had handled
344 or used camera traps, may have affected accuracy of identifications. However, these
345 measures of experience were not examined in relation to accuracy for this study. This is
346 partly because respondents could select multiple answers to the 'type of experience'
347 questions, but also because time is more likely to be a better predictor of experience. In this
348 modern era, information on mammal species, including images and descriptions, are widely
349 accessible to most members of the public. Thus, a dedicated respondent with access to such
350 resources may accurately identify fauna from images regardless of their experience with
351 mammal identification. This may have important implications for camera trap projects
352 relying on volunteers for image identification. However, intimate knowledge of target
353 species or study location is likely to be crucial for accurate identifications.

354

355 The strong positive relationship predicted between confidence and accuracy of
356 identifications, demonstrates an important 'safeguard' to this limitation of camera trapping.
357 Respondents with low accuracy were more likely to have a low confidence rating with their
358 identification, regardless of their experience. This suggests that respondents recognise

359 when they have a high likelihood of being incorrect. This is supported by the low confidence
360 ratings for small, less-distinctive mammals, for which accuracy levels were low. We use the
361 term 'safeguard', because recognizing when a species cannot be identified is more likely to
362 reduce potential negative consequences of misidentification. For example, if an individual
363 resembling a threatened species is captured in a low-quality image, there are two potential
364 biases: either an observer could misidentify the species thinking that it is too rare to be
365 considered, or identify it as the threatened species because a false-positive may be
366 perceived as preferable to a false-negative. The consequences of this can be significant
367 (Burns *et al.* 2018), as numerous mammals, especially in northern Australia, are considered
368 threatened. For some of these species, such as the Northern hopping mouse (*Notomys*
369 *aquilo*), camera traps are the most suitable survey method (Diete *et al.* 2016). Thus, the
370 ability to accurately identify threatened mammals from camera trap images is critical for
371 monitoring and management. Employing confidence ratings with species identifications in
372 future camera trap studies is likely to improve robustness of data obtained. Confidence
373 ratings may assist with determining images that require closer inspection, cautious
374 interpretation, or a live-trapping program for confirmation. Furthermore, low confidence
375 images may be excluded from analysis due to the potential for false positives/negatives
376 (Meek *et al.* 2014). Employing multiple observers may also improve reliability of species
377 identification (Oliveira-Santos *et al.* 2010), as the degree of agreement between observers
378 may perform better than confidence as a measure of uncertainty for a given identification.
379 Indeed, in our survey, the majority answer for each image was in perfect agreement with
380 the 'true' identification provided by the donor of the image.

381

382 Currently, species identification from camera trap images tends to be a *post hoc* process,
383 whereby species are recorded as they appear in images, and when difficult-to-distinguish
384 individuals arise, they may be sent to experts for verification (Antos and Yuen 2014; Tobler
385 *et al.* 2008). While this may work in some cases (large or distinctive species), we suggest the
386 adoption of an *a priori* approach. When practitioners are selecting experimental design,
387 they should also determine a species list for the study location, particularly small or
388 morphologically-similar species. An effort should be made to obtain images of these species
389 prior to camera deployment, therefore creating a reference library; familiarisation with
390 these images may aid identification. In our survey, only 31% of respondents used an image
391 reference library, compared to 73% relying on field guides. Meek *et al.* (2013) found 57%
392 used a reference library and 73% used field guides. Additionally, in some cases, camera
393 traps may not be the most suitable survey approach and this needs to be determined prior
394 to sampling (Meek and Vernes 2016).

395

396 Advances in ecology are not only assisted by novel concepts, robust experiments or
397 understanding of environmental systems, but also with the development of technology
398 (Burton *et al.* 2015). According to Young *et al.* (2018), however, advances in technology
399 used for camera trap management, the process from image collection to data organised for
400 analysis, is developing slowly. As such, image identification is still a mostly manual process
401 (Burns *et al.* 2018; Norouzzadeh *et al.* 2018; Young *et al.* 2018; Yu *et al.* 2013). Automatic
402 subject detection (determination of whether an animal is present) and automatic species
403 recognition are still in their infancy. Yu *et al.* (2013) employed techniques from computer
404 vision science to successfully (82% accuracy) identify 18 species from 7000 camera trap
405 images, and Norouzzadeh *et al.* (2018) used deep neural networks from artificial intelligence

406 to identify species with >93.8% accuracy. However, these approaches are not without
407 limitations. Large image databases and correctly identified images are required to teach the
408 program, disadvantageous for rare species and small datasets (Young *et al.* 2018). Since
409 small and morphologically similar species are most difficult for human observers to identify,
410 future automated identification software should focus on these species, employing a
411 combination of pelage colouration, morphological and behavioural features (e.g. gait)
412 (Burns *et al.* 2018; Yu *et al.* 2013).

413

414 Identification of fauna to species level is a crucial aspect of camera trap studies, and
415 consequences of misidentification are potentially significant. Knowledge of species'
416 distributions and behaviour are fundamental to management decisions, but are often
417 hindered because many terrestrial mammals are cryptic, nocturnal or rare (Swan *et al.*
418 2014b). Therefore, camera traps are emerging as a crucial tool for surveying mammals.
419 However, we found that accurate species identification is a significant limitation of this
420 survey tool, particularly for studies which focus on small mammals, or superficially non-
421 distinctive species. Development of computer-assisted programs and combining camera
422 trapping with other survey methods (e.g. live-trapping), is likely to greatly improve accuracy
423 of species identifications (Dundas *et al.* 2014; Norouzzadeh *et al.* 2018; Young *et al.* 2018; Yu
424 *et al.* 2013). Although only northern Australian species were included in our survey, the
425 results are likely to be applicable in any region with diverse small- or morphologically-similar
426 mammal communities (Meek *et al.* 2013; Vernes *et al.* 2014).

427

428 **Acknowledgements**

429 Research was supported by Tiwi Plantation Corporation, Plantation Management Partners,
430 The Tiwi Land Council and The Australian Research Council (DE130100434). We would like
431 to thank Ian Radford, Anna Miller, Rebecca Diете, William Ross and Hugh Davies for
432 providing camera trap images. We are grateful to everyone who participated in our survey.
433 This study was conducted with Human Ethics approval from Charles Darwin University
434 (H17001).

435

436 **References**

- 437 Antos M. J. & Yuen K. (2014) Camera trap monitoring for inventory and management
438 effectiveness in Victorian national parks: tailoring approaches to suit specific questions. In:
439 *Camera trapping in wildlife management and research* (eds P. Meek, P. Fleming, G. Ballard,
440 P. Banks, A. Claridge, J. Sanderson and D. Swann) pp. 13-26. CSIRO Publishing, VIC.
- 441 Ballard G., Meek P. D., Doak S., Fleming P. J. S. & Sparkes J. (2014) Camera traps, sand plots
442 and known events: what do camera traps miss? In: *Camera trapping in wildlife management
443 and research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A. Claridge, J. Sanderson and D.
444 Swann) pp. 189-202. CSIRO Publishing, VIC.
- 445 Burnham K. P. & Anderson D. R. (1998) *Model selection and inference: a practical
446 information-theoretic approach*. Springer-Verlag New York Inc., USA.
- 447 Burnham K. P. & Anderson D. R. (2003) *Model selection and multimodel inference: a
448 practical information-theoretic approach*. Springer Science & Business Media.
- 449 Burns P. A., Parrott M. L., Rowe K. C. & Phillips B. L. (2018) Identification of threatened
450 rodent species using infrared and white-flash camera traps. *Australian Mammalogy* **40**, 188-
451 97.
- 452 Burton A. C., Neilson E., Moreira D., Ladle A., Steenweg R., Fisher J. T., Bayne E. & Boutin S.
453 (2015) Wildlife camera trapping: a review and recommendations for linking surveys to
454 ecological processes. *Journal of Applied Ecology* **52**, 675-85.
- 455 Claridge A. W. & Paull D. J. (2014) How long is a piece of string? Camera trapping
456 methodology is question dependent. In: *Camera trapping in wildlife management and
457 research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A. Claridge, J. Sanderson and D.
458 Swann) pp. 205-14. CSIRO Publishing, VIC.
- 459 Claridge A. W., Paull D. J. & Barry S. C. (2010) Detection of medium-sized ground-dwelling
460 mammals using infrared digital cameras: an alternative way forward? *Australian
461 Mammalogy* **32**, 165-71.
- 462 Comer S., Speldewinde P., Tiller C., Clausen L., Pinder J., Cowen S. & Algar D. (2018)
463 Evaluating the efficacy of a landscape scale feral cat control program using camera traps and
464 occupancy models. *Scientific Reports* **8**.
- 465 Corey B., Radford I., Carnes K., Hatherley E. & Legge S. (2013) North-Kimberley landscape
466 conservation initiative: 2010-12 performance report. Department of Parks and Wildlife,
467 Kununurra, Western Australia.

468 Davies H. F., McCarthy M. A., Firth R. S. C., Woinarski J. C. Z., Gillespie G. R., Andersen A. N.,
469 Geyle H. M., Nicholson E. & Murphy B. P. (2017) Top-down control of species distributions:
470 feral cats driving the regional extinction of a threatened rodent in northern Australia.
471 *Diversity and Distributions* **23**, 272-83.

472 De Bondi N., White J. G., Stevens M. & Cooke R. (2010) A comparison of the effectiveness of
473 camera trapping and live trapping for sampling terrestrial small-mammal communities.
474 *Wildlife Research* **37**, 456-65.

475 Diets R. L., Meek P. D., Dickman C. R. & Leung L. K.-P. (2016) Ecology and conservation of
476 the northern hopping-mouse (*Notomys aquilo*). *Australian Journal of Zoology* **64**, 21-32.

477 Diets R. L., Meek P. D., Dickman C. R., Lisle A. & Leung L. K.-P. (2017) Diel activity patterns of
478 northern Australian small mammals: variation, fixity, and plasticity. *Journal of Mammalogy*,
479 1-10.

480 Dundas S. J., Adams P. J. & Fleming P. A. (2014) Can camera trap surveys provide reliable
481 population estimates for nondescript species? In: *Camera trapping in wildlife management*
482 *and research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A. Claridge, J. Sanderson and D.
483 Swann) pp. 173-9. CSIRO, Vic.

484 Falzon G., Meek P. D. & Vernes K. (2014) Computer-assisted identification of small
485 Australian mammals in camera trap imagery. In: *Camera trapping in wildlife management*
486 *and research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A. Claridge, J. Sanderson and D.
487 Swann) pp. 299-306. CSIRO Publishing, VIC.

488 Glen A. S., Cockburn S., Nichols M., Ekanayake J. & Warburton B. (2013) Optimising camera
489 traps for monitoring small mammals. *PLoS ONE* **8**, e67940.

490 Jenks K. E., Chanteap P., Damrongchainarong K., Cutter P., Cutter P., Redford T., Lynam A. J.,
491 Howard J. & Leimgruber P. (2011) Using relative abundance indices from camera-trapping to
492 test wildlife conservation hypotheses – an example from Khao Yai National Park, Thailand.
493 *Tropical Conservation Science* **4**, 113-31.

494 Meek P. D., Ballard G.-A. & Fleming P. J. S. (2015b) The pitfalls of wildlife camera trapping as
495 a survey tool in Australia. *Australian Mammalogy* **37**, 13-22.

496 Meek P. D., Ballard G.-A., Vernes K. & Fleming P. J. S. (2015) The history of wildlife camera
497 trapping as a survey tool in Australia. *Australian Mammalogy* **37**, 1-12.

498 Meek P. D., Fleming P. J. S., Ballard G., Banks P. B., Claridge A. W., McMahon S., Sanderson J.
499 & Swann D. E. (2014) Putting contemporary camera trapping in focus. In: *Camera trapping*
500 *in wildlife management and research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A.
501 Claridge, J. Sanderson and D. Swann) pp. 349-56. CSIRO Publishing, VIC.

502 Meek P. D. & Vernes K. (2016) Can camera trapping be used to accurately survey and
503 monitor the Hastings River mouse (*Pseudomys oralis*)? *Australian Mammalogy* **38**, 44-51.

504 Meek P. D., Vernes K. & Falzon G. (2013) On the reliability of expert identification of small-
505 medium sized mammals from camera trap photos. *Wildlife Biology in Practice* **9**, 1-19.

506 Moseby K. E. & Read J. L. (2014) Using camera traps to compare poison bait uptake by
507 invasive predators and non-target species. In: *Camera trapping in wildlife management and*
508 *research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A. Claridge, J. Sanderson and D.
509 Swann) pp. 131-9. CSIRO Publishing, VIC.

510 Nakagawa S. & Schielzeth H. (2013) A general and simple method for obtaining R^2 from
511 generalized linear mixed-effects models. *Methods in Ecology and Evolution* **4**, 133-42.

512 Nelson J. L., Scroggie M. P. & Belcher C. A. (2014) Developing a camera trap survey protocol
513 to detect a rare marsupial carnivore, the spotted-tailed quoll (*Dasyurus maculatus*). In:

514 *Camera trapping in wildlife management and research* (eds P. Meek, P. Fleming, G. Ballard,
515 P. Banks, A. Claridge, J. Sanderson and D. Swann) pp. 271-9. CSIRO Publishing, VIC.
516 Newey S., Davidson P., Nazir S., Fairhurst G., Verdicchio F., Irvine R. J. & van der Wal R.
517 (2015) Limitations of recreational camera traps for wildlife management and conservation
518 research: a practitioner's perspective. *Ambio*, 624-35.
519 Norouzzadeh M. S., Nguyen A., Kosmala M., Swanson A., Palmer M. S., Packer C. & Clune J.
520 (2018) Automatically identifying, counting, and describing wild animals in camera-trap
521 images with deep learning. *PNAS* **115**.
522 Oliveira-Santos L. G. R., Zucco C. A., Antunes P. C. & Crawshaw Jr P. G. (2010) Is it possible to
523 individually identify mammals with no natural markings using camera-traps? A controlled
524 case-study with lowland tapirs. *Mammalian Biology Zeitschrift fur Saugetierkunde* **75**, 375-8.
525 Quinn G. P. & Keough M. J. (2002) *Experimental design and data analysis for biologists*.
526 Cambridge University Press, Cambridge, UK.
527 Smith J. K. & Coulson G. (2012) A comparison of vertical and horizontal camera trap
528 orientations for detection of potoroos and bandicoots. *Australian Mammalogy* **34**, 196-201.
529 Swan M., Di Stefano J., Christie F., Steel E. & York A. (2014b) Detecting mammals in
530 heterogeneous landscapes: implications for biodiversity monitoring and management.
531 *Biodiversity Conservation* **23**, 343-55.
532 Tobler M. W., Carrillo-Percastegui S. E., Leite Pitman R., Mares R. & Powell G. (2008) An
533 evaluation of camera traps for inventorying large- and medium-sized terrestrial rainforest
534 mammals. *Animal Conservation* **11**, 169-78.
535 Urlus J., McCutcheon C., Gilmore D. & McMahon J. (2014) The effect of camera trap type on
536 the probability of detecting different size classes of Australian mammals. In: *Camera*
537 *trapping in wildlife management and research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks,
538 A. Claridge, J. Sanderson and D. Swann) pp. 111-21. CSIRO Publishing, Vic.
539 Van Dyck S., Gynther I. & Baker A. (2013) *Field companion to the mammals of Australia*.
540 New Holland Publishers, London.
541 Vernes K., Smith M. & Jarman P. J. (2014) A novel camera-based approach to understanding
542 the foraging behaviour of mycophagous mammals. In: *Camera trapping in wildlife*
543 *management and research* (eds P. Meek, P. Fleming, G. Ballard, P. Banks, A. Claridge, J.
544 Sanderson and D. Swann) pp. 215-24. CSIRO Publishing, VIC.
545 Young S., Rode-Margono J. & Amin R. (2018) Software to facilitate and streamline camera
546 trap data management: a review. *Ecology and Evolution*, 1-11.
547 Yu X., Wang J., Kays R., Jansen P. A., Wang T. & Huang T. (2013) Automated identification of
548 animal species in camera trap images. *EURASIP Journal on Image and Video Processing*
549 **2013**.
550

551 **Tables**

552 **Table 1** The 25 native mammal species and the number of images (N) of each included in an internet-based survey to assess accuracy of
 553 mammal identifications from camera trap images. The distinctiveness index (D) was an index calculated as: $distinctiveness = ((23 - S)/23) \times 100$,
 554 where S = number of species in the genus and 23 the maximum number of species in a single genus (*Pseudomys*).

	Species	Body mass (g)	Distinctiveness index (D%)	N	Proportion (%) of correct responses
Agile wallaby	<i>Macropus agilis</i>	15000	39.1	2	83
Dingo	<i>Canis dingo</i>	14000	95.7	3	100
Short-beaked echidna	<i>Tachyglossus aculeatus</i>	4 500	95.7	3	100
Short-eared /Wilkins rock wallaby	<i>Petrogale brachyotis/wilkinsi</i>	4 050	30.4	4	64
Common brushtail possum	<i>Trichosurus vulpecula</i>	2 625	87.0	2	96
Rock ringtail possum	<i>Petropseudes dahli</i>	1 640	95.7	1	64
Northern brown bandicoot	<i>Isoodon macrourus</i>	1 600	87.0	3	69
Scaly-tailed possum	<i>Wyulda squamicaudata</i>	1 450	95.7	2	60
Monjon	<i>Petrogale burbidgei</i>	1 258	30.4	2	47
Black-footed tree-rat	<i>Mesembriomys gouldii</i>	716	91.3	3	79
Northern quoll	<i>Daysurus hallucatus</i>	597	82.6	3	75
Golden bandicoot	<i>Isoodon auratus</i>	485	87.0	1	38

Golden-backed tree-rat	<i>Mesembriomys macrurus</i>	267	91.3	3	69
Brush-tailed phascogale	<i>Phascogale tapoatafa</i>	193	87.0	2	71
Brush-tailed rabbit-rat	<i>Conilurus penicillatus</i>	153	91.3	3	62
Kimberley rock-rat	<i>Zyzomys woodwardi</i>	140	78.3	1	47
Sugar glider	<i>Petaurus breviceps</i>	127	82.6	2	89
Pale field-rat	<i>Rattus tunneyi</i>	86	43.5	3	36
Grassland melomys	<i>Melomys burtoni</i>	68	82.6	2	44
Northern hopping-mouse	<i>Notomys aquilo</i>	40	60.9	3	68
Common rock-rat	<i>Zyzomys argurus</i>	36	78.3	4	53
Red-cheeked dunnart	<i>Sminthopsis virginiae</i>	35	17.4	2	51
Butler's dunnart	<i>Sminthopsis butleri</i>	23	17.4	3	55
Delicate mouse	<i>Pseudomys delicatulus</i>	10	0	3	51
				Total	60

557 **Table 2** Candidate model selection results for factors affecting accuracy of mammal
 558 identifications from camera trap images in an internet-based survey. Respondent was
 559 included as a random factor.

560 $\Delta AICc$ is the difference between second-order Akaike Information Criterion of a model and the minimum AICc; ω_i is the
 561 Akaike weight, a measure of the probability of a model being the best in the candidate set; D^2 is the proportion of deviance
 562 explained by each model compared to the null.

Model	AIC	$\Delta AICc$	ω_i	D^2
Body mass + confidence + experience + distinctiveness	3544.7	0.0	1.00	0.16
Body mass + confidence + distinctiveness	3570.4	25.7	0.00	0.15
Body mass + confidence + experience	3584.0	39.3	0.00	0.15
Body mass + confidence	3608.2	63.5	0.00	0.14
Confidence + experience + distinctiveness	3635.9	91.3	0.00	0.13
Confidence + distinctiveness	3657.2	112.5	0.00	0.13
Confidence + experience	3677.4	132.7	0.00	0.13
Confidence	3696.9	152.2	0.00	0.12
Body mass + distinctiveness + experience	3837.1	292.5	0.00	0.09
Body mass + distinctiveness	3868.5	323.8	0.00	0.08
Body mass + experience	3959.2	414.6	0.00	0.06
Body mass	3989.3	444.6	0.00	0.05
Distinctiveness + experience	4031.0	486.3	0.00	0.04
Distinctiveness	4056.6	511.9	0.00	0.04
Experience	4181.4	636.7	0.00	0.01
Null	4204.8	660.1	0.00	0.00

563

564

565 **Table 3** Set of candidate models and model selection results to explain variation in observer
 566 confidence in species identifications from camera trap images.

567 ΔAIC_c is the difference between second-order Akaike Information Criterion of a model and the minimum AICc; ω_i is the
 568 Akaike weight, a measure of the probability of a model being the best in the candidate set; D^2 is the proportion of deviance
 569 explained by each model compared to the null.

Model	AIC	ΔAIC_c	ω_i	D^2
Body mass + distinctiveness + experience	9926.9	0.0	0.99	0.090
Body mass + distinctiveness	9960.2	33.3	<0.001	0.087
Body mass + experience	10059.0	132.1	<0.001	0.078
Body mass	10090.9	164.0	<0.001	0.075
Distinctiveness + experience	10445.4	518.5	<0.001	0.043
Distinctiveness	10467.3	540.3	<0.001	0.040
Experience	10887.1	960.2	<0.001	0.002
Null	10904.6	977.6	<0.001	0.000

570

571 **Figure legends**

572 **Figure 1** Relationship between species body mass (g) and proportion of correct
573 identifications from camera trap images in an internet-based survey. Body mass for each
574 species was taken from Van Dyck *et al.* (2013) as either the average value, or the midpoint
575 of the male and female range provided. The best model was used for predictions (thick line)
576 and thin lines indicate 95% confidence intervals. $n=60$ images (circles).

577

578 **Figure 2** Relationship between distinctiveness of the species in a camera trap image and the
579 proportion of correct responses in an internet-based survey. The distinctiveness index was
580 calculated as: $((23-S)/23) \times 100$, where S is the number of species in a particular genus and
581 23 the maximum number of species in a single genus. The best model was used for predictions
582 (thick line) and thin lines indicate 95% confidence intervals. $n=60$ images (circles).

583

584 **Figure 3** Relationship between observer experience (years) and proportion of correct
585 species identifications in an internet-based survey. Experience was calculated as the mean
586 of time trapping mammals and the largest value of camera experience (either years using
587 camera traps or identifying camera trap images). The best model was used for predictions
588 (thick line) and thin lines indicate 95% confidence intervals. $n=178$ respondents (circles).

589

590

591 **Figure 4** Predicted relationship between observer confidence and proportion of correct
592 species identifications in an internet-based survey, where respondents were asked to assign
593 a confidence rating to each identified image with the following categories: >95%
594 (“definite”), 86-94% (“pretty sure”), 66-85% (“probable”), 50-65% (“possible”), 36-49% (“not

595 sure”) and <35% (“no idea”). Predictions were based on the model of best fit (thick line) and
596 thin lines indicate 95% confidence intervals.

597

598 **Figure 5** Modelled relationships between proportion of answers correct and observer

599 confidence for a) species body mass (g), b) observer experience (years) and c)

600 distinctiveness index $((23-S)/23) \times 100$, where S = number of species in genus and 23 =

601 maximum number of species in a genus). Respondents were asked to assign a confidence

602 rating to each identification in an internet-based survey with the categories: >95%

603 (“definite”), 86-94% (“pretty sure”), 66-85% (“probable”), 50-65% (“possible”), 36-49% (“not

604 sure”) and <35% (“no idea”). Predictions were based on the best candidate model.

605