1 **Double-observer approach with camera traps: Towards an unbiased density**

2 **estimation of unmarked animal populations**

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12

13 **Abstract**

14 Camera traps are a powerful tool for wildlife surveys. However, camera traps may not
15 always detect animals passing in front. This constraint may create a substantial bias in
16 estimating critical parameters such as the density of unmarked populations. We
17 proposed the 'double-observer approach' with camera traps to counter the constraint,
18 which involves setting up a paired camera trap at a station and correcting imperfect
19 detection with a hierarchical capture-recapture model for stratified populations. We
20 performed simulations to evaluate this approach's reliability and determine how to
21 obtain desirable data for this approach. We then applied it to 12 mammals in Japan and
22 Cameroon. The results showed that the approach could correct imperfect detection as
23 long as paired camera traps detect animals nearly independently (Correlation coefficient
24 < 0.2). Camera traps should be installed to monitor a predefined small focal area from
25 different directions to satisfy this requirement. The field surveys showed that camera
26 trap might miss animals by 3 %–40%, suggesting that current density estimation models
27 relying on perfect detection may underestimate animal density by the same order of
28 magnitude. We hope that our approach will be incorporated into existing density
29 estimation models to improve their accuracy.

30 **Introduction**

31 Camera trapping is an innovative research technique and has numerous advantages over
 32 classic approaches based on human observations. For example, this technique is
 33 minimally invasive for animals and habitats and can efficiently collect quantitative
 34 records of ground-dwelling mammals, even elusive and nocturnal species, with
 35 relatively low labour costs¹⁻³. Moreover, by combining it with well-established
 36 statistical approaches^{4,5}, wildlife occupancy can be reliably estimated^{6,7}, abundance or
 37 density determined⁸⁻¹⁰, and species richness assessed¹¹⁻¹³. Furthermore, commercially
 38 available camera traps are becoming cheaper, and their battery duration has also been
 39 improving¹⁴, allowing for large-scale surveys in space and time¹⁵. Data processing (e.g.
 40 species identification) may require a long time and heavy labour costs, but a novel
 41 technology using machine learning may drastically reduce the cost¹⁶⁻¹⁸. Given that
 42 camera trapping will be increasingly used to make critical decisions on wildlife
 43 conservation management, researchers must refine this technique further to avoid
 44 arriving at an erroneous conclusion.

45 One of the primary concerns regarding the application of camera traps may be
 46 that they may not always detect animals passing within the camera detection zone (i.e.
 47 imperfect detection)¹⁹. Studies have shown that camera sensitivity may be primarily a

48 function of animal body mass^{19,20} and may also be affected by many factors, such as
 49 other animal traits (e.g. typical behaviours), environmental conditions (e.g. temperature
 50 and vegetation), and camera efficiency (e.g. trigger speed)²⁰⁻²⁷. This constraint is one of
 51 the reasons why the number of animal passes captured by camera traps per unit time (i.e.
 52 trapping rate) does not always correlate with animal density and cannot be a reliable
 53 index of animal abundance²⁸. A series of statistical models are available to account for
 54 imperfect detections and reliably estimate animal occupancy and abundance⁴.
 55 Nonetheless, researchers cannot help assuming perfect or equal detectability in other
 56 situations. In particular, researchers have proposed several analytical approaches to
 57 estimate animal density without recognizing animal individuals²⁹⁻³⁷. However, most of
 58 these models, except for Chandler and Royle³⁸ and Ramsey *et al.*³⁶, assume that camera
 59 traps can detect animals passing in a specific area within the camera detection zone with
 60 absolute certainty (i.e. perfect detection). Rowcliffe *et al.*¹⁹ suggested that the effective
 61 area of the camera detection zone (codeterminants of the camera sensitivity) can be
 62 determined using a distance sampling approach by applying detection function models
 63 to data on the position where animals were first detected. Although this approach is an
 64 important step in quantifying camera sensitivity, it also requires perfect detection at a
 65 given point within the camera detection zone, which is still questionable.

66 A possible yet untested approach to correcting imperfect detection would be to
67 apply the 'independent double observer approach.' This approach has been used in
68 point-count surveys based on direct observations by human observers³⁹⁻⁴³. In this
69 approach, two observers (camera traps in our context) record animals concurrently and
70 independently, and the detection probability is estimated from the match or mismatch of
71 observation records. Two analytical models, the capture-recapture and *N*-mixture
72 models can be applied to correct imperfect detections⁴¹. The former requires that the
73 observers confer with each other regarding each observation, while the latter may be
74 based solely on the counts by each observer. Nichols *et al.*⁴¹ applied these two models to
75 bird surveys and reported that both models have potential, while the precision of
76 estimates was higher in the former approach. Given that timestamps within images
77 captured by camera traps would allow for efficient reconciling of each count, the
78 capture-recapture model may provide a reliable and efficient means to obtain unbiased
79 estimates of trapping rates.

80 A constraint in applying the capture-recapture model to the double-observer
81 approach may be the assumption that two observers (i.e. camera traps) detect animals
82 independently. If this assumption is violated, detection probability is overestimated,
83 underestimating the number of animal passes. Regrettably, in practice, the detection

84 probability by paired camera traps may depend on numerous unknown factors (e.g.
85 animal body mass, ambient temperature, etc.), resulting in correlated detections. One
86 viable method to deal with this issue would assume a beta distribution instead of a
87 Bernoulli distribution for the detection processes^{44,45}. However, this method may not be
88 a panacea, and thus it is necessary to determine to what extent of the heterogeneity this
89 modelling approach allows for⁴⁶.

90 This study tested the potential of a hierarchical capture-recapture model using
91 the Bayesian framework to correct imperfect detections and estimate the number of
92 animal passes. Firstly, we introduced the hierarchical capture-recapture model for
93 stratified populations. Secondly, Monte Carlo simulations were performed to evaluate
94 the reliability of this approach, focusing on to what extent the model can accommodate
95 the correlated detections. Thirdly, we performed additional simulations to determine
96 desirable camera selections and placements for this approach. Fourthly, we applied the
97 models to the datasets obtained from two different habitats, Cameroon and Japan, and
98 quantified the detection probability of 12 mammals with varying body sizes.

99

100 **Results**

101 **Testing the effectiveness of the hierarchical capture-recapture model**

102 The results of the Monte Carlo simulations showed that the hierarchal capture-recapture
 103 models could provide good estimates with a reasonable confidence interval coverage, as
 104 long as a pair of camera traps detects a passing animal nearly independently (Table 1).
 105 On the other hand, when the correlation coefficient was > 0.2 , detection probability was
 106 overestimated, underestimating the number of animal passes. This pattern did not differ
 107 largely between the lower (0.8) and higher (0.4) detection probabilities (Table 1).

108

109 **Determining suitable camera traps and their installations**

110 The simulations mimicking the detection processes of moving animals showed that
 111 camera models with a lower trigger speed produced a more correlated detection history
 112 (Table 2, Fig. 1). The degree of the correlations also depended on the camera
 113 placements. Even when using a camera model with high trigger speed, the detection
 114 histories of paired camera traps were highly correlated when monitoring the entire field
 115 of view ($r = 0.53$) or the small focal area from the same direction ($r = 0.27$). However,
 116 the correlation significantly decreased when monitoring the small focal area from the
 117 different directions ($r = 0.18$).

118

119 **Field surveys**

120 In total, 12 species were recorded more than 10 times (7 in Japan and 5 in Cameroon),
 121 which were targets for our analyses. Although none of the species was perfectly
 122 detected, the detection probability was estimated relatively high (> 0.8) except for
 123 Japanese field mice (95% CI: 0.56-0.64) and tree pangolins (0.62-0.91). The analysis
 124 results are summarised in Fig. 2 and Supplementary Table S1.

125

126 **Discussion**

127 The Monte-Carlo simulation showed that the hierarchical capture-recapture model
 128 assuming correlated detections (i.e. using a beta-binomial distribution) provided
 129 unbiased estimates of detection probability and the number of animal passes, as long as
 130 the correlation coefficients were ≤ 0.2 . However, as the correlation increased, the model
 131 produced more biased estimates. Regrettably, data obtained from two camera traps may
 132 not be sufficient to estimate the parameters of a beta distribution reliably. Indeed, when
 133 we assumed installing ten camera traps at each station, the model could provide
 134 unbiased estimates even with data having a correlation coefficient of 0.8
 135 (results not shown). Nonetheless, this installation is not practical, and it is more realistic

136 to carefully design a survey to obtain as much independent data as possible.

137 The simulation mimicking the detection processes of moving animals

138 suggested that camera traps should monitor a small focal area from different directions

139 to obtain nearly independent data. A pair of camera traps facing the same direction have

140 the same hazard landscape, so they often fail to detect animals passing through the

141 periphery of the focal area. On the other hand, camera traps installed in different

142 directions can compensate for weak areas with a lower detection probability by one

143 another. In addition, it may be critical to use a camera model with high trigger speed to

144 avoid missing fast-moving animals. There may be other viable approaches to address

145 heterogeneity in detection probability. For example, one could measure the distance and

146 angle of animals from the camera trap and incorporate them into the model as covariates.

147 This approach is called MRDS (Mark-Recapture Distance Sampling), a well-developed

148 theoretical framework. However, this approach does not always function well⁴⁶ and also

149 requires an intensive field survey. The installations proposed here may be much simpler

150 and could reduce the labour costs.

151 The results of our field survey showed that it is critical to account for possible

152 imperfect detection in actual analyses. Although the estimated detection probability was

153 relatively high (>0.8) for most species, camera traps could not detect any species

154 completely. In particular, the detection probability was lower for field mice and tree
 155 pangolins (Fig. 1), possibly reflecting the smaller body mass (field mice) or the scaly
 156 hairs preventing heat radiation from the body interior (tree pangolins). Given that the
 157 size and position of the focal area were specified to maximize the detection probability,
 158 the sensitivity of the camera model might be less than one throughout the detection zone
 159 for these species. This result warns against applying the current density estimation
 160 models without accounting for imperfect detection. In the present study, trapping rates
 161 were underestimated by 4 %–36%, which led directly to underestimating animal density
 162 by the same order of magnitude. Therefore, the double-observer approaches proposed
 163 here should be incorporated into the existing density estimation models relying on
 164 perfect detections.

165 We admit that a shortcoming of this approach remains. In particular, it is
 166 necessary to have more cameras available, which may be a constraint on
 167 implementation. Nonetheless, researchers may be able to challenge these constraints in
 168 various ways. For example, installing a pair of cameras at every camera station may not
 169 be necessary, as long as the variance in detection probability among camera stations is
 170 not too large. Instead, one may choose to install a pair of camera traps in locations with
 171 high trapping rates. It may be effective that the study period may be divided into two

172 parts: one in which two cameras are installed to estimate the detection probability and
 173 one in which one camera is installed to estimate the trapping rate. Furthermore, if our
 174 approach were used at different locations, it would be possible to extrapolate the results
 175 to new sites by incorporating environmental conditions and animal characteristics as
 176 covariates. Given that many surveys estimating the density of marked populations use
 177 paired camera traps at each camera station (to recognize individual animals reliably), it
 178 may also be possible to roughly assess the detection probability from currently available
 179 data using the approach proposed here.

180 This study showed that the double-observer approach, combined with
 181 hierarchical capture-recapture models using Bayesian frameworks, might be an effective
 182 option for estimating detection probabilities and the number of animal passes. We also
 183 suggest that commercially available camera traps have higher detection probability
 184 within a small focal area but still do not perfectly detect animals. The hierarchical
 185 capture-recapture model used here can estimate the distribution of detection probability
 186 and the number of animals passing concurrently, and thus, it is readily incorporated into
 187 the current density estimation models. We hope that our approach will be incorporated
 188 into them to improve their accuracy.

189

190 **Methods**

191 **Model framework**

192 The capture-recapture model applied here is the hierarchical model for stratified
 193 populations proposed by Royle *et al.*⁴⁷. The model aims to estimate local population
 194 size using capture-recapture data from multiple independent locations. In the following,
 195 we briefly describe the model in our context, including addressing heterogeneity in
 196 detection probability.

197 Let us consider that we establish S independent camera stations in a survey area.
 198 Then, we install K camera traps at each station to monitor exactly the same focal area
 199 (totally $S \times K$ camera traps will be used). We assume that these camera traps detect
 200 animals within the focal areas N_T times in total. For animal pass i ($i = 1, 2, 3, \dots, N_T$),
 201 we will obtain (1) at which station the animal is detected (hereafter station identity; g_i),
 202 and (2) how many of the K cameras at the station were successful in detecting the
 203 animal pass (hereafter detection history; y_i). The hierarchal capture-recapture model
 204 uses these two vector data, g_i and y_i .

205 Let the number of the animal passes at station s be N_s ($s = 1, 2, 3, \dots, S$). Then,
 206 we assume that N_s follows a Poisson distribution with a parameter λ . In this case, the

207 probability of passage i occurring at station s is expected to be $\frac{\lambda}{\lambda \times S}$. Thus, station

208 identity, g_i , can be modelled as follows:

209
$$g_i \sim \text{Categorical} \left(\frac{\lambda}{\lambda \times S} \right)$$

210 When the number of the animal passes at station s , N_s , may have larger variation than

211 expected from the Poisson case, we may assume a negative binomial distribution model

212 or may give a random effect to the parameter of the Poisson distribution at the camera

213 station level.

214 The detection history y_i can be modelled using a data augmentation procedure⁴⁷.

215 Specifically, the original detection y_i is artificially augmented by many $M - n$ passes

216 with all-zero histories (i.e. not detected by any camera). The augmented data will

217 consist of the passage that occurred but was not detected by any camera (false zero),

218 which occurs with probability ψ , and the passage that did not occur (structural zeros)

219 with the probability $1 - \psi$. A set of latent augmentation binary variables, $z_1, z_2, \dots, z_M$, is

220 introduced, which denotes the false zero ($z = 1$) and the structural zero ($z = 0$). That is

221
$$z_i \sim \text{Bernoulli}(\psi).$$

222 The augmented data $Y_i (y_1, y_2, \dots, y_n, 0, 0, \dots, 0)$ with zero inflation can be modelled

223 conditional on the latent variables z_i .

224
$$Y_i | z_i = 1 \sim \text{Binomial}(J, p)$$

225 When accounting for the heterogeneity of detection among animal passes, it can be
226 accommodated using a beta distribution as follows;

$$227 \quad Y_i | z_i = 1 \sim \text{Binomial}(J, p_i)$$

$$228 \quad p_i \sim \text{Beta}(\alpha, \beta)$$

229 Note that the expected total number of animal passes can be expressed as $\lambda \times S$. Thus,
230 ψ can be fixed as follows:

$$231 \quad \psi = \frac{\lambda \times S}{M}$$

232 For more details of the models, see Royle *et al.*⁴⁷.

233

234 **Testing the effectiveness of the hierarchical capture-recapture model**

235 We performed Monte Carlo simulations to evaluate the effectiveness of the hierarchical
236 capture-recapture model. Because the model reliability has been confirmed well⁴⁸, we
237 here focused on the effects of heterogeneity in detection probability on the accuracy and
238 precision of the estimates.

239 We assumed that the number of detections by camera traps followed a negative
240 binomial distribution with a mean of 5.0 and dispersion parameter 1.27, which deprived
241 the actual data on an ungulate in African rainforests³⁴. We also assumed two camera
242 traps at 30 stations (i.e. 60 camera traps in total). We generated detection histories (i.e.

243 the number of camera traps successfully detecting animals in each animal passage)
 244 using a beta-binomial distribution with the expected detection probability at 0.8 or 0.4.
 245 We varied the correlation coefficients ($= 1/(\alpha + \beta + 1)$,) from 0.1 to 0.5 in 0.1
 246 increments. The scale parameters of the beta distributions for each scenario are shown
 247 in Table 1.

248 We estimated the model parameters using the Markov chain Monte Carlo
 249 (MCMC) implemented in JAGS (version 3.4.0) in all the simulations. We assumed that
 250 the number of animal passes followed a negative binomial distribution, and the
 251 detection probability did a beta distribution. Since the estimation of scale parameters (α
 252 and β) of the beta distribution, we transformed as $\alpha = p * \phi$ and $\beta = p * (1 - \phi)$ (p is an
 253 expected detection probability). Then we used weakly informative prior (gamma
 254 distribution with shape = 10 and rate = 2) for ϕ while a non-informative uniform
 255 distribution from 0 to 1 for the detection probability⁴⁹. We generated three chains of
 256 3000 iterations after a burn-in of 1000 and thinned by 5. The convergence of models
 257 was determined using the Gelman–Rubin statistic, where values <1.1 indicated
 258 convergence. These procedures were repeated 300 times. The JAGS code is available as
 259 supplementary material (Supplementary R1).

260

261 **Determining a suitable camera installation**

262 The above simulations suggested that a key to safely applying the hierarchical
263 capture-recapture model may avoid correlated detections. To determine a preferred
264 survey design to secure independent detections, we performed additional simulations.
265 Specifically, we tested how the position and the trigger speed of camera traps may affect
266 the independence of detections by considering the process by which cameras detect
267 moving animals.

268 The simulation was performed using similar procedures taken by Rowcliffe *et*
269 *al.*¹⁹. We assumed that the sensor of camera traps has a two-dimensional detection
270 surface defining the instantaneous 'risk' (as analogous to the risk of mortality in
271 survivorship analysis) of an animal being detected at any given location within the
272 camera's field of view (FOV). The instantaneous risk landscape was defined with
273 respect to distance r and angle relative to the camera as follows:

$$274 \quad h = a \left(1 - \exp \left(- \left(r/s \right)^{-b} \right) \right) \exp(-\theta/c)$$

275 where a defines the maximum risk close to the sensor, s and b define the position and
276 shape of decline in risk with distance, respectively, and c defines the rate of decline in
277 risk with angle. We set a , s , b , and c at 0.2, 3.0, 5.0, and 0.5, respectively. Although
278 there is no empirical evidence for this particular function form, the simulated results

279 were comparable to those observed. Note that our interest is not in estimating the actual
280 values of the correlation but instead in obtaining information that will help us decide
281 what cameras to install and how to install them.

282 We made an animal pass through the risk landscape in a straight line in a
283 random direction. The animal movement speed (ms^{-1}) followed a log-normal
284 distribution with a mean ($\pm SD$) of 0.18 ± 0.15 m, which roughly accord with the speed
285 of red duikers in our study sites (Y Nakashima, unpublished data). We then generated a
286 random animal's position to be detected, considering the cumulative risk of detection
287 and the camera trap's trigger speed (for the details, see Rowcliffe *et al.*¹⁹).

288 We considered three designs of camera placements (Fig. 1). The first one is to
289 install two camera traps at the same position (i.e. mounted on the same tree) and in the
290 same direction to monitor the entire field of view within 10 m from the cameras (ins. 1).
291 The second and third one is assumed to monitor a specific small area within the FOV.
292 The focal area was a small equilateral triangle with a side length of 1.9m and was
293 centred within the FOV. The nearest vertex was set to be 1.9m away from the cameras.
294 This area corresponds to the highest detection probability in the camera model used in
295 our field study. This focal area is monitored from the same direction (ins. 2) or different
296 angles of 60 degrees (ins. 3). We then considered using camera models with a fast

297 trigger speed (0.1 s) and a slow (1.5 s) for each installation. Finally, we generated the
 298 detection history of 500 times animal passes and calculated the correlation coefficients
 299 between the two camera traps for each scenario.

300

301 **Field surveys**

302 We conducted a field survey in and around the Boumba-Bek and Nki National Parks in
 303 southeast Cameroon (October 2018 to January 2019) and the Boso Peninsula in Japan
 304 (August-November 2018). The study area of Cameroon consists primarily of evergreen
 305 and semi-deciduous forests. The annual rainfall is approximately 1,500 mm, and the
 306 mean annual temperature is *ca.* 24°C. Typically, the dry season occurs from December
 307 to February and the rainy season is from March to November. The Boso Peninsula was
 308 in the southern part of Chiba Prefecture in central Japan (35N °N, 140E). The vegetation
 309 consists of either broad-leaved evergreen forests (*Castanopsis sieboldii* and *Quercus*
 310 spp.) or coniferous plantations (*Cryptomeria japonica* and *Chamaecyparis obtusa*). The
 311 monthly mean temperature was 20.6 ± 5.9 °C during the study period, with the highest
 312 in August (27.4 °C) and the lowest (13.6 °C) in November.

313 The simulations suggest that camera traps monitor the predefined focal area
 314 from different positions (see below). According to the results, we used the camera traps

315 with a high trigger speed (0.15 s) (Browning Strike Force Pro, BTC-5HDP, Browning,
316 Missouri, US) at both study sites. We regarded two camera traps to monitor the same
317 equilateral triangle area as in the simulation from different directions by 60 degrees (the
318 right panel of Fig. 1). We surrounded the focal area with a white rope and manually
319 filmed it with camera traps as a reference. The rope was removed after filming to avoid
320 disturbing the animal behaviour. We set camera traps at approximately 0.7 m above
321 ground without baits or lures. We used the 'video mode' and designated the video length
322 as 20 s and the delay period between videos at 1 s (minimum delay period in this
323 product). In Japan, we established seven camera stations at least 2 km apart and
324 installed two camera traps at each station. In Cameroon, we set 26 camera stations at
325 least 2-km apart from each other. Since the number of camera stations is not enough to
326 estimate the expected number of animal passes in Japan, we focused on the detection
327 probability

328 We determined whether animals passed within or outside the focal area by
329 superimposing videos and the reference image. We used only images of animals
330 crossing the focal area for subsequent analyses. We then matched each detection from
331 the two cameras to determine whether two camera traps successfully recorded an animal
332 pass. We applied the model to the detection probability of the species detected more

333 than 10 times in both Japan and Cameroon. The analysis was limited to images in which
 334 the animal species were reliably identified. We plotted the estimated detection
 335 probability against the median value of body mass (kg), drawn from Ohdachi et al.⁵⁰ for
 336 animals in Japan and Kingdon⁵¹ for those in Cameroon.

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503

504 **Contributions**

505 YN conceived the ideas and designed the methodology; SH and YG collected the data;
 506 KM and YG performed video analyses; YN wrote the manuscript. All authors
 507 contributed critically to the drafts and approved the final manuscript for publication.

508

509 **Ethics declarations**

510 **Competing interests**

511 The authors declare no competing interests.

512

513 **Data availability**

514 All the data used here is available in Supplementary Information.

515 **Figure legends**

516 **Fig. 1.** A schematic diagram showing the installations of three focal areas assumed in
517 the simulation mimicking detection processes of moving animals. The circular sector
518 shows the hazard landscape of the detection zone. The open and filled circle shows the
519 positions of camera traps. In ins. 1 (left panel), the focal area was defined as the entire
520 field of view within 10 m from the cameras. In ins. 2 (centre panel), the focal was
521 restricted to an equilateral triangle with a side of 1.9 m. The distance from the camera to
522 the nearest vertex was assumed to be 1.9 m (shown in white lines). Finally, in ins. 3
523 (right panel), the same equilateral triangle was monitored from different angles of 60
524 degrees. The camera traps were assumed to have a sensor detection range of 42°. In the
525 right panel, the landscape of the second camera trap was shown in a grey polygon.

526
527 **Fig. 2.** The estimated detection probability of 12 species within a small focal area (1.56
528 m²) in Cameroon (5 species) and Japan (7 species) using the capture-recapture models
529 for stratified populations. Error bar shows the 95% credible interval.

530 **Table**

Table 1. Summary of the Monte Carlo simulations to test the reliability of the hierarchical capture-recapture model. Results are the mean of estimated median detection probability P , the expected number of animal passes (λ), and their 95% credible interval (CI) coverage of the densities. Parameter estimation of the capture-recapture model was performed using the Markov chain Monte Carlo (MCMC) method, and their variances and credible limits were calculated as the posterior summary.

Detection	Correlation	P		λ	
probability	Coefficient	Mean	CI Coverage (%)	Mean	CI Coverage (%)
0.8	0.1	0.79	94.0	5.13	90.7
	0.2	0.82	91.7	5.01	92.3
	0.3	0.85	71.0	4.85	90.0
	0.4	0.89	42.7	4.67	87.3
	0.5	0.92	13.7	4.55	89.7
0.4	0.1	0.37	96.3	5.48	86.3
	0.2	0.42	98.3	4.75	87.7

0.3	0.48	85.0	4.32	87.3
0.4	0.56	38.0	3.65	63.3
0.5	0.63	11.3	3.10	31.7

531

Table 2. Summary of the Monte Carlo simulations to test the reliability of the hierarchical capture-recapture model.

Results are the mean of estimated median detection probability P and the expected number of animal passes ($lambda$) and their 95% credible interval (CI) coverage of the densities. Parameter estimation of the capture-recapture model was performed using the Markov chain Monte Carlo (MCMC) method, and their variances and credible limits were calculated as the posterior summary.

Setting values				Estimated values			
Detection probability	Correlation Coefficient	Scale parameters		P		$lambda$	
		alpha	beta	Mean	CI Coverage (%)	Mean	CI Coverage (%)
0.8	0.1	7.20	1.80	0.79	94.0	5.13	90.7
	0.2	3.20	1.80	0.82	91.7	5.01	92.3

	0.3	1.87	0.47	0.85	71.0	4.85	90.0
	0.4	1.20	0.30	0.89	42.7	4.67	87.3
	0.5	0.80	0.20	0.92	13.7	4.55	89.7
0.4	0.1	0.40	0.60	0.37	96.3	5.48	86.3
	0.2	3.60	5.40	0.42	98.3	4.75	87.7
	0.3	1.60	2.40	0.48	85.0	4.32	87.3
	0.4	0.93	1.40	0.56	38.0	3.65	63.3
	0.5	0.40	0.60	0.63	11.3	3.10	31.7

Figure-1

Figure-2