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Abstract

Reducing threats to biodiversity is the key objective of ranger patrols in protected areas. However, efforts can be hampered by rangers' inability to detect threats, and poor understanding of threat abundance and distribution in a landscape. Snares are particularly problematic due to their cryptic nature and limited selectivity with respect to captured animals' species, sex, or age. Using an experimental approach, we investigated the effect of search effort, habitat, season, and team on rangers' detection of snares in a tropical forest landscape. We provide an effort-detection curve, and use our findings to make preliminary predictions about snare detection under different scenarios of patrol effort. Results suggest that the overall probability of a searcher detecting any given snare in a 0.25/km² area, assuming 60 minutes (or approximately 2km) of search effort is 20% (95% CI \pm 15-25%), with no significant effect of season, habitat or team. Our models suggested this would increase by approximately 10% with an additional 30mins/1km of search effort. Our preliminary predictions of the effectiveness of different patrolling scenarios show that detection opportunities are maximised at low effort levels by deploying multiple teams to a single area, but at high effort levels deploying single teams becomes more efficient. Our results suggest that snare detectability in tropical forest landscapes is likely to be low, and may not improve dramatically with increased search effort. Given this, managers need to consider whether intensive snare-removal efforts are the best use of limited resources; the answer will depend on their underlying objectives.

Keywords detection probability; hunting; law enforcement; protected areas; ranger patrols; Cambodia;

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1 Experimentally assessing the effect of search effort on snare detectability

2

3 Abstract

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5 efforts can be hampered by rangers' inability to detect threats, and poor understanding of threat
6 abundance and distribution in a landscape. Snares are particularly problematic due to their cryptic
7 nature and limited selectivity with respect to captured animals' species, sex, or age. Using an
8 experimental approach, we investigated the effect of search effort, habitat, season, and team on
9 rangers' detection of snares in a tropical forest landscape. We provide an effort-detection curve, and
10 use our findings to make preliminary predictions about snare detection under different scenarios of
11 patrol effort. Results suggest that the overall probability of a searcher detecting any given snare in a
12 0.25/km² area, assuming 60 minutes (or approximately 2km) of search effort is 20% (95% CI ± 15-
13 25%), with no significant effect of season, habitat or team. Our models suggested this would
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16 maximised at low effort levels by deploying multiple teams to a single area, but at high effort levels
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18 tropical forest landscapes is likely to be low, and may not improve dramatically with increased search
19 effort. Given this, managers need to consider whether intensive snare-removal efforts are the best
20 use of limited resources; the answer will depend on their underlying objectives.

21

22

23 Keywords

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26 **1. Introduction**

27 Protected area (PA) networks are a cornerstone of global efforts to conserve biodiversity (Bruner,
28 Bruner, Gullison, Rice, & Fonseca, 2001). Their success depends on effective management,
29 including the reduction of threats to species and habitats (Watson, Dudley, Segan, & Hockings,
30 2014). A primary tool available to PA managers to address threats is patrolling by ranger teams
31 (Hilborn et al., 2006; Lynam, Porter, & Campos-Arceiz, 2016). Through regular patrolling, rangers
32 monitor adherence to conservation rules, deter potential perpetrators, and punish infractions when
33 detected (Keane, Jones, Edward-Jones, & Milner-Gulland, 2008). To design optimal patrol
34 strategies, PA managers require robust information about the distribution and abundance of threats
35 in a landscape (Critchlow et al., 2017) alongside a means of assessing which approach is most likely
36 to yield the greatest conservation benefit at the lowest possible cost (Plumptre et al., 2014).

37

38 Data collected by rangers are increasingly used to map spatio-temporal trends in threats and
39 evaluate patrol performance. These are often collected by patrols for little additional cost (Brashares
40 & Sam, 2005). Subsequently, the data can be used with open-access tools such as the Spatial
41 Monitoring and Reporting Tool (SMART) to map threats and prioritize patrol effort within
42 conservation landscapes (Hötte et al., 2016; Stokes, 2010). However, gathering data is not the
43 primary objective of patrols and ranger-collected data may be subject to considerable bias (Keane et
44 al. 2011). Patrol data must therefore be handled with caution to avoid misleading conclusions and
45 ineffective targeting of patrol effort (Critchlow et al., 2015; Keane, Jones, & Milner-Gulland, 2011).
46 While a growing suite of statistical methods exists to account for these biases (see Critchlow et al.,
47 2015; Marescot, Lyet, Singh, Carter, & Gimenez, 2019; J. F. Moore et al., 2017), there is also a
48 broader need for independent tests of key aspects of patrol effectiveness, such as the amount of
49 patrol effort required to successfully detect a certain proportion of threats present within expansive
50 conservation landscapes (Dobson, Milner-Gulland, Beale, Ibbett, & Keane, 2018). Well-designed
51 experiments can provide effective and affordable means to trial different approaches, and have been
52 used to improve understanding of the effects of environmental covariates on the detectability of traps
53 set by hunters in both tropical forest (O’Kelly et al. 2018a) and savannah (Rija, 2017) landscapes.
54 However, no experimental study has yet explored the relationship between search effort and threat

55 detection, knowledge of which would enable PA managers to distribute patrol effort more efficiently,
56 and thereby improve PA effectiveness.

57

58 Hunting poses one of the greatest threats to wildlife in PAs globally (Ripple et al., 2016; Schulze et
59 al., 2018) and snares are one of the most prevalent hunting technologies used worldwide (Gray,
60 Hughes, et al., 2017; Harrison et al., 2016). Usually made from wire, cable, or nylon, snares are
61 affordable, accessible, and can trap a wide range of arboreal and terrestrial species, whether diurnal
62 or nocturnal (Borgerson, 2015; Ingram et al., 2017). Due to their limited selectivity with respect to
63 species, sex, or age of captured animals, snares are a potent threat to biodiversity (Noss, 1998).
64 Although animals sometimes escape snares, subsequent non-fatal injuries often jeopardize their
65 long-term survival (Gray, Lynam, et al., 2017). For example, chimpanzees with snare injuries have
66 been found to suffer significantly higher parasite loads than those without (Yersin, Asimwe,
67 Voordouw, & Zuberbühler, 2017). Unlike other forms of hunting, snares present a persistent threat to
68 wildlife as they remain operational in the landscape after a hunter has departed, and are difficult for
69 patrols to detect (Lindsey, Romanach, Tambling, Chartier, & Groom, 2011).

70

71 A key assumption is that the more patrol effort invested in searching, the more snares will be
72 discovered. However, the improvement in detection with effort has not been quantified and is likely to
73 be affected by factors such as habitat, season, atmospheric conditions (e.g. precipitation,
74 temperature), terrain and topography and the type of snare set (Keane et al. 2011; Jachmann 2008).
75 For example, snares which are physically connected and set in lines that stretch many hundreds of
76 metres may be more detectable than individual snares (O’Kelly et al. 2018b). In addition, snare
77 detection is influenced by rangers themselves. Studies of wildlife observation and plant detection
78 have recorded considerable variability between observers depending on their experience and
79 expertise (J. L. Moore, Hauser, Bear, Williams, & McCarthy, 2011; Sunde & Jessen, 2013). And,
80 even if rangers are capable of finding snares, they may not always be motivated to search
81 (Jachmann, 2008). Conservation law enforcement operations are typically under-resourced, with
82 rangers often inadequately trained, poorly remunerated, and insufficiently equipped to work in
83 challenging conditions (Belecky, Singh, & Moreto, 2018; Long, Grein, Boedicker, & Singh, 2016).

84

85 Here, we adopt an experimental approach to test how a vital element of patrol effectiveness – snare
86 detection – is affected by the amount of patrol effort invested. Our study provides an effort-detection
87 curve for snare detectability in a tropical forest context, investigates the effects of habitat and season
88 on detection probability, and assesses the extent to which performance varies between search
89 teams and individual searchers. We use our findings to predict the snare detection levels that could
90 be achieved in a Cambodian PA under different patrolling scenarios.

92 **2. Materials and Methods**

93

94 **2.1 Study Site**

95 The study was conducted in Keo Seima Wildlife Sanctuary (formerly Seima Protection Forest), a
96 2,927km² PA situated in Mondulkiri Province, eastern Cambodia (12°26'70"N, 106°E 94'90"). The
97 PA is topographically diverse, ranging in altitude from 60-750m (Evans et al., 2013). The habitat is
98 heterogeneous, and consists of a complex forest mosaic that includes deciduous dipterocarp and
99 fully evergreen forest (Walston, Davidson, & Men, 2001). The PA supports populations of Asian
100 elephant (*Elephas maximus*) and wild cattle (*Bos spp.*), alongside globally significant primate
101 populations. In 2011, a systematic survey conducted over 2200km, detected 1300 snares in 140
102 different locations in the PA, with an experimentally calculated detection rate of 28-36% (O'Kelly et
103 al. 2018a).

104

105 **2.2 Experimental design**

106 *Setting snares*

107 We adapted a methodology originally piloted by O'Kelly et al. (2018b), and established five 3.25km
108 transects around a patrol station (Fig. 1, Appendix S1). Habitat here is highly heterogenous;
109 comprised of a mosaic that reflect vegetation types found across the wider landscape. The area also
110 supports a full complement of species, which occur in relatively high densities. Either side of each
111 transect, we delineated 6 x 0.25km² (500m x 500m) quadrats at 50m intervals (Appendix S1). This
112 quadrat size was chosen so teams could conduct intensive searches in realistic time-frames. Within
113 each quadrat we set between zero and 15 snares (the number randomly drawn from a Poisson
114 distribution with mean = 7.5), based on estimates of typical snare densities identified by other
115 studies (Dobson et al., 2019). Single foot snares made from black nylon string (5mm), an
116 inexpensive material often used by hunters in this area, were set without a trigger mechanism to
117 prevent harm to wildlife, and all snares were successfully removed at the end of each transect
118 survey.

119

120 We recruited local guides from surrounding communities, who were instructed to set single snares
121 as a local hunter might, in locations they deemed suitable to catch popular prey species such as wild

122 pig (*Sus scrofa*), Northern red muntjac (*Muntiacus vaginalis*) and sambar (*Rusa unicolor*). Prior to
123 setting snares, teams explored each quadrat for 30 minutes to identify suitable snare locations. Once
124 set, teams recorded the GPS coordinates of each snare and the dominant habitat type of the
125 quadrat. Teams were asked not to disclose the location or number of snares set in each quadrat to
126 other teams or to leave obvious signs of their presence which future teams might use as cues.
127

128 **2.3 Data Collection**

129 *Searching for snares*

130 The experiment required four separate teams, each led by a staff member from the Wildlife
131 Monitoring Team of Wildlife Conservation Society (WCS) Cambodia. Team leaders had expertise in
132 snare detection, and were accompanied by two other searchers – either a local guide or another
133 WCS staff member. WCS staff remained the same in each team, but changes in availability meant
134 that local guides varied between transects. All team members searched for snares, with team
135 leaders also recording data, coordinating the search strategy and ensuring searchers stayed within
136 quadrat boundaries. Each team was allocated quadrats to search for a designated time period. No
137 quadrat was searched simultaneously by more than one team, and teams never searched quadrats
138 in which they had set snares. To maximize statistical power and to account for the considerable
139 challenge of implementing the survey at a larger scale, each quadrat was searched three times, for a
140 fixed search duration varying between 15 and 90 minutes in 15-minute intervals (Appendix S1).
141 Every effort was made to minimize the effect of previous searches on the detectability of snares by
142 subsequent teams.

143
144 Teams were encouraged to search purposefully by following cues in the landscape (e.g. human
145 footprints, wildlife tracks, cut vegetation). The start and finish time, the vegetation type in the
146 quadrat, the distance travelled, the GPS locations of the search routes and any artificial or real
147 snares detected were recorded throughout. We also recorded search order, to account for the fact
148 that the more a quadrat was searched, the more cues were left in the landscape. The later the
149 search, the harder for searchers to differentiate between cues set by the snare setting team (clues)
150 and those left by previous searchers (decoy cues). Teams were shadowed by first author HI to
151 ensure that protocols were adhered to, and to observe and question teams on their choice of snare

152 placement and search strategies. We included the presence of HI as a variable within our models, to
153 assess whether her observation of the search team had any effect on detection performance. The
154 methodology was piloted in December 2016, and conducted during dry season in January-February
155 2017 and wet season in October-November 2017.

156

157 **2.4 Ethical Considerations**

158 Employing local community members with relevant hunting experience helped to ensure that artificial
159 snares were realistic, but raised several ethical issues. Firstly, by participating, local guides risked
160 implicating themselves in illegal activity (e.g. by affirming their hunting expertise or knowledge of
161 suitable hunting grounds within the PA). To mitigate this risk, only former hunters recommended by
162 WCS were recruited. Prior to participation, the experimental nature and purpose of the research was
163 explained to local guides, and voluntary verbal consent to participate was sought. Individuals were
164 assured that no information or inferences about their hunting knowledge would be passed onto
165 authorities. An additional concern was that the experiments would introduce individuals to new
166 hunting grounds. However, after consultation with WCS it was decided that the risk was negligible;
167 most local guides were born in or around the PA, and were highly familiar with the study landscape.
168 Protocols were reviewed and approved by the University of Oxford Central University Research
169 Ethics Committee (Ref No. R43030/RE002), with permission to conduct research granted by the
170 Royal Government of Cambodia.

171

172 **2.5 Analysis**

173 Analyses were performed in R version 3.5.1 (R Core Team, 2017) using the package rstanarm
174 (Goodrich, Gabry, Ali, & Brilleman, 2018). We fitted a series of hierarchical generalised linear models
175 to the data, expressing different hypotheses about the factors influencing snare detection. These
176 were compared using WAIC, a Bayesian information criterion akin to AIC (Watanabe, 2010). The
177 response variable in every model was a binary indicator of whether or not each snare was detected
178 during a given search period. The full set of predictor variables used in one or more of these models
179 is shown in Table 1. Effort was represented by either time or distance. Based on a comparison of
180 WAIC between models 1 and 2 (intercept and grouping parameters only, no covariates), time was
181 chosen as the better-fitting effort measure for model explorations which included covariates,

182 although the two measures were highly correlated (Spearman's Rho = 0.79, 95% CI =77-81; Fig.
183 S2a). Effort measured as time was experimentally manipulated rather than observed, so was centred
184 around 45 minutes (50% of the maximum search time) and included in the model using hours as the
185 unit of measurement. Effort measured as distance and distance to the nearest snare were observed
186 quantities so were scaled by subtracting the mean and dividing by two standard deviations, either
187 precisely (for effort) or using approximate values for the mean and standard deviation (for distance to
188 the nearest snare) to improve the interpretability of the coefficients. All other models included
189 variables for quadrat search order and previous snare detections. Two snare density-related
190 variables were next added, and finally we explored three models which also included variables
191 related to season, team, or placement within the environment.

192

193 Model parameters were given weakly informative Students-t priors with 7 degrees of freedom and
194 scale 2.5, except for the intercept which was given a Normal prior with mean 0 and standard
195 deviation 10. Weakly informative priors were chosen to stabilise computation and to express our
196 weak prior beliefs that very large effects would be rare (Gelman, Jakulin, Pittau, & Su, 2008). The
197 coefficients for transect ID, quadrat ID, date, setting team ID and searching team ID were each given
198 independent hierarchical LKJ priors with regularization parameter 1 (Lewandowski, Kurowicka, &
199 Joe, 2009). For each model, 2000 Markov Chain Monte Carlo (MCMC) samples were drawn from
200 four independent chains. Convergence of MCMC chains was evaluated using trace-plots and the
201 Gelman-Rubin diagnostic, with values <1.05 taken to indicate that convergence had been reached
202 (Gelman et al. 2013). The fit of the model with the lowest WAIC value was examined using graphical
203 posterior predictive checks.

204

205 Using the effort-detection relationship derived from our fitted model, and assuming replication of the
206 search strategies employed during our experiment, we explored how ~~sequentially~~ dividing search
207 effort within a quadrat across multiple teams might affect detection probability. We assumed that n
208 teams searched the same quadrat independently and sequentially and that each team had the same
209 constant probability, p, of detecting snares that were present. We therefore modelled the proportion
210 of snares remaining after all searches were completed, r, as:

211

$$r = 1 - (1 - p)^n$$

212 Deploying more search teams is likely to incur transaction costs (e.g. more time is required to travel
213 to sites, and additional salary is required to pay more team leaders). In the absence of empirical
214 data, we incorporated these costs by expressing them in terms of effort lost from the total budget: 10
215 minutes of search effort was removed from the initial total for each extra team added, and the
216 remaining effort was then split equally between all teams (i.e. at 90 minutes, four teams would
217 search for ~~20-15~~ minutes each). To examine the sensitivity of our findings to the steepness of the
218 effort-detection relationship w~~w~~ We also explored the difference in results when the slope of the effort-
219 detection curve was 50% higher or lower than the observed slope on the logit scale, in order to
220 determine the sensitivity of our results to the specific shape of the effort-detection curve.

221 **3. Results**

222

223 **3.1 Effect of search effort on detection probability**

224 *3.1.1 Snare locations*

225 In total, 886 artificial snares were set, 442 in dry season and 444 in wet season. Local guides
226 reported that they generally sought specific features when placing snares; for example, water
227 sources (66% of snares set), animal trails (44%), animal signs (e.g. footprints or faeces; 44%), or
228 fruiting trees (2%).

229

230 *3.1.2 Detection probability*

231 A total of 535 artificial snare detections was recorded out of a possible 2661 opportunities, with a
232 detection rate of 0.20 averaged across the entire experiment, or 0.24 per hour of searching. In
233 addition, 55 real snares were detected. These detections were not included in analyses, as once
234 detected real snares were removed, meaning subsequent search teams had no opportunity to detect
235 them. 42% of the total population of artificial snares were discovered; 26% were found by only a
236 single team, 13% by two teams, and 3% by all three search teams (S2, Fig. 2).

237

238 *3.1.3 Predictors of snare detectability*

239 The magnitude and direction of the effect of all covariates were consistent across the set of
240 candidate models considered (see Appendix S2). The best-fitting model (Model 8; Table 2) included
241 time spent searching, quadrat search order, number of times a snare was previously detected, snare
242 clustering and density (Fig. 3), and batches of variables describing the variability between transects,
243 between quadrats within transects, over time and between the teams responsible for setting and
244 searching for snares (Figs. S2d-f). The model did not include season, vegetation type within the
245 quadrat, or the proximity of the snare to water, animal trails or animal signs. Model 9, which included
246 variables relating to the team leader, and the presence of author HI as an observer of the search
247 team, was only marginally less supported while other models were much less well supported (Table
248 2). However, the effects of team leader and HI's presence in model 9 were inconclusive (Fig. S2b).

249

250 The overall probability of searchers detecting any given snare on the first search of an area was 20%
251 (95% CI \pm 15-25%), assuming 60 minutes (or approximately 2km) of search effort. Detection
252 probability increased by approximately 10% for every additional 30mins/1km of search effort from
253 approximately 8% with 15 mins of search to approximately 30% with 90 mins (Fig. 4). Snares which
254 were previously detected by a search team were more likely to be detected in subsequent searches
255 (mean raw detection rates: Never previously detected = 0.17; Detected once previously = 0.33;
256 Detected twice previously = 0.54; Fig. 3). Perhaps because previous searchers left cues, such as
257 footprints or cut branches, which made it easier for subsequent searchers to follow their path.
258 Accounting for this, there was an effect of whether the quadrat was being searched for the first,
259 second or third time, with lower rates of detection in the second search than the first, but no clear
260 difference between the first and third searches (mean raw detection rates: First search = 0.21;
261 Second search = 0.16; Third search = 0.24). Snares were more easily detected when they were
262 placed in closer proximity to other snares in a quadrat, but there was no effect of snare density on
263 detection rates (Fig. 3).

264

265 *3.1.4 Team variability*

266 The identity of the setting and searching teams had little effect on the probability of detection (Fig.
267 S2c). Differences in success were largely attributable to the performance of specific individuals; over
268 40% of all snare detections were achieved by three searchers, and the best searchers were
269 disproportionately from the professional WCS wildlife monitoring team rather than local guides (Fig.
270 5). Although WCS staff were responsible for recording data, there was little opportunity for them to
271 claim snares found by others for themselves, as each searcher's detections were verifiable via
272 timestamped GPS tracks of each individuals' search route. We found no evidence that any false
273 recording occurred. Field observations of searchers suggested that detection was mainly influenced
274 by skill and experience. A peer- and self-evaluation exercise suggested that peers more accurately
275 predicted others' detection abilities than individuals did themselves (Appendix S3). The best-
276 performing individual was a WCS employee born in a local village who hunted in childhood.

277

278 **3.2 Effective allocation of search effort**

279 ~~Simulations of search effort allocation~~Our fitted models show that as the amount of total search effort
280 increases from 15 to 90 minutes, ~~the proportion of snares detected by a single team detection~~ can
281 be expected to increase by approximately 20% ~~(Fig. 6)~~. ~~Simulations of search effort allocation~~
282 ~~suggest that a~~At low search efforts, a 10% increase in detection can be expected for each additional
283 team searching (Fig. 6). For example, four teams searching the same quadrat at separate times for 5
284 minutes each (in total 20 minutes) may find up to 25% of snares. However, as search effort
285 increases, it can become more efficient to deploy just one team, rather than multiple teams -
286 particularly when the relationship between effort and snare detection is steeper.

287 4. Discussion

288 PA managers increasingly require information about the best allocation of patrol effort (Lynam et al.,
289 2016). Our results suggest that overall, the ability of rangers to detect snares is low. Although
290 detection increased with distance between snares and search effort, 60 minutes of searching
291 (approximately 2 km) resulted in the detection of 20% (\pm 15-25%) of snares, comparable to the 15%
292 detection reported by O'Kelly et al. (2018b) at similar levels of search effort. Higher detection rates
293 might be achieved by deploying more teams to search within a specific area for shorter periods.

294 However, this finding assumes teams independently search the same area, that they are not reliant
295 on cues left by previous searchers, that detected snares are left in situ, and that each search team
296 has equal detection probability. In reality, few of these assumptions are met. Regardless, However,
297 given the large size of most PAs, these recommendation to deploy multiple teams within a specific
298 area for shorter periods may be financially and logistically unviable unless there is a particular
299 reason to concentrate on a specific "hotspot". Ultimately, more effective and efficient use of
300 resources will be achieved by deploying a single team to intensively search one area.

301

302 Surprisingly, we found no effect of snare density on detection probability. While setting more snares
303 might result in more potential opportunities for snares to be found, searchers still need to target their
304 efforts in the right places. The skill of individual searchers, along with search effort were stronger
305 predictors of detection probability, highlighting the need for PA managers to carefully select
306 personnel with demonstrated skill at detecting snares for patrols. Also unexpected, was that
307 detection was higher during the first and third searches than the second. One reason may have
308 been due to time of day. The second search was usually conducted in the afternoon, when
309 temperatures often exceeded 33°C. By this point individuals had already exerted substantial effort in
310 searching and were physically and mentally fatigued. Our results along with observations during the
311 study, highlight the need for PA managers to carefully consider environmental factors such as
312 temperature when designing patrolling strategies. Managers must demonstrate an awareness of the
313 physical and psychological demands patrolling places on individuals and adapt patrols accordingly
314 (Belecky et al., 2018; Moreto, 2015).

315

316 Many PA management regimes prioritise and invest heavily in patrol-based snare removal efforts.
317 However, the low detectability of snares, despite high levels of search effort, raises questions about
318 the efficiency of this approach. If the primary aim of snare removal is to reduce animal mortality to
319 sustainable levels, snare detection and removal rates must be high enough to alleviate pressure on
320 remaining wildlife populations. Knowing what is “high enough” requires robust estimates of snare
321 detection, as well as a good understanding of snare-related mortality rates and their impact on
322 species population trends. Currently, however, there is virtually no empirical information on any of
323 these parameters. If the aim is to deter snaring, then detectability must be high enough to raise costs
324 sufficiently to make it unprofitable (Gray, Hughes, et al., 2017). If the aim is to visibly advertise to
325 potential offenders that snaring is an issue taken seriously by PA managers, then making snare
326 removal efforts visible to communities could be beneficial, even if the actual percentage removed is
327 low. PA managers must therefore consider their aims carefully. All these objectives may benefit from
328 targeted snare removal in known hunting and/or wildlife hotspots, especially if accompanied by
329 legislative reform, consistent enforcement that criminalises the possession of snares, and measures
330 which ensure a high proportion of successful prosecutions occur (Gray, Hughes, et al., 2017).
331 Currently, however, little is known about whether snare removal actually deter hunters, and if so,
332 what the spatial and temporal extents of a deterrent effect are. Better understanding of the relative
333 deterrent effect of different law enforcement strategies on snare hunters' behaviour is urgently
334 required. PA managers should also look beyond snare removal efforts, to other interventions, such
335 as community outreach and alternative livelihoods, which could help to alleviate hunting pressure.
336 However, better understanding of the effect such interventions may have on hunter behaviour is still
337 needed. Any intervention adopted will require careful design, and must be underpinned by a rigorous
338 monitoring and evaluation programme, so that the impact can be empirically assessed (Veríssimo
339 and Wan, 2019).

340

341 The finding that WCS staff members were better at locating snares than local guides was contrary to
342 our expectations, but it makes sense. WCS staff had more experience searching for other peoples'
343 snares, and were also more motivated to do so. Local guides were paid on a daily basis, rather than
344 per snare detection, and thus had no long-term incentive (nor contractual obligation) to perform well.
345 The work was considered hard for little reward, and was potentially against their own interests. Often

346 the exercise was received with bemusement by local guides, who in some cases viewed the setting
347 of ineffective snares as wasted effort. By contrast, WCS staff employed on permanent contracts, with
348 personal and professional interests in protecting wildlife, expressed the desire to improve their
349 snare-detection abilities and had a greater appreciation of the value of experimental work. Investing
350 effort in developing incentive schemes that reward individual performance may increase detections.
351 However, these require careful consideration to ensure they are equitable, affordable and
352 impermeable to 'cheating'. Few studies have assessed the impact incentives schemes have on
353 snare removal; further experimental research would help to clarify their potential for impacting snare
354 abundance and the prevalence of snare hunting.

355
356 There is a debate about the costs and benefits associated with hiring rangers from local communities
357 versus those from 'outside' (Paley, 2015). Whilst our study provides some evidence of the benefits of
358 the former, realistically our sample size was too small to draw any credible conclusions. Additionally,
359 we must consider that the artificial nature of our experiment meant that it was devoid of the usual
360 conflicts of interest which can occur when employing local rangers to remove snares possibly set by
361 relatives or neighbours (Paley 2015). Within conservation, the social factors that affect the behaviour
362 and performance of rangers is relatively under-researched (although see Moreto et al. 2015; Spira et
363 al. 2019), and greater empirical understanding of the factors that incentivise and disincentivise
364 rangers during different patrolling activities is needed.

365
366 Prior to the study we hypothesised that both habitat and season would affect snare detection,
367 however we found no evidence for either effect in our experiment. In the case of habitat, this might
368 be due to the relatively high within-quadrat habitat variability. Working in the same PA, (O'Kelly et al.
369 (2018b) found a 9% difference in the detectability of single snares in mixed forest (14%) compared to
370 evergreen forest (23%). However, O'Kelly et al.'s comparisons were made between two spatially
371 distinct areas with very different habitats, while the habitat measurements within this study recorded
372 small differences between vegetation within a single area. The lack of an effect of season is perhaps
373 more surprising. In tropical forests, hunters are usually more active during wet season, when soil
374 conditions are more amenable to snare placement (Ibbett et al., n.d.; van Vliet and Nasi, 2008). We
375 expected that the soft soil would also make the tracks of wildlife and snare setters more visible,

376 providing searchers with clues to follow. The lack of seasonal difference in our study may be due to
377 logistical constraints, which forced us to conduct surveys towards the end of the wet season
378 (October-November). Unfortunately, a shorter wet season in 2017 meant that rains had effectively
379 stopped by the time we surveyed the last two transects, resulting in less contrast in physical and
380 meteorological conditions than expected.

381
382 Our study demonstrates the utility of a field experiment as an effective and affordable approach to
383 hypothesis testing. Rarely used in conservation contexts, experiments have many advantages; they
384 can be replicable, results can be independently verified, and importantly, they enable researchers to
385 control for extraneous variables so conclusions about the effects of individual variables can more
386 confidently be drawn (Karban, Huntzinger, & Pearse, 2014). However, as with any scientific
387 research, they require careful design and there are limits to their ability to accurately mimic reality.
388 For example, in our experiments, searches were carried out over small areas (0.25km²), and only
389 teams of three were deployed. In reality, PA managers work at much larger spatial and temporal
390 resolutions; patrols are planned over hundreds of km², effort is measured in days rather than
391 minutes, and patrols are usually comprised of 4-7 rangers (Bowman, 2013). The maximum number
392 of snares set per quadrat was limited to 15, yet local guides reported that in reality they saturate
393 suitable areas (e.g. around salt licks, or fruiting trees) with snares to maximise capture opportunities.
394 During the experiment they felt unable to do so due to the limited number of snares, and because
395 they didn't want to increase snare detectability for other teams. Indeed, our results confirm that
396 snares set in closer proximity to each other were more likely to be found than those set-in isolation.
397 Guides sometimes felt required to set snares even in the absence of suitable habitat or wildlife signs,
398 potentially resulting in unrealistic snare placement and/or densities too high for the habitat type.
399 While we acknowledge this bias may have affected snare detectability, we mitigated its impact on
400 our estimates by explicitly modelling the effect of the setting team on detection probability. This
401 variation may also be reflective of reality. Hunters naturally vary in their hunting skill and experience,
402 meaning some snares will always be set in suboptimal locations, and some will be harder to detect
403 than others.

404

405 This study provides an effort-detection curve for snare removal for a tropical forest context, and
406 highlights how a quantitative understanding of snare detectability can benefit PA managers. In
407 addition, our parameter estimates can be incorporated into statistical analyses of ranger-collected
408 data to draw more robust conclusions about snare abundance and distribution within this
409 conservation landscape. Although the applicability of our findings is limited to sites characterised by
410 similar habitat types and hunting behaviours, our experimental protocol provides a framework
411 adaptable to different contexts, which can be used to explore efficient allocation of resources for
412 other conservation threats.

413

414

415

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425

426 **Data accessibility**

427 Data available from <https://ukdataservice.ac.uk/>.

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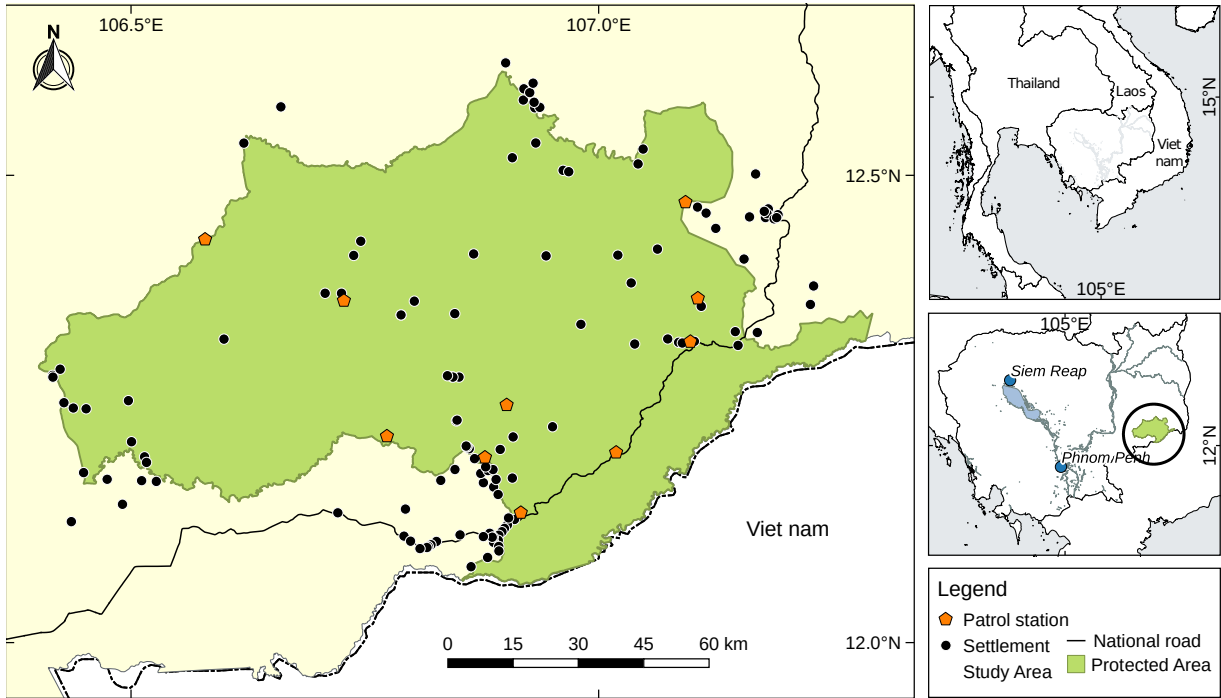
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564 **Figures**



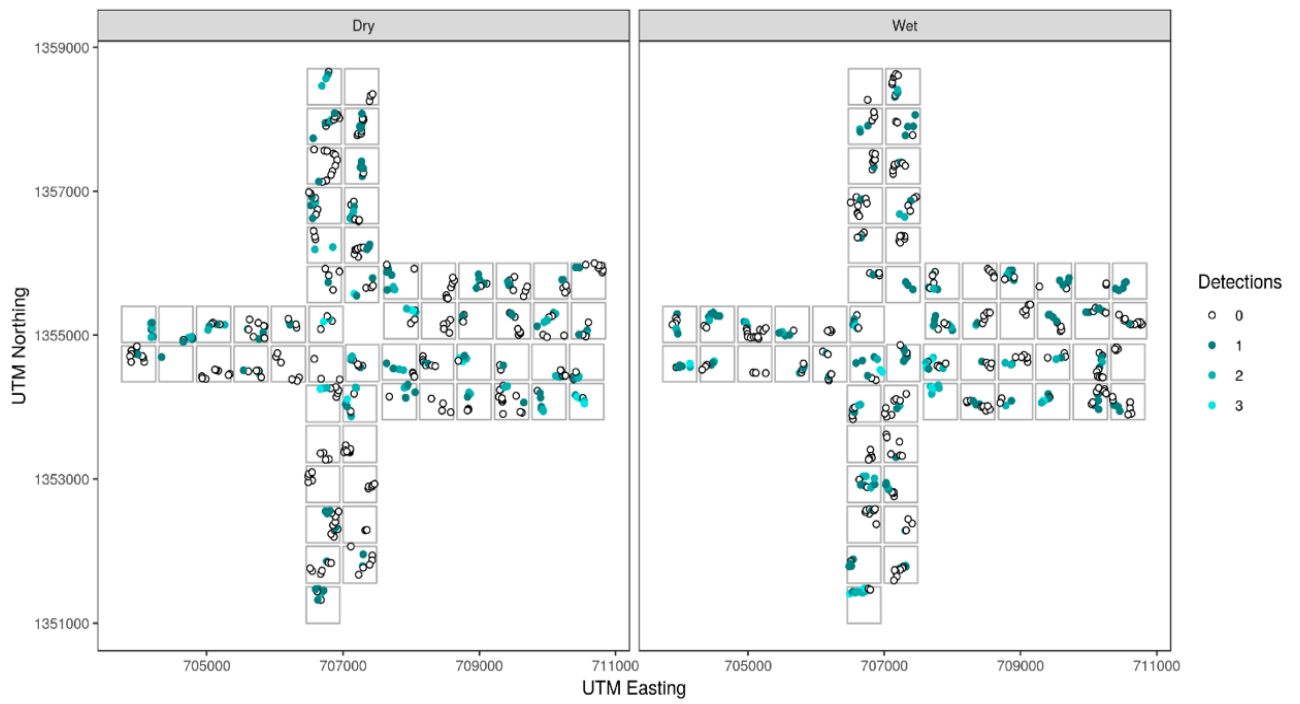
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567 Figure 1. Keo Seima Wildlife Sanctuary, Mondulkiri province, Cambodia. Study area highlighted in

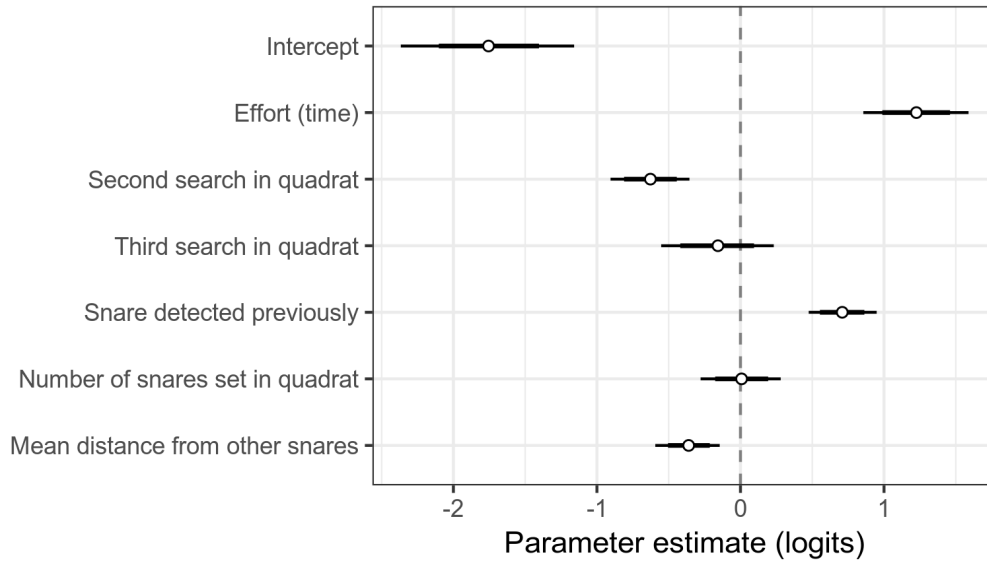
568 grey circle.

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570
 571 Figure 2. Detections in situ; colour coding represents the number of teams which detected a given
 572 snare.
 573

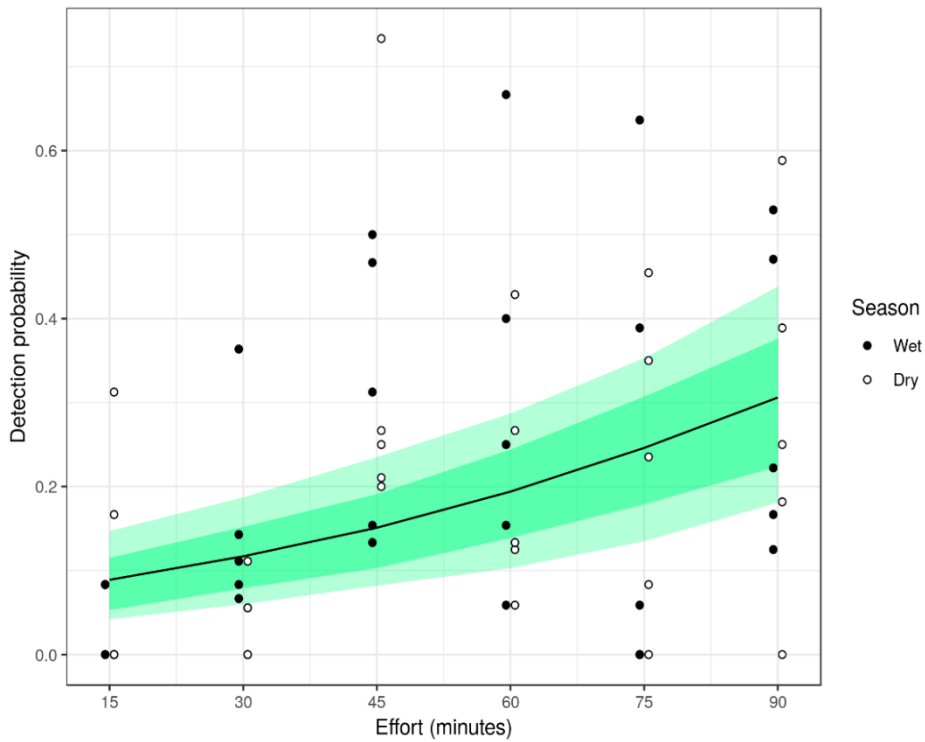
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576 Figure 3. Parameter estimates for the best-fitting model, Model 8. Points represent the mean
577 estimate; thick lines represent 80% credible intervals and thinner lines represent 95% credible
578 intervals.

579



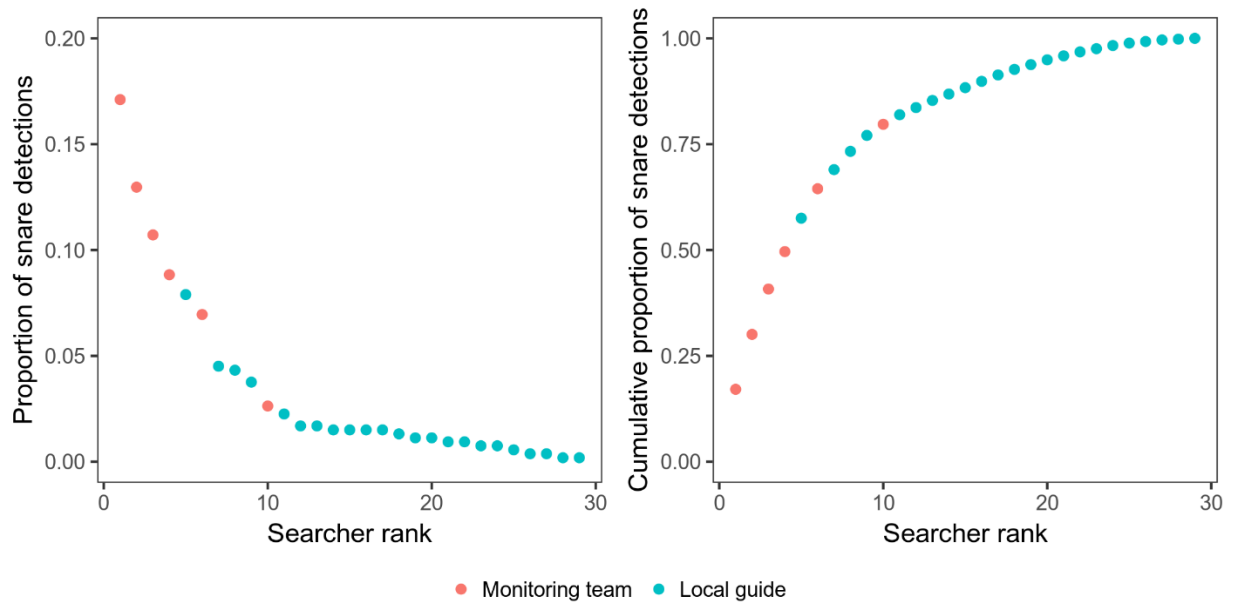
580

581 Figure 4. Effort-detection curve. Black line indicates mean probability of snare detection at differing
 582 levels of effort, predicted from the best-fitting model (Model 8) under the assumption that the quadrat
 583 has not previously been searched. Light green shading indicates the 95% credible interval for
 584 detection probability, while the darker green shading indicates the 85% credible interval. Summaries
 585 of the proportion of snares detected in each transect in the raw data are plotted as filled circles for
 586 wet season and open circles for dry season.

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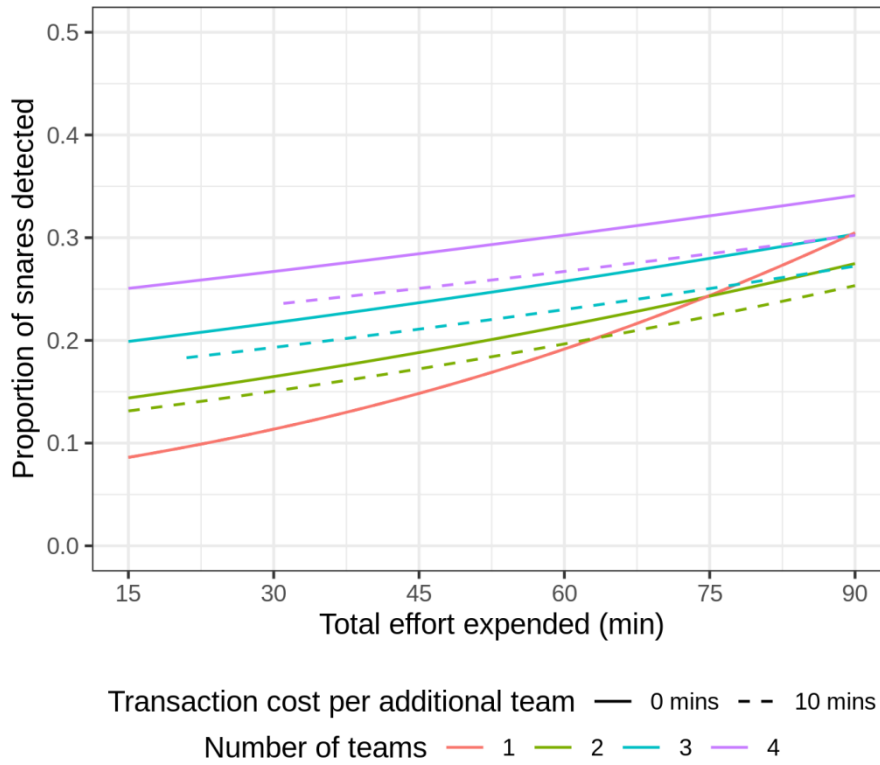
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Figure 5. Proportion of snares detected by individual searchers.

592

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594



595

596 Figure 6. Modelled effect of dividing total search effort across multiple search teams on detection
597 probability, when effects of effort on detection and transaction costs vary.

598

599 **Tables**

600 Table 1. Description of variables and interaction terms, and their inclusion in the candidate models fitted to the snare detection data. Grouping variables are
601 shown below the dividing line.

Variable	Description	Type	Levels	Model											
				0	1	2	3	4	5	6	7	8	9	10	
Effort (time)	Time (minutes) spent searching each quadrat for snares	Continuous	Centred on 45 minutes & scaled by dividing by 60		X		X	X	X	X	X	X	X	X	X
Effort (distance)	Total distanced travelled (km) during each search	Continuous	Centred on its mean value & scaled by two standard deviations				X								
Quadrat search order	Search order	Factor	1 st , 2 nd , 3 rd					X	X	X	X	X	X	X	X
Previous snare detections	Number of times the snare was previously detected by other teams	Factor	0, 1, 2					X	X	X	X	X	X	X	X
Distance to nearest snare	Mean distance (m) of a snare to other snares within the same quadrat	Continuous	Centred on 150m & scaled by dividing by 100						X	X	X	X	X	X	X
No. of snares set in quadrat	Total number of snares set in the quadrat	Continuous	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15						X	X	X	X	X	X	X
Season	Season in which quadrat was searched	Factor	Wet, Dry							X	X				X
Season: Effort		Interaction term									X				X
HI present during search	Whether HI accompanied the team during the quadrat search	Factor	Yes, No											X	X
Team leader	ID of the team leader	Factor	1, 2, 3, 4											X	X
Vegetation type	Dominant vegetation type within the quadrat	Factor	Bamboo, mixed-deciduous, semi-evergreen										X		X
Presence of animal trail	Whether the snare was set on an animal trail	Factor	Yes, No										X		X
Presence of animal sign	Whether the snare was set near wildlife signs (e.g. foot prints, dung)	Factor	Yes, No										X		X

Presence of water	Whether the snare was set near a stream, river, pond or salt lick	Factor	Yes, No									X			X	
Transect	Transect ID	Factor	1, 2, 3, 4, 5	X	X	X	X	X	X	X	X	X	X	X	X	
Quadrat within transect	Quadrat ID	Factor	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	X	X	X	X	X	X	X	X	X	X	X	X	
Date	Date each search was conducted	Factor	DD-MM-YY	X	X	X	X	X	X	X	X	X	X	X	X	
Team setting snares	ID of the team that set snares in the quadrat	Factor	W1, W2, W3, W4, D1, D2, D3, D4											X	X	X
Team searching for snares	ID of the team searching for snares in the quadrat	Factor	1, 2, 3, 4											X	X	X

602

603

604 Table 2. WAIC values for the fitted models, the difference from the best-fitting model (δ WAIC) and
605 the standard error of that difference ($SE(\delta$ WAIC)). See Table 1 for models.

Model	WAIC	δ WAIC	$SE(\delta$ WAIC)
8	2412.7	0.0	--
9	2414.1	1.5	1.8
10	2424.2	11.5	3.4
4	2461.4	48.7	14.4
5	2462.9	50.2	14.4
7	2465.3	52.6	14.2
6	2465.5	52.9	14.4
3	2471.8	59.1	16.0
1	2515.5	102.8	21.6
0	2527.6	114.9	23.0
2	2532.9	120.2	22.4

606

Experimentally assessing the effect of search effort on snare detectability

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Author Contributions

The research was primarily led by HI, but all authors contributed to the research conception and study design. HI collected the data; AK analysed the data; HI led the writing of the manuscript.

All authors contributed critically to the drafts and granted final approval for publication.

1 Experimentally assessing the effect of search effort on snare detectability

2

3 Abstract

4 Reducing threats to biodiversity is the key objective of ranger patrols in protected areas. However,
5 efforts can be hampered by rangers' inability to detect threats, and poor understanding of threat
6 abundance and distribution in a landscape. Snares are particularly problematic due to their cryptic
7 nature and limited selectivity with respect to captured animals' species, sex, or age. Using an
8 experimental approach, we investigated the effect of search effort, habitat, season, and team on
9 rangers' detection of snares in a tropical forest landscape. We provide an effort-detection curve, and
10 use our findings to make preliminary predictions about snare detection under different scenarios of
11 patrol effort. Results suggest that the overall probability of a searcher detecting any given snare in a
12 0.25/km² area, assuming 60 minutes (or approximately 2km) of search effort is 20% (95% CI \pm 15-
13 25%), with no significant effect of season, habitat or team. Our models suggested this would
14 increase by approximately 10% with an additional 30mins/1km of search effort. Our preliminary
15 predictions of the effectiveness of different patrolling scenarios show that detection opportunities are
16 maximised at low effort levels by deploying multiple teams to a single area, but at high effort levels
17 deploying single teams becomes more efficient. Our results suggest that snare detectability in
18 tropical forest landscapes is likely to be low, and may not improve dramatically with increased search
19 effort. Given this, managers need to consider whether intensive snare-removal efforts are the best
20 use of limited resources; the answer will depend on their underlying objectives.

21

22

23 Keywords

24 Detection probability; hunting; law enforcement; protected areas; ranger patrols; Cambodia

26 **1. Introduction**

27 Protected area (PA) networks are a cornerstone of global efforts to conserve biodiversity (Bruner,
28 Bruner, Gullison, Rice, & Fonseca, 2001). Their success depends on effective management,
29 including the reduction of threats to species and habitats (Watson, Dudley, Segan, & Hockings,
30 2014). A primary tool available to PA managers to address threats is patrolling by ranger teams
31 (Hilborn et al., 2006; Lynam, Porter, & Campos-Arceiz, 2016). Through regular patrolling, rangers
32 monitor adherence to conservation rules, deter potential perpetrators, and punish infractions when
33 detected (Keane, Jones, Edward-Jones, & Milner-Gulland, 2008). To design optimal patrol
34 strategies, PA managers require robust information about the distribution and abundance of threats
35 in a landscape (Critchlow et al., 2017) alongside a means of assessing which approach is most likely
36 to yield the greatest conservation benefit at the lowest possible cost (Plumptre et al., 2014).

37

38 Data collected by rangers are increasingly used to map spatio-temporal trends in threats and
39 evaluate patrol performance. These are often collected by patrols for little additional cost (Brashares
40 & Sam, 2005). Subsequently, the data can be used with open-access tools such as the Spatial
41 Monitoring and Reporting Tool (SMART) to map threats and prioritize patrol effort within
42 conservation landscapes (Hötte et al., 2016; Stokes, 2010). However, gathering data is not the
43 primary objective of patrols and ranger-collected data may be subject to considerable bias (Keane et
44 al. 2011). Patrol data must therefore be handled with caution to avoid misleading conclusions and
45 ineffective targeting of patrol effort (Critchlow et al., 2015; Keane, Jones, & Milner-Gulland, 2011).
46 While a growing suite of statistical methods exists to account for these biases (see Critchlow et al.,
47 2015; Marescot, Lyet, Singh, Carter, & Gimenez, 2019; J. F. Moore et al., 2017), there is also a
48 broader need for independent tests of key aspects of patrol effectiveness, such as the amount of
49 patrol effort required to successfully detect a certain proportion of threats present within expansive
50 conservation landscapes (Dobson, Milner-Gulland, Beale, Ibbett, & Keane, 2018). Well-designed
51 experiments can provide effective and affordable means to trial different approaches, and have been
52 used to improve understanding of the effects of environmental covariates on the detectability of traps
53 set by hunters in both tropical forest (O’Kelly et al. 2018a) and savannah (Rija, 2017) landscapes.
54 However, no experimental study has yet explored the relationship between search effort and threat

55 detection, knowledge of which would enable PA managers to distribute patrol effort more efficiently,
56 and thereby improve PA effectiveness.

57

58 Hunting poses one of the greatest threats to wildlife in PAs globally (Ripple et al., 2016; Schulze et
59 al., 2018) and snares are one of the most prevalent hunting technologies used worldwide (Gray,
60 Hughes, et al., 2017; Harrison et al., 2016). Usually made from wire, cable, or nylon, snares are
61 affordable, accessible, and can trap a wide range of arboreal and terrestrial species, whether diurnal
62 or nocturnal (Borgerson, 2015; Ingram et al., 2017). Due to their limited selectivity with respect to
63 species, sex, or age of captured animals, snares are a potent threat to biodiversity (Noss, 1998).
64 Although animals sometimes escape snares, subsequent non-fatal injuries often jeopardize their
65 long-term survival (Gray, Lynam, et al., 2017). For example, chimpanzees with snare injuries have
66 been found to suffer significantly higher parasite loads than those without (Yersin, Asimwe,
67 Voordouw, & Zuberbühler, 2017). Unlike other forms of hunting, snares present a persistent threat to
68 wildlife as they remain operational in the landscape after a hunter has departed, and are difficult for
69 patrols to detect (Lindsey, Romanach, Tambling, Chartier, & Groom, 2011).

70

71 A key assumption is that the more patrol effort invested in searching, the more snares will be
72 discovered. However, the improvement in detection with effort has not been quantified and is likely to
73 be affected by factors such as habitat, season, atmospheric conditions (e.g. precipitation,
74 temperature), terrain and topography and the type of snare set (Keane et al. 2011; Jachmann 2008).
75 For example, snares which are physically connected and set in lines that stretch many hundreds of
76 metres may be more detectable than individual snares (O’Kelly et al. 2018b). In addition, snare
77 detection is influenced by rangers themselves. Studies of wildlife observation and plant detection
78 have recorded considerable variability between observers depending on their experience and
79 expertise (J. L. Moore, Hauser, Bear, Williams, & McCarthy, 2011; Sunde & Jessen, 2013). And,
80 even if rangers are capable of finding snares, they may not always be motivated to search
81 (Jachmann, 2008). Conservation law enforcement operations are typically under-resourced, with
82 rangers often inadequately trained, poorly remunerated, and insufficiently equipped to work in
83 challenging conditions (Belecky, Singh, & Moreto, 2018; Long, Grein, Boedicker, & Singh, 2016).

84

85 Here, we adopt an experimental approach to test how a vital element of patrol effectiveness – snare
86 detection – is affected by the amount of patrol effort invested. Our study provides an effort-detection
87 curve for snare detectability in a tropical forest context, investigates the effects of habitat and season
88 on detection probability, and assesses the extent to which performance varies between search
89 teams and individual searchers. We use our findings to predict the snare detection levels that could
90 be achieved in a Cambodian PA under different patrolling scenarios.

92 **2. Materials and Methods**

93

94 **2.1 Study Site**

95 The study was conducted in Keo Seima Wildlife Sanctuary (formerly Seima Protection Forest), a
96 2,927km² PA situated in Mondulkiri Province, eastern Cambodia (12°26'70"N, 106°E 94'90"). The
97 PA is topographically diverse, ranging in altitude from 60-750m (Evans et al., 2013). The habitat is
98 heterogeneous, and consists of a complex forest mosaic that includes deciduous dipterocarp and
99 fully evergreen forest (Walston, Davidson, & Men, 2001). The PA supports populations of Asian
100 elephant (*Elephas maximus*) and wild cattle (*Bos spp.*), alongside globally significant primate
101 populations. In 2011, a systematic survey conducted over 2200km, detected 1300 snares in 140
102 different locations in the PA, with an experimentally calculated detection rate of 28-36% (O'Kelly et
103 al. 2018a).

104

105 **2.2 Experimental design**

106 *Setting snares*

107 We adapted a methodology originally piloted by O'Kelly et al. (2018b), and established five 3.25km
108 transects around a patrol station (Fig. 1, Appendix S1). Habitat here is highly heterogenous;
109 comprised of a mosaic that reflect vegetation types found across the wider landscape. The area also
110 supports a full complement of species, which occur in relatively high densities. Either side of each
111 transect, we delineated 6 x 0.25km² (500m x 500m) quadrats at 50m intervals (Appendix S1). This
112 quadrat size was chosen so teams could conduct intensive searches in realistic time-frames. Within
113 each quadrat we set between zero and 15 snares (the number randomly drawn from a Poisson
114 distribution with mean = 7.5), based on estimates of typical snare densities identified by other
115 studies (Dobson et al., 2019). Single foot snares made from black nylon string (5mm), an
116 inexpensive material often used by hunters in this area, were set without a trigger mechanism to
117 prevent harm to wildlife, and all snares were successfully removed at the end of each transect
118 survey.

119

120 We recruited local guides from surrounding communities, who were instructed to set single snares
121 as a local hunter might, in locations they deemed suitable to catch popular prey species such as wild

122 pig (*Sus scrofa*), Northern red muntjac (*Muntiacus vaginalis*) and sambar (*Rusa unicolor*). Prior to
123 setting snares, teams explored each quadrat for 30 minutes to identify suitable snare locations. Once
124 set, teams recorded the GPS coordinates of each snare and the dominant habitat type of the
125 quadrat. Teams were asked not to disclose the location or number of snares set in each quadrat to
126 other teams or to leave obvious signs of their presence which future teams might use as cues.
127

128 **2.3 Data Collection**

129 *Searching for snares*

130 The experiment required four separate teams, each led by a staff member from the Wildlife
131 Monitoring Team of Wildlife Conservation Society (WCS) Cambodia. Team leaders had expertise in
132 snare detection, and were accompanied by two other searchers – either a local guide or another
133 WCS staff member. WCS staff remained the same in each team, but changes in availability meant
134 that local guides varied between transects. All team members searched for snares, with team
135 leaders also recording data, coordinating the search strategy and ensuring searchers stayed within
136 quadrat boundaries. Each team was allocated quadrats to search for a designated time period. No
137 quadrat was searched simultaneously by more than one team, and teams never searched quadrats
138 in which they had set snares. To maximize statistical power and to account for the considerable
139 challenge of implementing the survey at a larger scale, each quadrat was searched three times, for a
140 fixed search duration varying between 15 and 90 minutes in 15-minute intervals (Appendix S1).
141 Every effort was made to minimize the effect of previous searches on the detectability of snares by
142 subsequent teams.

143
144 Teams were encouraged to search purposefully by following cues in the landscape (e.g. human
145 footprints, wildlife tracks, cut vegetation). The start and finish time, the vegetation type in the
146 quadrat, the distance travelled, the GPS locations of the search routes and any artificial or real
147 snares detected were recorded throughout. We also recorded search order, to account for the fact
148 that the more a quadrat was searched, the more cues were left in the landscape. The later the
149 search, the harder for searchers to differentiate between cues set by the snare setting team (clues)
150 and those left by previous searchers (decoy cues). Teams were shadowed by first author HI to
151 ensure that protocols were adhered to, and to observe and question teams on their choice of snare

152 placement and search strategies. We included the presence of HI as a variable within our models, to
153 assess whether her observation of the search team had any effect on detection performance. The
154 methodology was piloted in December 2016, and conducted during dry season in January-February
155 2017 and wet season in October-November 2017.

156

157 **2.4 Ethical Considerations**

158 Employing local community members with relevant hunting experience helped to ensure that artificial
159 snares were realistic, but raised several ethical issues. Firstly, by participating, local guides risked
160 implicating themselves in illegal activity (e.g. by affirming their hunting expertise or knowledge of
161 suitable hunting grounds within the PA). To mitigate this risk, only former hunters recommended by
162 WCS were recruited. Prior to participation, the experimental nature and purpose of the research was
163 explained to local guides, and voluntary verbal consent to participate was sought. Individuals were
164 assured that no information or inferences about their hunting knowledge would be passed onto
165 authorities. An additional concern was that the experiments would introduce individuals to new
166 hunting grounds. However, after consultation with WCS it was decided that the risk was negligible;
167 most local guides were born in or around the PA, and were highly familiar with the study landscape.
168 Protocols were reviewed and approved by the University of Oxford Central University Research
169 Ethics Committee (Ref No. R43030/RE002), with permission to conduct research granted by the
170 Royal Government of Cambodia.

171

172 **2.5 Analysis**

173 Analyses were performed in R version 3.5.1 (R Core Team, 2017) using the package rstanarm
174 (Goodrich, Gabry, Ali, & Brilleman, 2018). We fitted a series of hierarchical generalised linear models
175 to the data, expressing different hypotheses about the factors influencing snare detection. These
176 were compared using WAIC, a Bayesian information criterion akin to AIC (Watanabe, 2010). The
177 response variable in every model was a binary indicator of whether or not each snare was detected
178 during a given search period. The full set of predictor variables used in one or more of these models
179 is shown in Table 1. Effort was represented by either time or distance. Based on a comparison of
180 WAIC between models 1 and 2 (intercept and grouping parameters only, no covariates), time was
181 chosen as the better-fitting effort measure for model explorations which included covariates,

182 although the two measures were highly correlated (Spearman's Rho = 0.79, 95% CI =77-81; Fig.
183 S2a). Effort measured as time was experimentally manipulated rather than observed, so was centred
184 around 45 minutes (50% of the maximum search time) and included in the model using hours as the
185 unit of measurement. Effort measured as distance and distance to the nearest snare were observed
186 quantities so were scaled by subtracting the mean and dividing by two standard deviations, either
187 precisely (for effort) or using approximate values for the mean and standard deviation (for distance to
188 the nearest snare) to improve the interpretability of the coefficients. All other models included
189 variables for quadrat search order and previous snare detections. Two snare density-related
190 variables were next added, and finally we explored three models which also included variables
191 related to season, team, or placement within the environment.

192

193 Model parameters were given weakly informative Students-t priors with 7 degrees of freedom and
194 scale 2.5, except for the intercept which was given a Normal prior with mean 0 and standard
195 deviation 10. Weakly informative priors were chosen to stabilise computation and to express our
196 weak prior beliefs that very large effects would be rare (Gelman, Jakulin, Pittau, & Su, 2008). The
197 coefficients for transect ID, quadrat ID, date, setting team ID and searching team ID were each given
198 independent hierarchical LKJ priors with regularization parameter 1 (Lewandowski, Kurowicka, &
199 Joe, 2009). For each model, 2000 Markov Chain Monte Carlo (MCMC) samples were drawn from
200 four independent chains. Convergence of MCMC chains was evaluated using trace-plots and the
201 Gelman-Rubin diagnostic, with values <1.05 taken to indicate that convergence had been reached
202 (Gelman et al. 2013). The fit of the model with the lowest WAIC value was examined using graphical
203 posterior predictive checks.

204

205 Using the effort-detection relationship derived from our fitted model, and assuming replication of the
206 search strategies employed during our experiment, we explored how dividing search effort within a
207 quadrat across multiple teams might affect detection probability. We assumed that n teams searched
208 the same quadrat independently and sequentially and that each team had the same constant
209 probability, p , of detecting snares that were present. We therefore modelled the proportion of snares
210 remaining after all searches were completed, r , as:

211

$$r = 1 - (1 - p)^n$$

212 Deploying more search teams is likely to incur transaction costs (e.g. more time is required to travel
213 to sites, and additional salary is required to pay more team leaders). In the absence of empirical
214 data, we incorporated these costs by expressing them in terms of effort lost from the total budget: 10
215 minutes of search effort was removed from the initial total for each extra team added, and the
216 remaining effort was then split equally between all teams (i.e. at 90 minutes, four teams would
217 search for 15 minutes each). To examine the sensitivity of our findings to the steepness of the effort-
218 detection relationship we also explored the difference in results when the slope of the effort-
219 detection curve was 50% higher or lower than the observed slope on the logit scale, in order to
220 determine the sensitivity of our results to the specific shape of the effort-detection curve.

221 **3. Results**

222

223 **3.1 Effect of search effort on detection probability**

224 *3.1.1 Snare locations*

225 In total, 886 artificial snares were set, 442 in dry season and 444 in wet season. Local guides
226 reported that they generally sought specific features when placing snares; for example, water
227 sources (66% of snares set), animal trails (44%), animal signs (e.g. footprints or faeces; 44%), or
228 fruiting trees (2%).

229

230 *3.1.2 Detection probability*

231 A total of 535 artificial snare detections was recorded out of a possible 2661 opportunities, with a
232 detection rate of 0.20 averaged across the entire experiment, or 0.24 per hour of searching. In
233 addition, 55 real snares were detected. These detections were not included in analyses, as once
234 detected real snares were removed, meaning subsequent search teams had no opportunity to detect
235 them. 42% of the total population of artificial snares were discovered; 26% were found by only a
236 single team, 13% by two teams, and 3% by all three search teams (S2, Fig. 2).

237

238 *3.1.3 Predictors of snare detectability*

239 The magnitude and direction of the effect of all covariates were consistent across the set of
240 candidate models considered (see Appendix S2). The best-fitting model (Model 8; Table 2) included
241 time spent searching, quadrat search order, number of times a snare was previously detected, snare
242 clustering and density (Fig. 3), and batches of variables describing the variability between transects,
243 between quadrats within transects, over time and between the teams responsible for setting and
244 searching for snares (Figs. S2d-f). The model did not include season, vegetation type within the
245 quadrat, or the proximity of the snare to water, animal trails or animal signs. Model 9, which included
246 variables relating to the team leader, and the presence of author HI as an observer of the search
247 team, was only marginally less supported while other models were much less well supported (Table
248 2). However, the effects of team leader and HI's presence in model 9 were inconclusive (Fig. S2b).

249

250 The overall probability of searchers detecting any given snare on the first search of an area was 20%
251 (95% CI \pm 15-25%), assuming 60 minutes (or approximately 2km) of search effort. Detection
252 probability increased by approximately 10% for every additional 30mins/1km of search effort from
253 approximately 8% with 15 mins of search to approximately 30% with 90 mins (Fig. 4). Snares which
254 were previously detected by a search team were more likely to be detected in subsequent searches
255 (mean raw detection rates: Never previously detected = 0.17; Detected once previously = 0.33;
256 Detected twice previously = 0.54; Fig. 3). Perhaps because previous searchers left cues, such as
257 footprints or cut branches, which made it easier for subsequent searchers to follow their path.
258 Accounting for this, there was an effect of whether the quadrat was being searched for the first,
259 second or third time, with lower rates of detection in the second search than the first, but no clear
260 difference between the first and third searches (mean raw detection rates: First search = 0.21;
261 Second search = 0.16; Third search = 0.24). Snares were more easily detected when they were
262 placed in closer proximity to other snares in a quadrat, but there was no effect of snare density on
263 detection rates (Fig. 3).

264

265 *3.1.4 Team variability*

266 The identity of the setting and searching teams had little effect on the probability of detection (Fig.
267 S2c). Differences in success were largely attributable to the performance of specific individuals; over
268 40% of all snare detections were achieved by three searchers, and the best searchers were
269 disproportionately from the professional WCS wildlife monitoring team rather than local guides (Fig.
270 5). Although WCS staff were responsible for recording data, there was little opportunity for them to
271 claim snares found by others for themselves, as each searcher's detections were verifiable via
272 timestamped GPS tracks of each individuals' search route. We found no evidence that any false
273 recording occurred. Field observations of searchers suggested that detection was mainly influenced
274 by skill and experience. A peer- and self-evaluation exercise suggested that peers more accurately
275 predicted others' detection abilities than individuals did themselves (Appendix S3). The best-
276 performing individual was a WCS employee born in a local village who hunted in childhood.

277

278 **3.2 Effective allocation of search effort**

279 Our fitted models show that as the amount of total search effort increases from 15 to 90 minutes, the
280 proportion of snares detected by a single team can be expected to increase by approximately 20%.

281 Simulations of search effort allocation suggest that at low search efforts, a 10% increase in detection
282 can be expected for each additional team searching (Fig. 6). For example, four teams searching the
283 same quadrat at separate times for 5 minutes each (in total 20 minutes) may find up to 25% of
284 snares. However, as search effort increases, it can become more efficient to deploy just one team,
285 rather than multiple teams - particularly when the relationship between effort and snare detection is
286 steeper.

287 **4. Discussion**

288 PA managers increasingly require information about the best allocation of patrol effort (Lynam et al.,
289 2016). Our results suggest that overall, the ability of rangers to detect snares is low. Although
290 detection increased with distance between snares and search effort, 60 minutes of searching
291 (approximately 2 km) resulted in the detection of 20% (\pm 15-25%) of snares, comparable to the 15%
292 detection reported by O'Kelly et al. (2018b) at similar levels of search effort. Higher detection rates
293 might be achieved by deploying more teams to search within a specific area for shorter periods.
294 However, this finding assumes teams independently search the same area, that they are not reliant
295 on cues left by previous searchers, that detected snares are left in situ, and that each search team
296 has equal detection probability. In reality, few of these assumptions are met. Regardless, given the
297 large size of most PAs, the recommendation to deploy multiple teams within a specific area for
298 shorter periods may be financially and logistically unviable unless there is a particular reason to
299 concentrate on a specific "hotspot". Ultimately, more effective and efficient use of resources will be
300 achieved by deploying a single team to intensively search one area.

301
302 Surprisingly, we found no effect of snare density on detection probability. While setting more snares
303 might result in more potential opportunities for snares to be found, searchers still need to target their
304 efforts in the right places. The skill of individual searchers, along with search effort were stronger
305 predictors of detection probability, highlighting the need for PA managers to carefully select
306 personnel with demonstrated skill at detecting snares for patrols. Also unexpected, was that
307 detection was higher during the first and third searches than the second. One reason may have
308 been due to time of day. The second search was usually conducted in the afternoon, when
309 temperatures often exceeded 33°C. By this point individuals had already exerted substantial effort in
310 searching and were physically and mentally fatigued. Our results along with observations during the
311 study, highlight the need for PA managers to carefully consider environmental factors such as
312 temperature when designing patrolling strategies. Managers must demonstrate an awareness of the
313 physical and psychological demands patrolling places on individuals and adapt patrols accordingly
314 (Belecky et al., 2018; Moreto, 2015).

315

316 Many PA management regimes prioritise and invest heavily in patrol-based snare removal efforts.
317 However, the low detectability of snares, despite high levels of search effort, raises questions about
318 the efficiency of this approach. If the primary aim of snare removal is to reduce animal mortality to
319 sustainable levels, snare detection and removal rates must be high enough to alleviate pressure on
320 remaining wildlife populations. Knowing what is “high enough” requires robust estimates of snare
321 detection, as well as a good understanding of snare-related mortality rates and their impact on
322 species population trends. Currently, however, there is virtually no empirical information on any of
323 these parameters. If the aim is to deter snaring, then detectability must be high enough to raise costs
324 sufficiently to make it unprofitable (Gray, Hughes, et al., 2017). If the aim is to visibly advertise to
325 potential offenders that snaring is an issue taken seriously by PA managers, then making snare
326 removal efforts visible to communities could be beneficial, even if the actual percentage removed is
327 low. PA managers must therefore consider their aims carefully. All these objectives may benefit from
328 targeted snare removal in known hunting and/or wildlife hotspots, especially if accompanied by
329 legislative reform, consistent enforcement that criminalises the possession of snares, and measures
330 which ensure a high proportion of successful prosecutions occur (Gray, Hughes, et al., 2017).
331 Currently, however, little is known about whether snare removal actually deter hunters, and if so,
332 what the spatial and temporal extents of a deterrent effect are. Better understanding of the relative
333 deterrent effect of different law enforcement strategies on snare hunters' behaviour is urgently
334 required. PA managers should also look beyond snare removal efforts, to other interventions, such
335 as community outreach and alternative livelihoods, which could help to alleviate hunting pressure.
336 However, better understanding of the effect such interventions may have on hunter behaviour is still
337 needed. Any intervention adopted will require careful design, and must be underpinned by a rigorous
338 monitoring and evaluation programme, so that the impact can be empirically assessed (Veríssimo
339 and Wan, 2019).

340

341 The finding that WCS staff members were better at locating snares than local guides was contrary to
342 our expectations, but it makes sense. WCS staff had more experience searching for other peoples'
343 snares, and were also more motivated to do so. Local guides were paid on a daily basis, rather than
344 per snare detection, and thus had no long-term incentive (nor contractual obligation) to perform well.
345 The work was considered hard for little reward, and was potentially against their own interests. Often

346 the exercise was received with bemusement by local guides, who in some cases viewed the setting
347 of ineffective snares as wasted effort. By contrast, WCS staff employed on permanent contracts, with
348 personal and professional interests in protecting wildlife, expressed the desire to improve their
349 snare-detection abilities and had a greater appreciation of the value of experimental work. Investing
350 effort in developing incentive schemes that reward individual performance may increase detections.
351 However, these require careful consideration to ensure they are equitable, affordable and
352 impermeable to 'cheating'. Few studies have assessed the impact incentives schemes have on
353 snare removal; further experimental research would help to clarify their potential for impacting snare
354 abundance and the prevalence of snare hunting.

355
356 There is a debate about the costs and benefits associated with hiring rangers from local communities
357 versus those from 'outside' (Paley, 2015). Whilst our study provides some evidence of the benefits of
358 the former, realistically our sample size was too small to draw any credible conclusions. Additionally,
359 we must consider that the artificial nature of our experiment meant that it was devoid of the usual
360 conflicts of interest which can occur when employing local rangers to remove snares possibly set by
361 relatives or neighbours (Paley 2015). Within conservation, the social factors that affect the behaviour
362 and performance of rangers is relatively under-researched (although see Moreto et al. 2015; Spira et
363 al. 2019), and greater empirical understanding of the factors that incentivise and disincentivise
364 rangers during different patrolling activities is needed.

365
366 Prior to the study we hypothesised that both habitat and season would affect snare detection,
367 however we found no evidence for either effect in our experiment. In the case of habitat, this might
368 be due to the relatively high within-quadrat habitat variability. Working in the same PA, (O'Kelly et al.
369 (2018b) found a 9% difference in the detectability of single snares in mixed forest (14%) compared to
370 evergreen forest (23%). However, O'Kelly et al.'s comparisons were made between two spatially
371 distinct areas with very different habitats, while the habitat measurements within this study recorded
372 small differences between vegetation within a single area. The lack of an effect of season is perhaps
373 more surprising. In tropical forests, hunters are usually more active during wet season, when soil
374 conditions are more amenable to snare placement (Ibbett et al., n.d.; van Vliet and Nasi, 2008). We
375 expected that the soft soil would also make the tracks of wildlife and snare setters more visible,

376 providing searchers with clues to follow. The lack of seasonal difference in our study may be due to
377 logistical constraints, which forced us to conduct surveys towards the end of the wet season
378 (October-November). Unfortunately, a shorter wet season in 2017 meant that rains had effectively
379 stopped by the time we surveyed the last two transects, resulting in less contrast in physical and
380 meteorological conditions than expected.

381
382 Our study demonstrates the utility of a field experiment as an effective and affordable approach to
383 hypothesis testing. Rarely used in conservation contexts, experiments have many advantages; they
384 can be replicable, results can be independently verified, and importantly, they enable researchers to
385 control for extraneous variables so conclusions about the effects of individual variables can more
386 confidently be drawn (Karban, Huntzinger, & Pearse, 2014). However, as with any scientific
387 research, they require careful design and there are limits to their ability to accurately mimic reality.
388 For example, in our experiments, searches were carried out over small areas (0.25km²), and only
389 teams of three were deployed. In reality, PA managers work at much larger spatial and temporal
390 resolutions; patrols are planned over hundreds of km², effort is measured in days rather than
391 minutes, and patrols are usually comprised of 4-7 rangers (Bowman, 2013). The maximum number
392 of snares set per quadrat was limited to 15, yet local guides reported that in reality they saturate
393 suitable areas (e.g. around salt licks, or fruiting trees) with snares to maximise capture opportunities.
394 During the experiment they felt unable to do so due to the limited number of snares, and because
395 they didn't want to increase snare detectability for other teams. Indeed, our results confirm that
396 snares set in closer proximity to each other were more likely to be found than those set-in isolation.
397 Guides sometimes felt required to set snares even in the absence of suitable habitat or wildlife signs,
398 potentially resulting in unrealistic snare placement and/or densities too high for the habitat type.
399 While we acknowledge this bias may have affected snare detectability, we mitigated its impact on
400 our estimates by explicitly modelling the effect of the setting team on detection probability. This
401 variation may also be reflective of reality. Hunters naturally vary in their hunting skill and experience,
402 meaning some snares will always be set in suboptimal locations, and some will be harder to detect
403 than others.

404

405 This study provides an effort-detection curve for snare removal for a tropical forest context, and
406 highlights how a quantitative understanding of snare detectability can benefit PA managers. In
407 addition, our parameter estimates can be incorporated into statistical analyses of ranger-collected
408 data to draw more robust conclusions about snare abundance and distribution within this
409 conservation landscape. Although the applicability of our findings is limited to sites characterised by
410 similar habitat types and hunting behaviours, our experimental protocol provides a framework
411 adaptable to different contexts, which can be used to explore efficient allocation of resources for
412 other conservation threats.

413

414

415

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425

426 **Data accessibility**

427 Data available from <https://ukdataservice.ac.uk/>.

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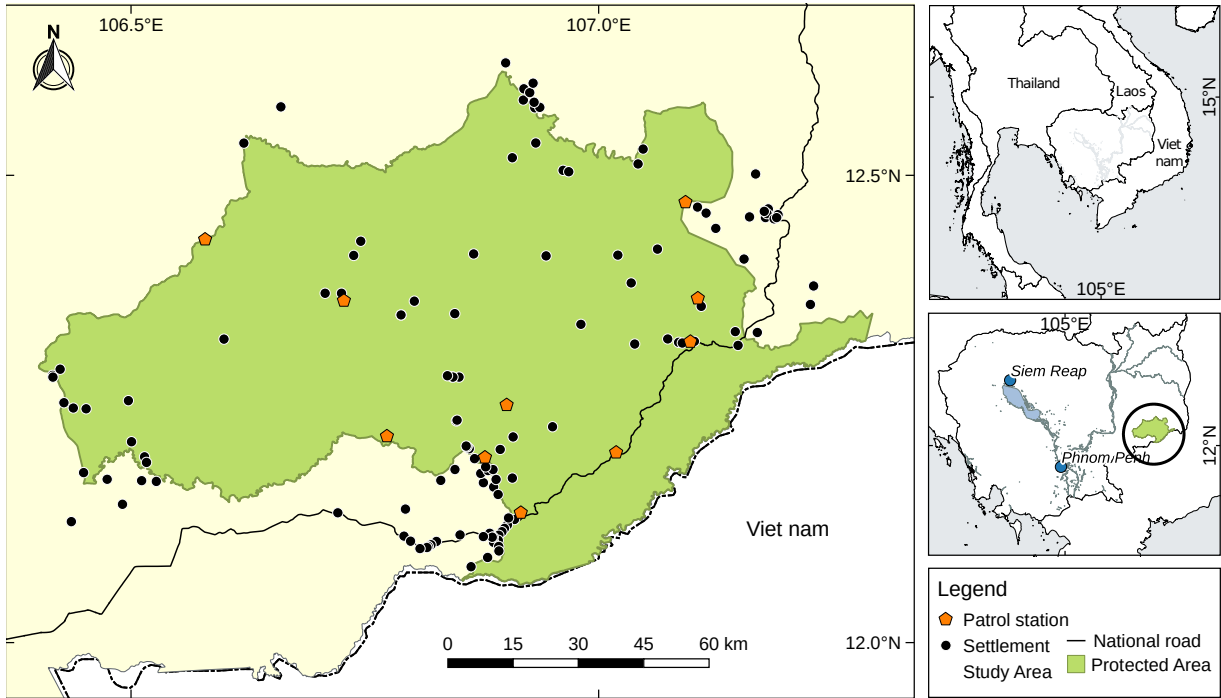
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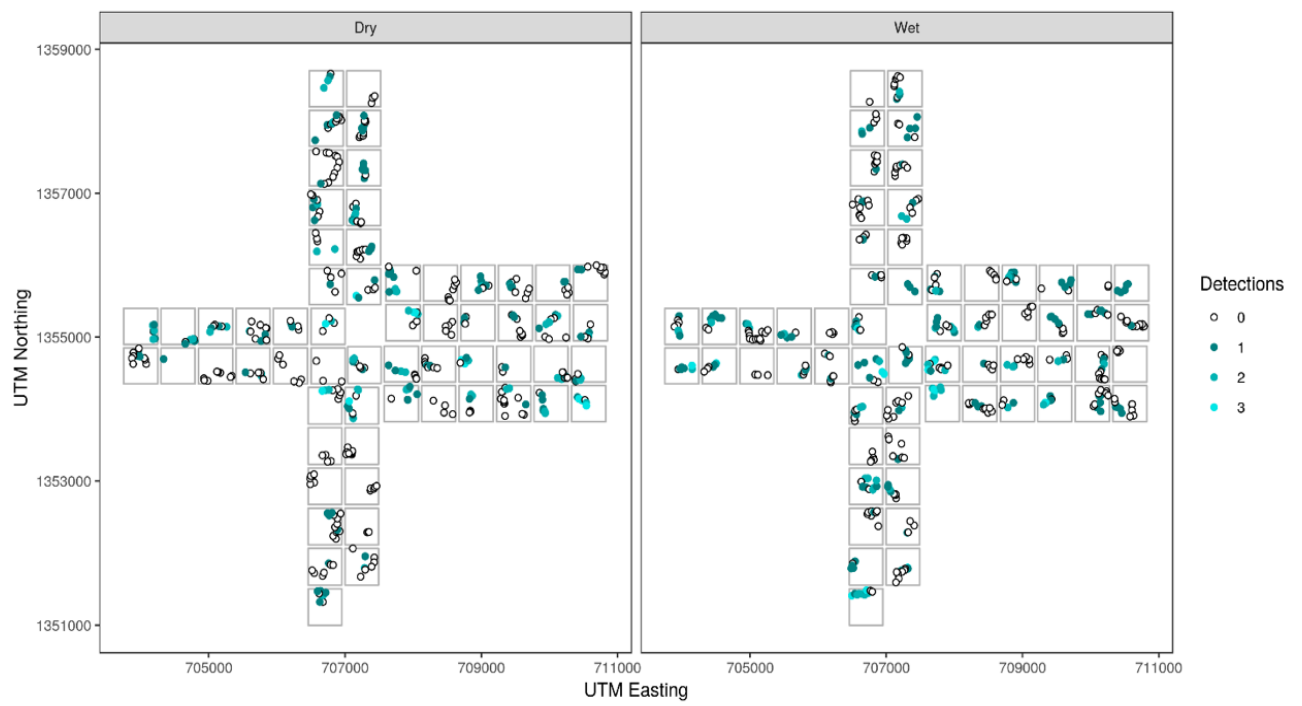


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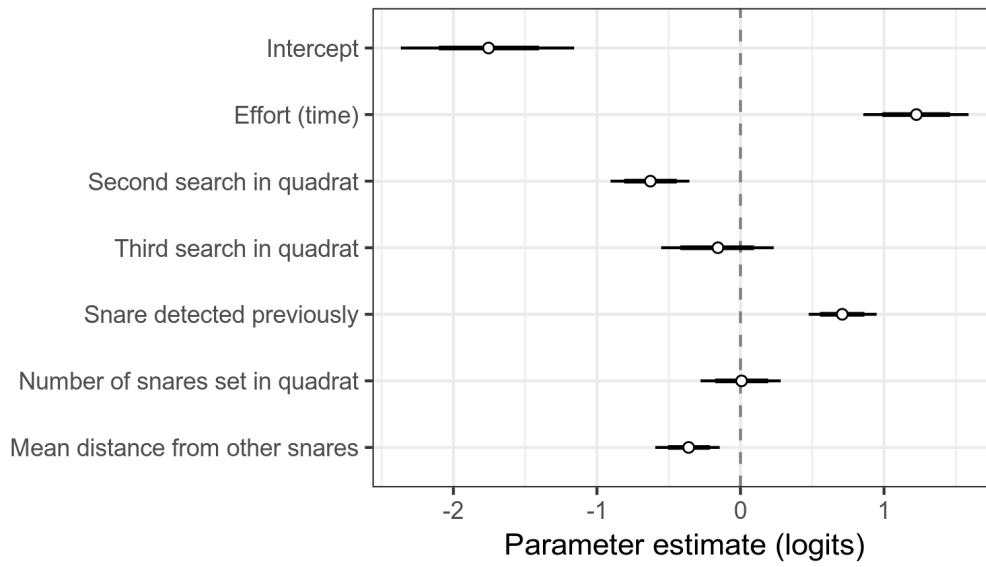
567 Figure 1. Keo Seima Wildlife Sanctuary, Mondulkiri province, Cambodia. Study area highlighted in
568 grey circle.

569



570
 571 Figure 2. Detections in situ; colour coding represents the number of teams which detected a given
 572 snare.
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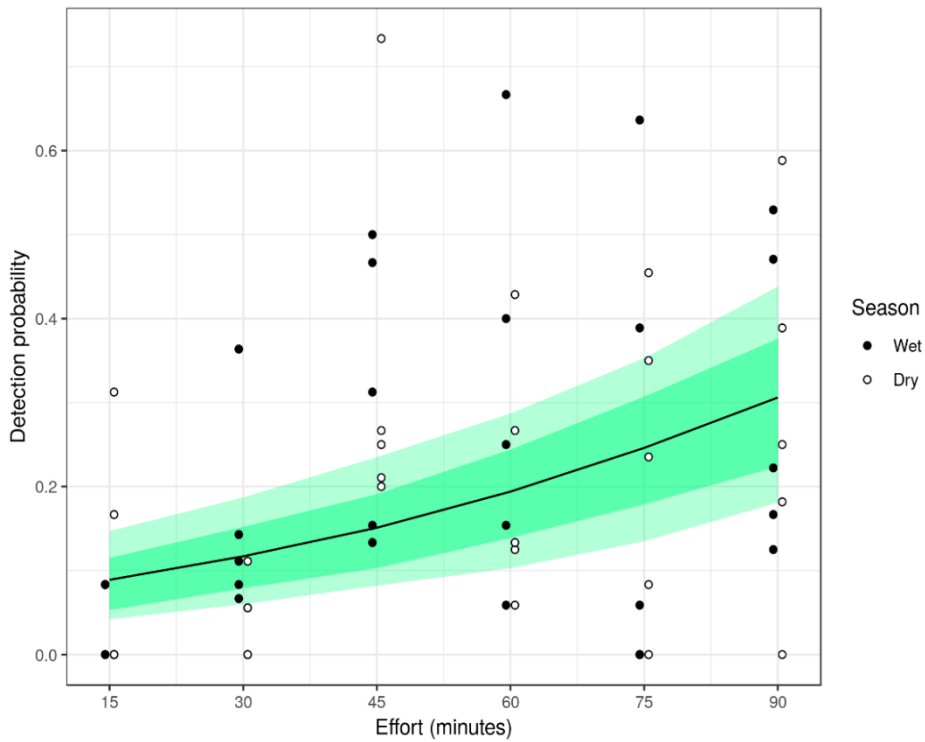
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575

576 Figure 3. Parameter estimates for the best-fitting model, Model 8. Points represent the mean
577 estimate; thick lines represent 80% credible intervals and thinner lines represent 95% credible
578 intervals.

579



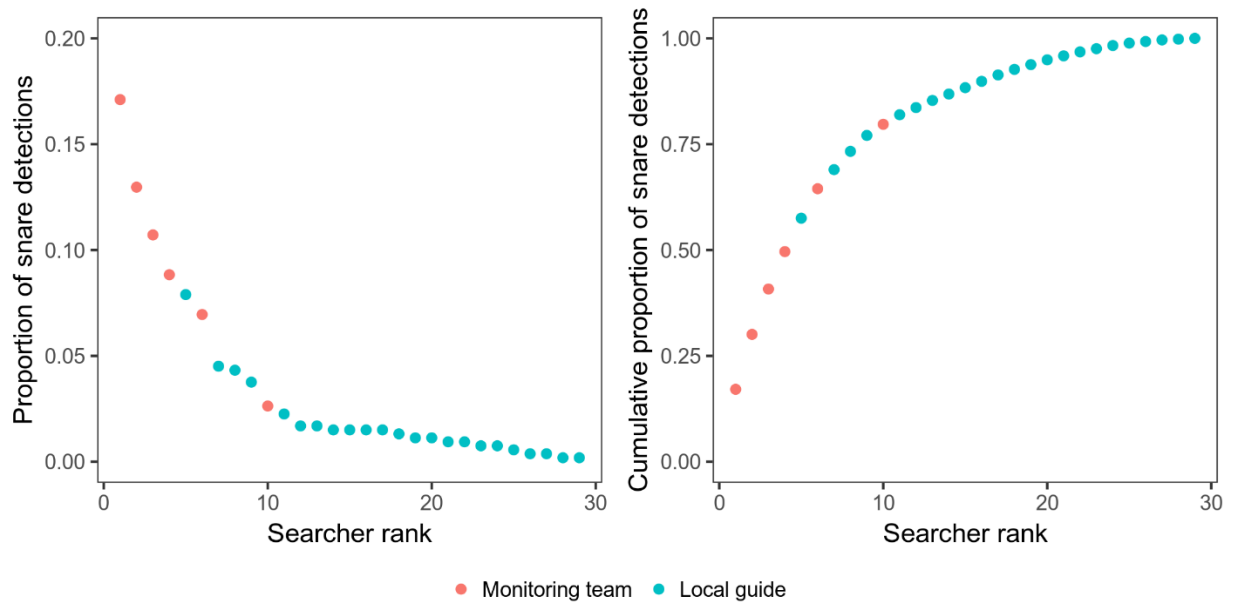
580

581 Figure 4. Effort-detection curve. Black line indicates mean probability of snare detection at differing
 582 levels of effort, predicted from the best-fitting model (Model 8) under the assumption that the quadrat
 583 has not previously been searched. Light green shading indicates the 95% credible interval for
 584 detection probability, while the darker green shading indicates the 85% credible interval. Summaries
 585 of the proportion of snares detected in each transect in the raw data are plotted as filled circles for
 586 wet season and open circles for dry season.

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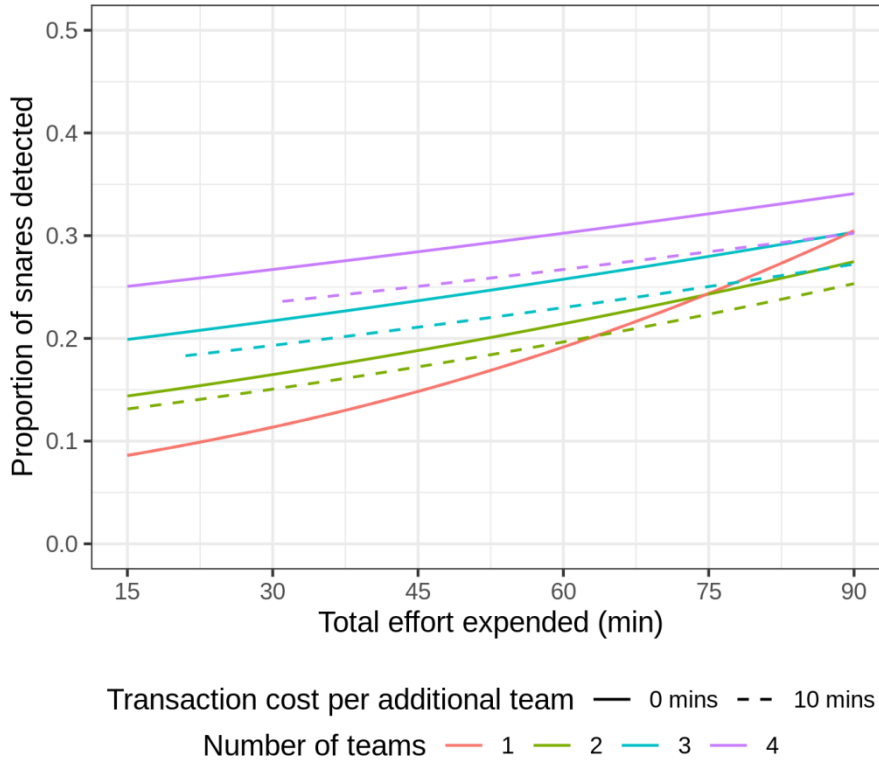
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Figure 5. Proportion of snares detected by individual searchers.

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595

596 Figure 6. Modelled effect of dividing total search effort across multiple search teams on detection
597 probability, when effects of effort on detection and transaction costs vary.

598

599 **Tables**

600 Table 1. Description of variables and interaction terms, and their inclusion in the candidate models fitted to the snare detection data. Grouping variables are
 601 shown below the dividing line.

Variable	Description	Type	Levels	Model											
				0	1	2	3	4	5	6	7	8	9	10	
Effort (time)	Time (minutes) spent searching each quadrat for snares	Continuous	Centred on 45 minutes & scaled by dividing by 60		X		X	X	X	X	X	X	X	X	X
Effort (distance)	Total distanced travelled (km) during each search	Continuous	Centred on its mean value & scaled by two standard deviations				X								
Quadrat search order	Search order	Factor	1 st , 2 nd , 3 rd					X	X	X	X	X	X	X	X
Previous snare detections	Number of times the snare was previously detected by other teams	Factor	0, 1, 2					X	X	X	X	X	X	X	X
Distance to nearest snare	Mean distance (m) of a snare to other snares within the same quadrat	Continuous	Centred on 150m & scaled by dividing by 100					X	X	X	X	X	X	X	X
No. of snares set in quadrat	Total number of snares set in the quadrat	Continuous	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15					X	X	X	X	X	X	X	X
Season	Season in which quadrat was searched	Factor	Wet, Dry						X	X					X
Season: Effort		Interaction term								X					X
HI present during search	Whether HI accompanied the team during the quadrat search	Factor	Yes, No											X	X
Team leader	ID of the team leader	Factor	1, 2, 3, 4											X	X
Vegetation type	Dominant vegetation type within the quadrat	Factor	Bamboo, mixed-deciduous, semi-evergreen										X		X
Presence of animal trail	Whether the snare was set on an animal trail	Factor	Yes, No										X		X
Presence of animal sign	Whether the snare was set near wildlife signs (e.g. foot prints, dung)	Factor	Yes, No										X		X

Presence of water	Whether the snare was set near a stream, river, pond or salt lick	Factor	Yes, No									X			X	
Transect	Transect ID	Factor	1, 2, 3, 4, 5	X	X	X	X	X	X	X	X	X	X	X	X	
Quadrat within transect	Quadrat ID	Factor	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	X	X	X	X	X	X	X	X	X	X	X	X	
Date	Date each search was conducted	Factor	DD-MM-YY	X	X	X	X	X	X	X	X	X	X	X	X	
Team setting snares	ID of the team that set snares in the quadrat	Factor	W1, W2, W3, W4, D1, D2, D3, D4											X	X	X
Team searching for snares	ID of the team searching for snares in the quadrat	Factor	1, 2, 3, 4											X	X	X

602

603

604 Table 2. WAIC values for the fitted models, the difference from the best-fitting model (δ WAIC) and
605 the standard error of that difference ($SE(\delta$ WAIC)). See Table 1 for models.

Model	WAIC	δ WAIC	$SE(\delta$ WAIC)
8	2412.7	0.0	--
9	2414.1	1.5	1.8
10	2424.2	11.5	3.4
4	2461.4	48.7	14.4
5	2462.9	50.2	14.4
7	2465.3	52.6	14.2
6	2465.5	52.9	14.4
3	2471.8	59.1	16.0
1	2515.5	102.8	21.6
0	2527.6	114.9	23.0
2	2532.9	120.2	22.4

606

Experimentally assessing the effect of search effort on snare detectability

Electronic Supplementary Materials

Appendix S1. Experimental Design

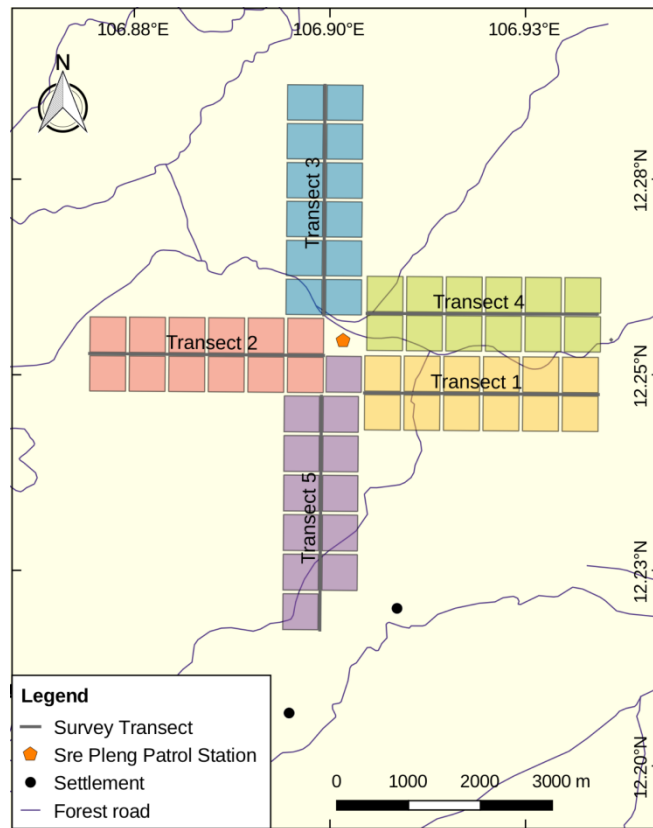


Figure S1a. Location of transects within Keo Seima Wildlife Sanctuary. Five 3.25km long transects were established radiating out from Sre Pleng patrol station. The bottom right quadrat on Transect 5 was relocated to directly below the patrol station due to insufficient forest cover in the original location. Along each transect, 12x 0.25km² (500m x 500m) quadrats were demarcated in QGIS. Each quadrat was numbered, with quadrats 1 & 2 always nearest the patrol station, and quadrats 11 & 12 always furthest from the patrol station.

Table S1a. Example of allocation of a team’s quadrat searches. Numbers in the table represent quadrat ID numbers.

Team	Quadrats in which team set snares	Quadrat search order								
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th
1	6, 10, 12	1	3	5	7	9	11	2	4	8
2	2, 4, 8	11	9	7	5	3	1	6	10	12
3	5, 9, 11	2	4	6	8	10	12	1	3	7
4	1, 3, 7	12	10	8	6	4	2	5	9	11
	Day 1			Day 2				Day 3		



Figure S1b. Levels of search effort allocated per quadrat in a given transect. Search times were fixed across transects. Quadrat ID is shown in the centre of each quadrat.

Appendix S2. Further analyses

Table S2a. Repeated snare detections

Season	Dry		Wet		Total	
	N	%	N	%	N	%
Snares detected by 0 teams	265	60%	249	56%	514	58%
Snares detected by 1 team	104	23%	130	30%	234	26%
Snares detected by 2 teams	61	14%	52	12%	113	13%
Snares detected by 3 teams	12	3%	13	3%	25	3%
Total detections	177	40%	195	44%	372	42%

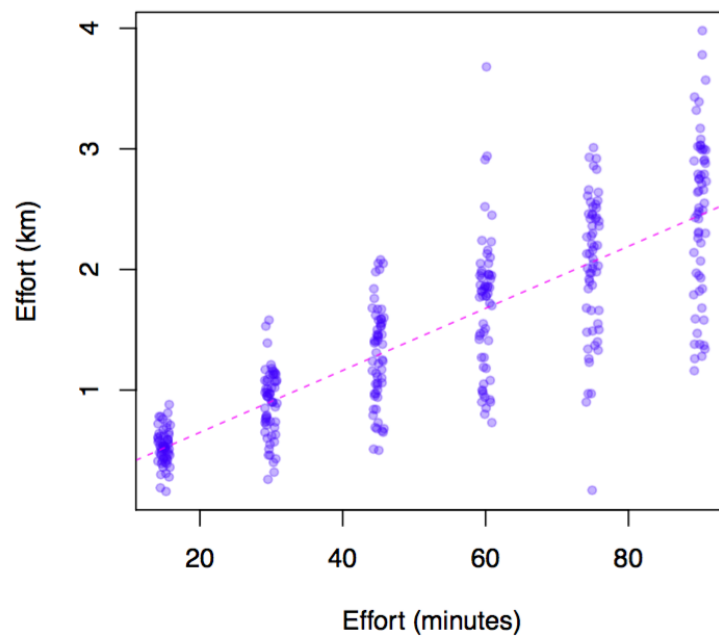


Figure S2a. Relationship between two different measures of effort - distance searched (km) and time spent searching (minutes)

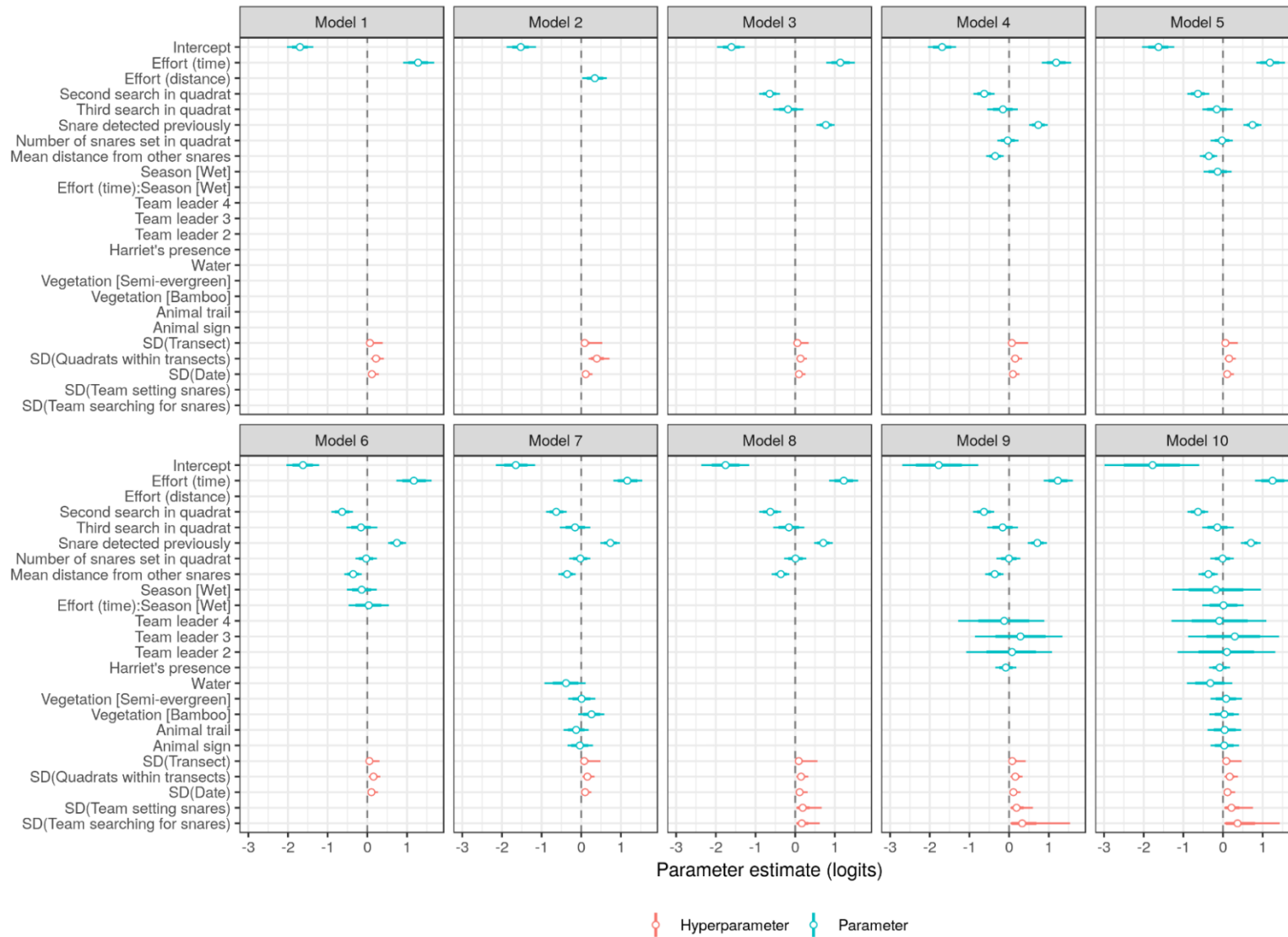


Figure S2b. Parameter estimates for the full candidate set of 10 models. Points represent the mean estimate; thick lines represent 80% credible intervals and thin lines represent 95% credible intervals. Estimates for the standard deviations of hyperpriors for grouping variables are coloured pink while other parameters are coloured turquoise.

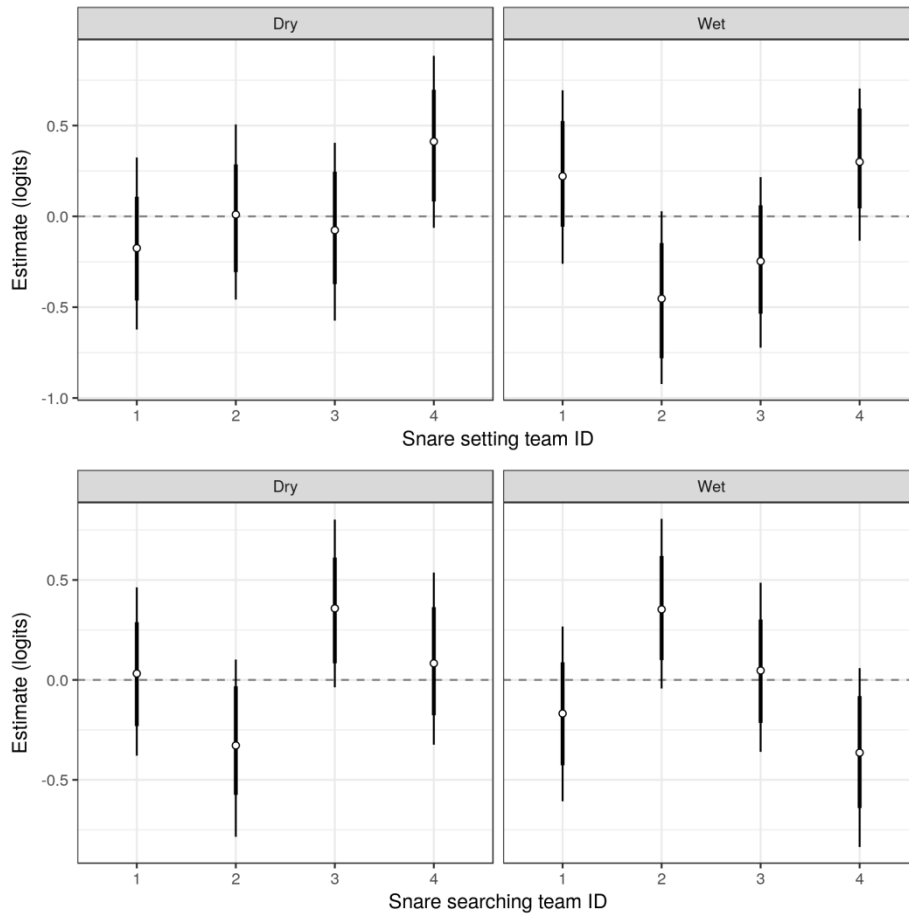


Figure S2c. Comparison of parameter estimates for the effects of the snare setting team (top) and the team searching for snares (bottom) on snare detectability. Results show variability between seasons, but broadly teams that set snares that were less detectable, were more likely find snares set by other teams (e.g. Team 2 in wet season).

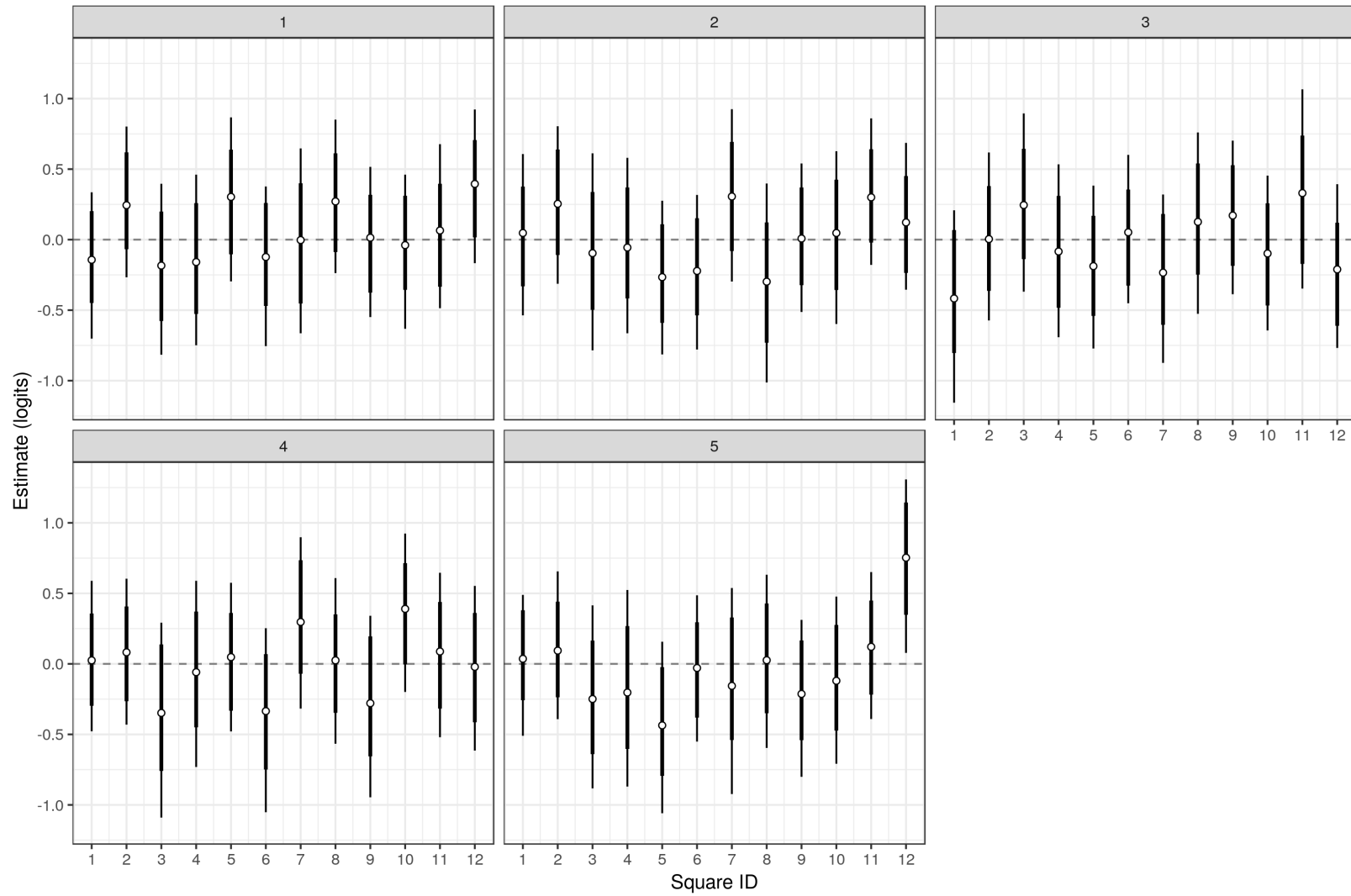


Figure S2d. Comparison of parameter estimates for the effects of Quadrat ID on snare detectability. Results show variability between quadrats, but broadly this was non-significant.

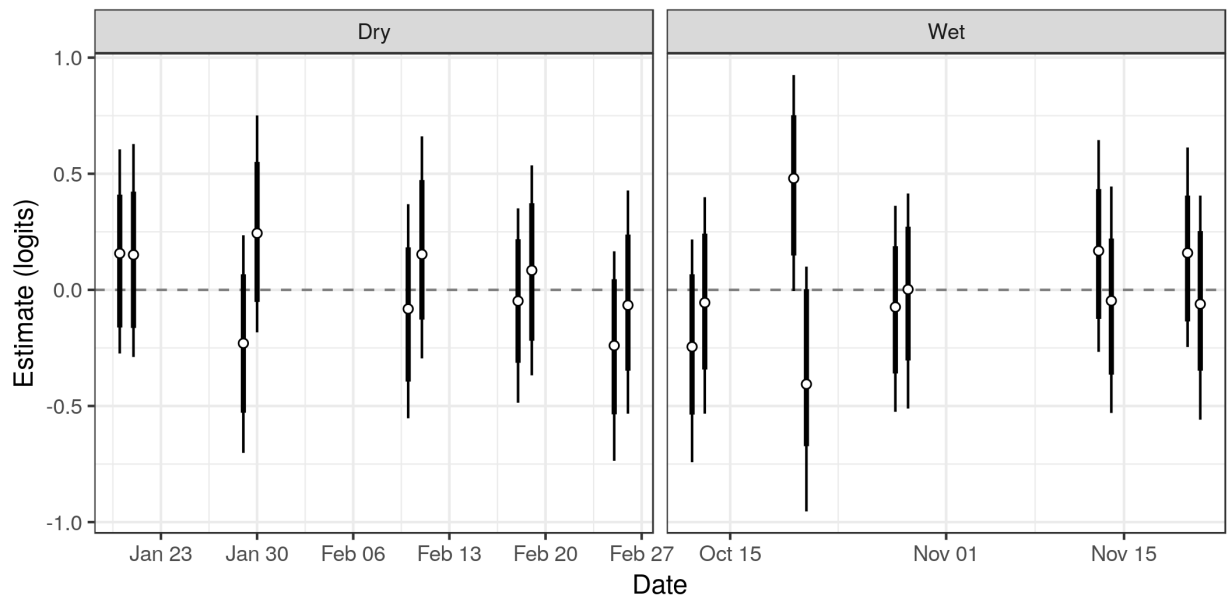


Figure S2e. Comparison of parameter estimates for the effects of season on snare detectability.

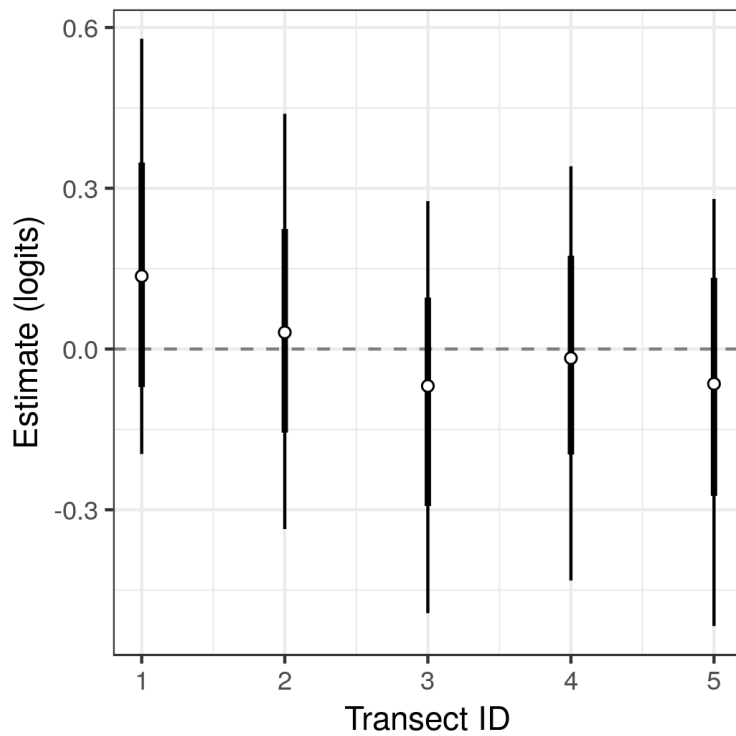


Figure S2f. Comparison of parameter estimates for the effects of transect on snare detectability.

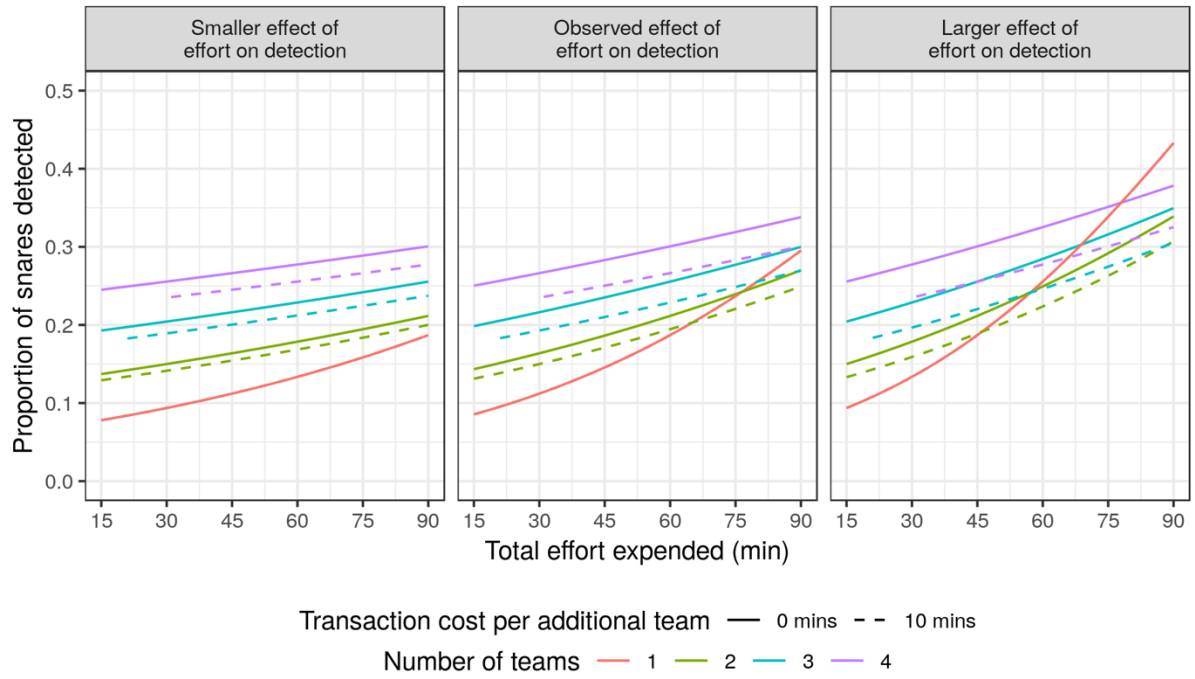


Figure S2g. Variations in modelled effect of dividing total search effort across multiple search teams on detection probability, when effects of effort on detection and transaction costs vary.

Appendix S3. Assessing the performance of individual searchers

Typically, the assignment of rangers to patrolling tasks is undertaken by supervisors, who allocate roles based on their assessment of individual's ability to perform them. Those in possession of certain characteristics (e.g. years on the job, rank, age) may be perceived to be experts, and are therefore assumed to perform better. However, this assumption does not always hold true. The relationship between perceived expertise and actual performance has not been explored in PA management, including the relationship between perceived ability to find snares and actual snare-finding ability.

Predicting performance

Prior to the start of the dry season survey, we asked searchers basic questions about their expertise with regards to setting and searching for snares, how long they had lived or worked in the study area, and whether they thought snares would be easier to find in the wet or dry season. In order to gauge expectations of self-performance we asked individuals *"How well do you think you will perform? where 0 = means you will find no snares, and 10 = means you will find all the snares"*. We then asked each individual to judge how well they thought each of their peers would perform by asking the question *"How well do you think XXXX will perform? If 0 = means they will find no snares, and 10 = means they will find all the snares"*. This exercise was conducted on the first day of the snare experiment fieldwork. Only eight of the 29 local guides were present for this exercise, meaning that consistent predictions of performance and actual performance rankings were only available for the five WCS staff.

We averaged the predictions of performance given to each individual by their peers, and ranked the scores to identify who peers expected to perform best and worst. During analysis, we compared both self and peer predictions against actual performance.

Results

Searcher experience

In total, 35 searchers participated in the study; six individuals from WCS, and 29 local guides. Only one WCS member grew up in KSWs and had experience setting snares as a child, all others originated from different parts of the country. WCS staff had spent on average 11.5 years (37% of their lives) working in KSWs. In contrast, most local guides had lived in KSWs their whole life, and all but one guide set snares as a child. Based on the length of time spent living in KSWs we predicted that local guides would be more familiar with the forest habitat, distribution of wildlife and hunting techniques and thus would be better at detecting snares than WCS staff. However, we found this to be untrue. The mean number of snares detected per transect by each

WCS employee was 6 (min: 2; max: 22) compared to 3 snares per local guides (min: 0, max: 9). The six WCS staff were responsible for detecting 59% of the total snares found.

Self-prediction vs peer-prediction

Of WCS staff, two individuals thought they would find more snares than their peers expected them to (Table 3). These two individuals were both older and in more senior positions. The other three WCS staff members expected to find fewer snares than their peers predicted. No group estimates were available for Searcher F. Results showed that once averaged and ranked, peer-predictions accurately predicted actual performance. Only one individual (the worst performing individual) correctly predicted their own performance. Overall, aggregated and ranked peer-predictions provided a better estimate of performance than self-prediction.

Table 3: Self and peer predictions of performance versus actual performance, measured by the number of successful detections per individual divided by the number of detection opportunities.

Participant	Self		Peer		Actual performance		
	Prediction	Rank	Prediction	Rank	(Detections / Opportunities)		Rank
Searcher C	7	4.5	8.7	1	91 / 597	15%	1
Searcher F	7	4.5	NA	NA	70 / 670	10%	2
Searcher E	8	2.5	8.1	2	57 / 670	8%	3
Searcher D	9	1	7.5	3	47 / 668	7%	4
Searcher A	8	2.5	7.3	4	35 / 658	5%	5
Searcher B	4	6	6.6	5	14 / 483	3%	6
					314 / 2661	12%	

*Predictions based on a scale where 0 = Will find no snares, 10 = Will find all snares.