

1 **Dealing with trade-offs in destructive sampling designs for**
2 **occupancy surveys**

3

4 Running head: Trade-offs in destructive sampling

5

6 Stefano Canessa^{1,*}, Geoffrey W. Heard¹, Peter Robertson², Ian R. K. Sluiter²

7

8 ¹ School of BioSciences, University of Melbourne, Victoria, Australia

9 ² School of Science, Information Technology and Engineering, Federation University,

10 Ballarat, Victoria, Australia.

11 * (corresponding author): Ph: +61-3-8344 0120, E-mail: science@canessas.com

12

13 **Keywords.** Bayesian; decision analysis; detection; monitoring; optimisation; replication;

14 wildlife.

15 **Abstract**

16 Occupancy surveys should be designed to minimise false absences. This is commonly
17 achieved by increasing replication or increasing the efficiency of surveys. In the case of
18 destructive sampling designs, in which searches of individual microhabitats represent the
19 repeat surveys, minimising false absences leads to an inherent trade-off. Surveyors can
20 sample more low quality microhabitats, bearing the resultant financial costs and producing
21 wider-spread impacts, or they can target high quality microhabitats where the focal species is
22 more likely to be found and risk more severe impacts on local habitat quality. We show how
23 this trade-off can be solved with a decision-theoretic approach, using the Millewa Skink
24 *Hemiergis millewae* from southern Australia as a case study. *Hemiergis millewae* is an
25 endangered reptile that is best detected using destructive sampling of grass hummocks.
26 Within sites that were known to be occupied by *H. millewae*, logistic regression modelling
27 revealed that lizards were more frequently detected in large hummocks. If this model is an
28 accurate representation of the detection process, searching large hummocks is more efficient
29 and requires less replication, but this strategy also entails destruction of the best microhabitats
30 for the species. We developed an optimisation tool to calculate the minimum combination of
31 the number and size of hummocks to search to achieve a given cumulative probability of
32 detecting the species at a site, incorporating weights to reflect the sensitivity of the results to
33 a surveyor's priorities. The optimisation showed that placing high weight on minimising
34 volume necessitates impractical replication, whereas placing high weight on minimising
35 replication requires searching very large hummocks which are less common and may be vital
36 for *H. millewae*. While destructive sampling methods are sometimes necessary, surveyors
37 must be conscious of the ecological impacts of these methods. This study provides a simple
38 tool for identifying sampling strategies that minimise those impacts.

39

40 **Introduction**

41 Occupancy surveys are fundamental to mapping and monitoring species distributions [1], as
42 well as habitat modelling [2], systematic conservation planning [3] and environmental impact
43 assessments [4,5]. In their simplest application, occupancy surveys provide strict assessments
44 of the presence or absence of a species at a given locality; the species is present if it is
45 detected and absent if it is not. However, this intuitive result is confounded by the fact that
46 species may go undetected during a survey, producing a “false absence” [6,7,8]. False
47 absences can lead to biased estimates of the probability of occupancy [9,10], and may
48 undermine the application of survey results.

49

50 The reliability of occupancy surveys therefore depends on achieving a sufficiently high
51 probability of detecting the target species if it is present [6,7]. Estimates of the probability of
52 detection during a single survey can be derived using occupancy models, which jointly
53 estimate the probability of site occupancy [5,11,12]. In turn, one can estimate the number of
54 surveys needed to increase the cumulative probability of detection at each site to some
55 desired threshold [13,14]. However, the number of surveys also influences the overall size
56 and cost of a survey program. Hence, in addition to the primary objective of attaining a
57 desired cumulative probability of detection, surveyors will also strive to minimise replication.
58 Several examples exist of how to approach this problem from an economic perspective
59 [5,13,15]. However, certain survey types also have important ecological costs which need to
60 be considered in survey design. Destructive sampling of favoured microhabitats is an
61 example.

62

63 Destructive sampling techniques are employed to detect cryptic animals that cannot be
64 readily observed or trapped. Occupancy surveys that use destructive sampling entail

65 searching and destroying favoured microhabitats of the focal species within a given site; in
66 which case searches of multiple microhabitats may be considered equivalent to repeated
67 surveys at each site [16, p. 162]. Examples of destructive sampling include raking beds of
68 leaf litter when searching for fossorial lizards [17], prizing open or lifting (and therein
69 destroying) decaying woody cover when sampling salamanders [18,19], removing exfoliating
70 bark from trees when searching for arboreal arthropods [20] and drag-netting beds of aquatic
71 vegetation for fish or amphibian larvae [18,21]. If microhabitats do not vary in quality for the
72 target species, then the probability of detection at each microhabitat will not vary, and
73 minimising the impacts of destructive sampling is equivalent to minimising the number of
74 microhabitats searched. However, microhabitats usually vary in quality, in which case the
75 focal species is more likely to utilise (and be detected in) some microhabitats than others. In
76 turn, this produces a trade-off in destructive sampling designs, between minimising the loss
77 of high quality microhabitats and minimising replication. To minimise replication, the most
78 effective approach is to sample the highest quality microhabitats, because this confers a
79 higher probability of detection per sampling unit. However, this would also lead to the
80 destruction of the highest quality microhabitats for the target species. Conversely, one could
81 limit sampling to lower quality microhabitats, but the resulting increase in replication may
82 come at considerable financial cost and produce wider-spread impacts on the focal species.

83

84 This combination of objectives - attaining a threshold cumulative probability of detection
85 whilst balancing sampling replication and impacts on high quality microhabitats - leads to an
86 optimisation problem that we believe has not previously been solved. Here we show that
87 when a model of the sampling process for a given species is available, it is possible to use a
88 simple decision-theoretic approach to solve this trade-off in destructive sampling designs. We

89 demonstrate this approach using the design of surveys for the Millewa Skink *Hemiergis*
90 *millewae* Coventry, a locally endangered lizard from southern Australia [22].

91

92 **Methods**

93 *Case study and field surveys*

94 In the state of Victoria, *Hemiergis millewae* is recognized as critically endangered, occurring
95 only in the semi-arid Mallee vegetation of the far north-west [23]. *Hemiergis millewae*
96 inhabits hummocks of *Triodia scariosa* ('Spinifex'), and the most effective means of
97 surveying for this species is to rake and dismantle individual *Triodia* hummocks [24]. While
98 this ensures that individual lizards are found if they occupy a hummock, it entails destruction
99 of the hummock and possibly a reduction in the habitat suitability of the site for the species.
100 Hence, while further surveys are required to ascertain the conservation requirements of *H.*
101 *millewae* in Victoria [23,24], it is important to minimise the impacts of these surveys on the
102 species.

103

104 Two of us (PR and IS) conducted surveys for *H. millewae* at 52 sites across the Murray-
105 Sunset National Park in north-western Victoria in the Austral autumn of 2011 to improve
106 knowledge of the distribution of this species [24]. Sites were rectangular quadrats measuring
107 50 m by 20 m, each including multiple *Triodia* hummocks. A variable number of these
108 hummocks were searched at each site, dependent on hummock density and when and if
109 *H. millewae* was found (surveys were terminated as soon as an individual was detected). Each
110 hummock was methodically dismantled and searched for individual lizards. Sand and litter
111 beneath the hummock were also gently raked for lizards sheltering therein. The dimensions of
112 each *Triodia* hummock were measured, and hummock volume (m³) estimated by assuming a

113 standard rectangular shape. The growth phase of each hummock was also recorded as: 1 =
114 seedling, 2 = immature clump, 3 = mature clump, 4 = mature clump with central tillers
115 beginning to collapse, 5 = central tillers collapsed forming a broken or unbroken ring.
116 Distance to the nearest hummock and the leaf litter cover around each hummock were also
117 measured. All survey work undertaken during this study was carried out in accordance with
118 the requirements of animal ethics and research permits (ethics approval n. 22-08, issued by
119 the Wildlife and Small Institutions Animal Ethics Committee of the Department of Primary
120 Industries; research permit n. 10004684, issued by Department of Sustainability and
121 Environment in accord with Wildlife Act 1975 and National Parks Act 1975).

122

123 *Statistical analysis*

124 Initially, we sought to model the probabilities of site occupancy and detection of *H. millewae*
125 through the use of a standard occupancy model [11], using individual hummocks within a site
126 as replicate surveys, and seeking relationships between hummock characteristics and the
127 probability of detection on a per hummock basis. However, the data were insufficient to
128 separate the probability of site occupancy and detection, and hence, to gain estimates of the
129 effects of individual hummock properties on the probability of detection. Therefore, we
130 assessed the influence of hummock attributes on the detection of *H. millewae* using data from
131 the subset of sites at which this species was observed at least once (19 sites and 85
132 hummocks), in which case occupancy of these sites by the species was certain (following
133 [7,25]). Candidate logistic regression models were fitted to the hummock-level detection data
134 from known occupied sites as follows:

$$\begin{aligned} \text{logit}(p_i) &= \alpha + \beta X_i, \\ Y_i &\sim \text{Bernoulli}(p_i) \end{aligned} \qquad \text{Eqn 1}$$

136 where Y_i is the detection or non-detection of *H. millewae* in hummock i , represented as a
137 Bernoulli variable with probability p_i , which is a logistic function of hummock attribute X_i .
138 Due to sample size limitations, additive combinations of hummock attributes were not
139 assessed. We also fitted a “null” model with constant p . This led to a candidate set of five
140 single-variable models (null, hummock volume, hummock growth phase, distance to nearest
141 hummock and surrounding leaf litter). Treating detections in different hummocks as
142 independent was justified by the fact that detections were not spatially correlated (Moran I
143 statistic standard deviate = -0.397, p -value = 0.654).

144

145 The relative fit of these models to the data was assessed using the deviance information
146 criterion [DIC: 26]. DIC balances the unexplained variance in the model and the number of
147 parameters. The model with the lowest DIC value (DIC_{\min}) is considered the most
148 parsimonious, and models with $\Delta DIC < 2$ ($\Delta DIC = DIC - DIC_{\min}$) are considered largely
149 indistinguishable. Model fitting was completed using JAGS [27], with uninformative priors
150 for all parameters (code and data provided in supporting information S1 and S2). For each
151 model we ran 100,000 iterations on three Markov chains, after discarding the first 50,000
152 iterations as a burn-in. The model with the greatest support was used to estimate the
153 cumulative probability of detection (P) at a site after surveying n hummocks, as [7]:

$$154 \quad P = 1 - \prod_{i=1}^n (1 - p_i) \quad \text{Eqn 2}$$

155 where p_i is the probability of detection at hummock i as given by Eqn 1.

156

157 Equation 2 shows that P increases with n ; however, when p_i depends on the characteristics of
158 the hummocks searched, as per Eqn 1, it is also possible to increase P by selectively
159 searching particularly suitable hummocks. As above, the decision about which parameter to
160 manipulate depends on the relative importance given to the number or the quality of the

161 hummocks searched. We explored how the optimal survey program varied depending on this
 162 importance. A weighting (w_n) of between 0 and 1 was assigned to the alternative objectives of
 163 minimising the number of hummocks sampled and minimising the quality of hummocks
 164 searched, with the total weight summing to one. We combined the two variables influencing
 165 P (n : number of hummocks searched; X : predictor of the quality of each hummock searched)
 166 into a single objective function of aggregate impact (A) to be minimised. This function differs
 167 slightly depending on the relationship between detection and the predictor of hummock
 168 (microhabitat) quality. When the relationship is positive, the aggregate impact A can be
 169 calculated as:

$$170 \quad A = \frac{n - \min(n)}{\max(n) - \min(n)} \times w_n + \frac{X - \min(X)}{\max(X) - \min(X)} \times (1 - w_n) \quad \text{Eqn 3}$$

171 where n and X are each rescaled to range between 0 and 1 (by subtracting the minimum value
 172 observed during field surveys and dividing by the observed range), and w_n indicates the
 173 weight on replication and $1 - w_n$ the weight on microhabitat quality. In the event of a negative
 174 relationship between detection and the microhabitat-related predictor, Eqn 3 can be
 175 reformulated as:

$$176 \quad A = \frac{n - \min(n)}{\max(n) - \min(n)} \times w_n + \frac{\max(X) - X}{\max(X) - \min(X)} \times (1 - w_n) \quad \text{Eqn 4}$$

177
 178 We used the Solver add-in in MS Excel to minimise the value of A by finding the optimal
 179 combination of n and X (assuming all n surveyed hummocks have quality X or better). To
 180 reflect the influence of n and X on the probability of detection, we replaced p_i in Eqn 2 with
 181 the back-transformed logistic expression from Eqn 1 (using the mean estimated parameters),
 182 and set the resulting P as a constraint of the optimisation. We carried out the analysis for a
 183 target of $P = 0.95$ across all possible weights on hummock number and quality. We also set
 184 the minimum and maximum values for n and X observed in the field as constraints to the

185 optimisation, to prevent the optimal strategy from entailing unrealistic or impractical values
186 of n and X . The spread sheet for the optimisation is provided in supporting information S3.

187

188 *Sensitivity analysis*

189 In the procedure described above, we chose to subset the data and only analyse detections
190 from sites that were known to be occupied; however, some of the sites where *H. millewae*
191 was not observed might in fact have been occupied. If so, the regression parameters in Eqn 1
192 could be overestimates of the true relationship between hummock characteristics and the
193 probability of detection. Therefore, we repeated all analyses using the full dataset, which
194 represents the other end of the uncertainty spectrum (the possibility that all sites where the
195 species was not detected were in fact occupied, and hence, the full data provides accurate
196 estimates of the effects of hummock characteristics on the probability of detection). We
197 repeated the model selection procedure and obtained estimates for Eqn 1 from the model with
198 the highest DIC support. We then re-evaluated the optimal survey protocol (as per Eqn 3)
199 using the hummock-detection relationship estimated from the entire dataset.

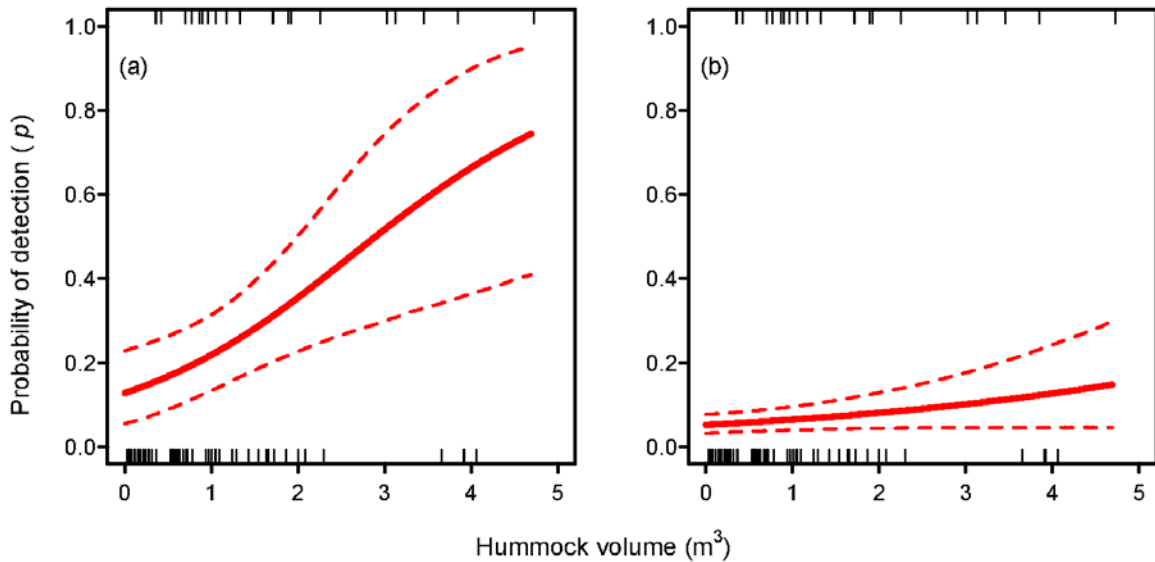
200

201 **Results**

202 Within the subset of sites that were known to be occupied by *H. millewae*, the model that
203 included hummock volume as a predictor of the probability of detection (p_i) received the
204 most support (DIC = 88.4). The second-best model, including hummock stage, received
205 effectively no support (Δ DIC = 7.8). The probability of detection in a given hummock
206 increased linearly with its volume (Figure 1a). As expected, results changed when we
207 modelled hummock detection data from all sites. The model including hummock volume still
208 showed the highest level of support based on DIC (the null model being second, with Δ DIC =

209 1.4). However, the estimated relationship between hummock volume and skink detection was
210 less markedly positive (Figure 1b).

211



212

213 **Figure 1. Relationship between the volume of a hummock and the probability of detecting**

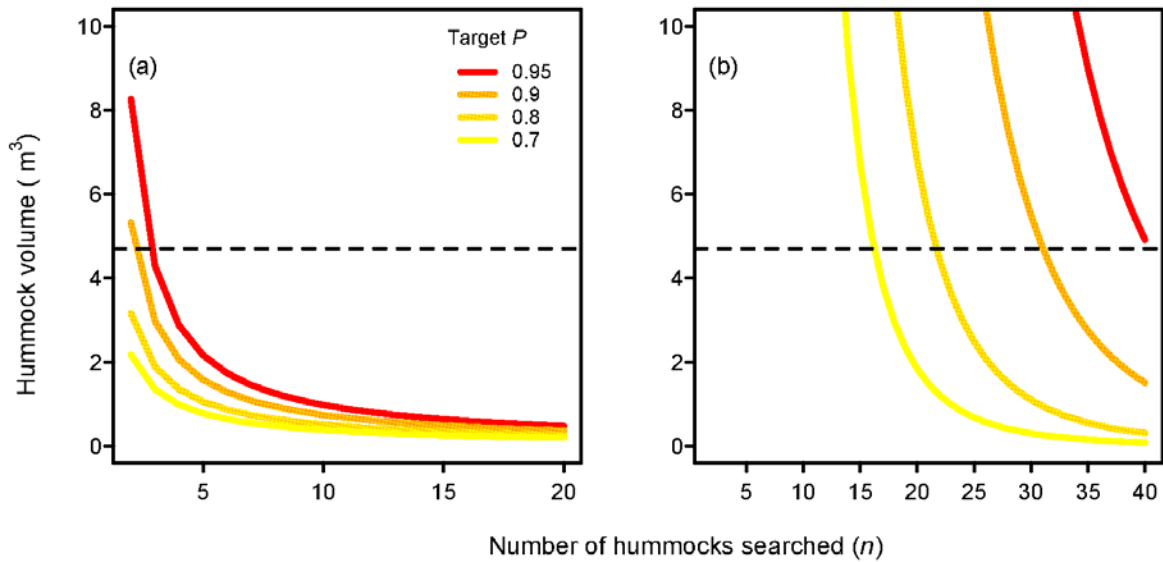
214 *Hemiergis millewae* in that hummock. Panel (a) depicts the relationship estimated from sites with
215 known occupancy only; panel (b) depicts the relationship estimated from the full set of surveyed sites.

216 Dashed lines represent 95% credible intervals. Inner tick marks display the volume of hummocks in
217 which *H. millewae* was detected (top) or not detected (bottom).

218

219 Figure 2a depicts the trade-off between the number and size of hummocks that must be
220 sampled to achieve a threshold cumulative probability of detection (P) using the relationship
221 between hummock volume and the probability of detection estimated from known occupied
222 sites. In general, the minimum volume of hummocks searched needed to increase
223 considerably when searching less than five hummocks (Figure 2a). When the probability of
224 detection was estimated using the full dataset, the cumulative probability of detection
225 depended almost exclusively on replication, as detection would increase appreciably only
226 under unrealistic values of hummock volume ($>10 \text{ m}^3$). In turn, high targets for the

227 cumulative probability of detection could only be achieved with very large amounts of
 228 replication, even for the maximum value of hummock volume observed in the field ($n = 17$
 229 for $P = 0.7$, $n = 22$ for $P = 0.8$, $n = 31$ for $P = 0.9$ and $n = 45$ for $P = 0.95$; Figure 2b).
 230



231
 232 **Figure 2. Relationship between search strategies and the cumulative probability of detection of**
 233 ***Hemiergis millewae* at a site.** The solid lines show the number of *Triodia* hummocks that must be
 234 searched at each site to achieve a given cumulative probability of detection (P) of *H. millewae*,
 235 dependent on the minimum volume of each hummock searched. Panel (a) depicts the relationship
 236 using the detection model derived from sites with known occupancy only; panel (b) depicts the
 237 relationship using the detection model derived from the full set of surveyed sites. Contour lines depict
 238 this relationship for four different values of P : 0.95, 0.9, 0.8 and 0.7 (top to bottom). The dashed
 239 horizontal line indicates the maximum hummock volume recorded in the model data.
 240
 241 Figure 3a depicts the minimum combination of the number and volume of hummocks that
 242 must be searched at a site to reach a cumulative probability of detecting *H. millewae* of 0.95
 243 while minimising aggregate impact, dependent on the weight given to minimising the number
 244 of hummocks searched per site (w_n), and assuming the relationship between hummock

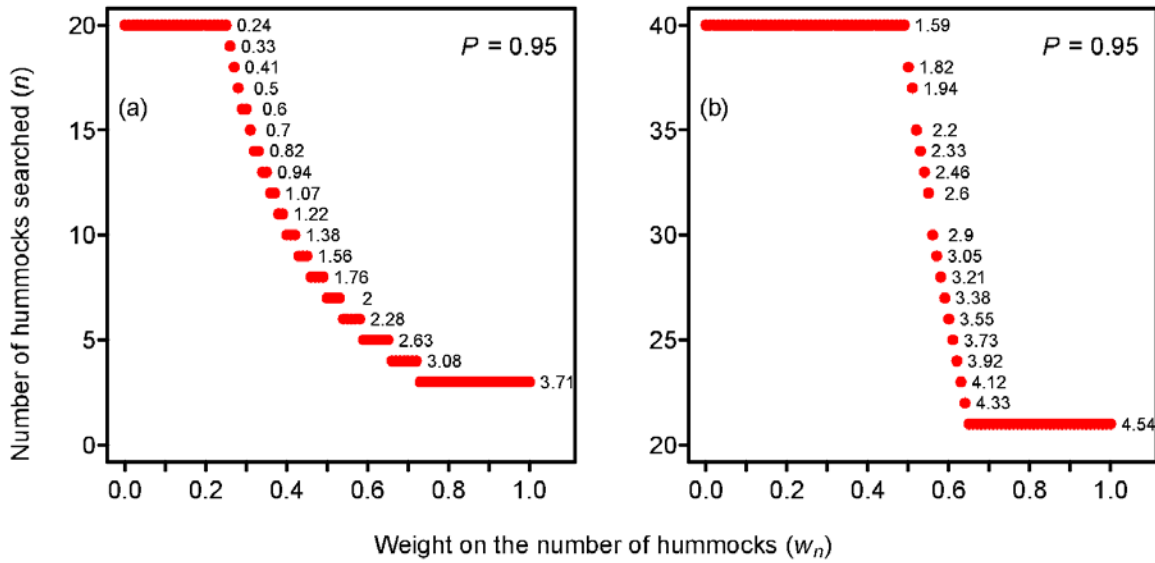
245 volume and detection estimated from the subset of sites that were known to be occupied.
246 Placing high weight on reducing the volume of hummocks searched (low w_n) necessitated
247 high sampling replication. For $P = 0.95$ and w_n between 0 and 0.25, this was equivalent to the
248 upper constraint we set in the optimisation problem ($n = 20$). Only two of the 52 sites
249 surveyed during this study received an equivalent level of replication, suggesting that this
250 level of replication may not be practical in many situations. The number of hummocks to be
251 sampled fell exponentially as w_n increased once a particular threshold of this weight was
252 crossed ($w_n = 0.26$). However, when high weight was placed on minimising replication ($w_n \geq$
253 0.66) the optimal strategy required very large hummocks to be searched. For example, $P =$
254 0.95 could be achieved by searching three very large hummocks (3.71 m^3) at a site (Figure
255 3b), but only six hummocks in the training data were this size or greater (7%). These results
256 reflect the constraints we chose for the optimisation: in this sense, the optimisation not only
257 identifies the minimum number and size of hummocks to search given differing weights on
258 these two criteria, but can also indicate how practical those weightings are for real-world
259 field surveys.

260

261 For the case in which the probability of detection per hummock was estimated from the full
262 dataset, no detection target above 0.7 could be achieved under the original constraint of $n \leq$
263 20 hummocks searched per site, as this would require unrealistic values of hummock volume
264 (as above). Removing this constraint allows optimal strategies to be calculated, but they were
265 likely to be impractical (Figure 3b). For example, a detection target of 0.95 could only be
266 reached by sampling at least 40 hummocks of 1.59 m^3 (Figure 3b); equating to 42 hummocks
267 of above average size (the mean observed in the field was 1.12 m^3).

268

269



270

271 **Figure 3. Optimal search strategies for *Hemiergis millewae*.** The plot depicts the minimum number
 272 of *Triodia* hummocks that must be searched at each site to reach a cumulative probability of detection
 273 of *H. millewae* of 0.95, dependent on the minimum volume of each hummock searched and the weight
 274 (importance) given to either minimising replication or the quality of hummocks searched. The x-axis
 275 displays the weight on minimising the number of hummocks sampled (w_n). The weight on minimising
 276 the volume of each hummock searched is 1 minus w_n . Hence, a value of 0.5 on the x-axis corresponds
 277 to placing equal weight on minimising the number of hummocks sampled and minimising their
 278 quality. The text to the right of each combination shows the minimum volume of the hummocks to be
 279 searched to achieve the threshold cumulative probability of detection of 0.95. Panel (a) indicates the
 280 optimal strategies based on the detection model derived from sites with known occupancy only; panel
 281 (b) describes the optimal strategies based on the detection model derived from the full set of surveyed
 282 sites.

283

284 Discussion

285 Our method provides a simple solution to the trade-off implicit in destructive sampling
 286 designs for occupancy surveys as exemplified by the case of *H. millewae*. Our results suggest
 287 that larger *Triodia* hummocks are preferentially used by *H. millewae*, and may be an

288 important microhabitat for this species. Yet, if this is true, dismantling large hummocks is
289 also the most effective survey technique for this species. Hence, when designing occupancy
290 surveys for *H. millewae*, surveyors face a dilemma: they need to reduce the probability of
291 false absences to an acceptable level, but must also minimise the number and quality of
292 hummocks sampled. Our optimisation approach can be used to identify survey strategies that
293 solve this trade-off, dependent on the importance surveyors give to the number and quality of
294 the microhabitats that will be affected at each site.

295

296 When the relationship between hummock characteristics and the probability of detection was
297 estimated from known occupied sites, the trade-off in our case study became especially
298 important if high weight was placed on minimising the number of hummocks to be sampled
299 per site ($w_n \geq 0.66$). Under this constraint, the number of hummocks to sample at each site
300 was small (three), but the size of these hummocks needed to be large ($\geq 3.71 \text{ m}^3$) to attain a
301 cumulative probability of detection of 0.95. As above, hummocks of this size were rare in the
302 field data (7%). Hence, targeting hummocks of this size entails the removal of a locally
303 scarce and potentially important resource for *H. millewae*. Since lower threshold values of P
304 would require less searching effort, they would also entail less overall impacts; however,
305 even moderate detection targets and weight on minimising the number of hummocks sampled
306 could lead to impacts of some magnitude on the target species. For example, re-running our
307 analysis with $P = 0.8$ and $w_n = 0.4$ indicated that five hummocks of at least 1.5 m^3 would
308 need to be destroyed to attain the detection threshold. Less than one-third of hummocks in
309 our training dataset were equal to or greater than this size, indicating that they are also a
310 relatively uncommon and potentially important resource. Selecting very large hummocks can
311 also create further problems: here, we interpret spatial sub-units within a site (hummocks) as
312 temporal replicates. Destructive sampling necessarily occurs without replacement, and could

313 generate bias due to the dependency between samples [28]. This bias may become more
314 severe as the ‘population’ (the subset of hummocks with the desired characteristics) becomes
315 smaller.

316

317 Considerations such as these are fundamental to setting the weighting scheme in our
318 approach. Ideally, the weight given to either minimising replication or minimising the quality
319 of microhabitats sampled would reflect information on the impact of different sampling
320 protocols on the target species. Where available, occupancy or population models could be
321 used to establish the effect of microhabitat removal on population trends [see for example
322 19,29], and weights derived based on the sensitivity of the species to microhabitat loss. One
323 could even extend the approach presented here to explicitly take the modelled effect of
324 microhabitat loss on population trends into account. For example, the decrease in occupancy
325 or population size that would result from a given sampling strategy (i.e., combination of n
326 and X) could be used as the basis for defining A (the aggregate impact) in the objective
327 function (Eqn 3). The aim would remain to minimise A using Eqn 3 whilst maintaining the
328 desired value of P , because both would be determined by the values of n and X (P through
329 Eqn 1 and 2, and A through the occupancy or population model). As above, our data were
330 insufficient to model site occupancy by *H. millewae* while accounting for imperfect detection.
331 However, should subsequent studies enable the relationship between the probability of site
332 occupancy and site hummock attributes to be estimated, the change in the probability of site
333 occupancy that would result from a given survey strategy (based on the reduction in the
334 density and volume of hummocks it would cause) could be considered directly in the
335 objective function.

336

337 Nevertheless, obtaining quantitative estimates of the impacts of particular sampling regimes
338 may not be possible in many situations. Our simple weighting scheme allows expert
339 judgement on the sensitivity of the target species to destructive sampling to be incorporated
340 into the sampling design. With an appropriate experimental design, adaptive management
341 approaches [30] could be used to learn about the actual impacts of different sampling regimes
342 and update the subjective weightings. Practical aspects of sampling will also influence the
343 range of feasible survey strategies. In our case study, we set upper thresholds for the number
344 and volume of hummocks to search based on the values observed in the field. Moreover, as
345 we have shown here, one can reference the optimal combination of the number and quality of
346 microhabitats to search for a given weighting scheme back to data on the density and quality
347 of microhabitats that are available in the field, to assess the practicality of each weighting
348 scheme. Our simple method therefore also allows the realities of sampling to be accounted
349 for when identifying the optimal sampling regime. We view this as a particularly useful
350 feature of the optimisation approach presented here.

351

352 Uncertainty will also surround the estimates of the relationship between the features of
353 microhabitats and detection of the target species. A common cause of uncertainty will be the
354 scarcity of existing data. In our case study, this problem led to us being unable to fit a
355 standard occupancy model to the data. We chose instead to model the effect of microhabitat
356 characteristics on the probability of detection using data from sites with known occupancy;
357 however, this might have led to overestimates of the true microhabitat-detection relationship.
358 If so, the recommended optimal strategy may be insufficient to meet the target cumulative
359 probability of detection. On the other hand, if some or all of the sites where the species was
360 not detected were truly unoccupied, using all available data might produce underestimates of
361 the microhabitat-detection relationship. In this case, the cumulative probability of detection

362 given by the recommended optimal strategy may exceed the target probability; and a strategy
363 with a lower aggregate impact could have been chosen instead.

364

365 The effects of uncertainty will be higher when heavy emphasis is placed on minimising
366 replication or minimising impacts on high quality microhabitats, because, as revealed by our
367 optimisations, extreme weightings lead to extreme sampling regimes (very high replication or
368 very high quality of microhabitats to sample). Surveyors should ideally assess the
369 ramifications of uncertainty in the microhabitat-detection relationship for the optimal
370 sampling strategy. In a Bayesian context, investigators can do so by repeating the
371 optimisation when sampling randomly from the posterior distribution of the parameters of the
372 detection model. Our spreadsheet can be used to run simulations of this kind, by sampling at
373 random from specified parameter distributions for the coefficients of the detection model
374 instead of entering fixed values. One can then identify the optimal search strategy for each
375 combination of parameter estimates, and obtain a distribution of optimal strategies which
376 reflects parametric uncertainty. Several add-ins to MS Excel such as MCSimSolver
377 ([http://www3.wabash.edu/econometrics/EconometricsBook/Basic%20Tools/ExcelAddIns/M](http://www3.wabash.edu/econometrics/EconometricsBook/Basic%20Tools/ExcelAddIns/MCSimSolver.htm)
378 [CSimSolver.htm](http://www3.wabash.edu/econometrics/EconometricsBook/Basic%20Tools/ExcelAddIns/MCSimSolver.htm)) can be used to run such simulations.

379

380 In this study, we limited our scope to the impacts of hummock destruction on the target
381 species. However, destructive sampling for *H. millewae* will impact, to some degree,
382 numerous co-occurring species in Mallee environments that utilise *Triodia* hummocks
383 [23,31,32,33]. Impacts on co-occurring species may be an important consideration for
384 destructive sampling designs in general. These additional impacts can be accounted for using
385 the approach we have presented here. As for the single-species case, the weighting scheme
386 could be set using expert opinion on the impact of sampling on other species, or quantitative

387 estimates of the ecological impact of particular sampling designs could be incorporated
388 directly into the objective function.

389

390 Non-destructive sampling methods are always preferable, but destructive searches are
391 necessary for some species. Yet studies that rely on such methods run the risk of undermining
392 their very purpose, by negatively impacting the focal species or community [19]. When
393 destructive methods are necessary, practitioners should carefully consider the trade-off
394 between minimising replication and minimising the destruction of high quality microhabitats.
395 The method we have presented provides a simple quantitative tool for assessing this trade-off.

396

397 **Acknowledgements**

398 We thank Karen Nalder and Karin Sluiter (Mallee Catchment Management Authority for
399 administering the project, and Kym Schramm and Richard Prentice (Parks Victoria) for their
400 assistance. Thanks are extended to Paul Coventry for assistance with fieldwork and to Sally
401 Edwards for data entry. Cindy Hauser, Michael McCarthy and two anonymous referees
402 provided very useful comments on an earlier draft.

403

404 **References**

405 1. Elith J, Leathwick JR (2009) Species distribution models: ecological explanation and
406 prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics* 40:
407 677-697.

408 2. Gu W, Swihart RK (2004) Absent or undetected? Effects of non-detection of species
409 occurrence on wildlife-habitat models. *Biological Conservation* 116: 195-203.

- 410 3. Rondinini C, Wilson KA, Boitani L, Grantham H, Possingham HP (2006) Tradeoffs of
411 different types of species occurrence data for use in systematic conservation planning.
412 *Ecology Letters* 9: 1136-1145.
- 413 4. Garrard GE, Bekessy SA, McCarthy MA, Wintle BA (2008) When have we looked hard
414 enough? A novel method for setting minimum survey effort protocols for flora surveys.
415 *Austral Ecology* 33: 986-998.
- 416 5. Tyre AJ, Tenhumberg B, Field SA, Niejalke D, Parris KM, et al. (2003) Improving
417 precision and reducing bias in biological surveys: estimating false-negative error rates.
418 *Ecological Applications* 13: 1790-1801.
- 419 6. McArdle BH (1990) When are rare species not there? *Oikos* 57: 276-277.
- 420 7. Kéry M (2002) Inferring the absence of a species: a case study of snakes. *Journal of*
421 *Wildlife Management* 66: 330-338.
- 422 8. Wintle BA, Walshe TV, Parris KM, McCarthy MA (2012) Designing occupancy surveys
423 and interpreting non-detection when observations are imperfect. *Diversity and Distributions*
424 18: 417-424.
- 425 9. MacKenzie DI (2005) What are the issues with presence-absence data for wildlife
426 managers? *Journal of Wildlife Management* 69: 849-860.
- 427 10. Kéry M, Schmidt BR (2008) Imperfect detection and its consequences for monitoring for
428 conservation. *Community Ecology* 9: 207-216.
- 429 11. MacKenzie DI, Nichols JD, Lachman GB, Droege S, Royle JA, et al. (2002) Estimating
430 site occupancy rates when detection probabilities are less than one. *Ecology* 83: 2248-2255.

- 431 12. Wintle BA, McCarthy MA, Parris KM, Burgman MA (2004) Precision and bias of
432 methods for estimating point survey detection probabilities. *Ecological Applications* 14: 703-
433 712.
- 434 13. Field SA, Tyre AJ, Possingham HP (2005) Optimizing allocation of monitoring effort
435 under economic and observational constraints. *Journal of Wildlife Management* 69: 473-482.
- 436 14. Bailey LL, Hines JE, Nichols JD, MacKenzie DI (2007) Sampling design trade-offs in
437 occupancy studies with imperfect detection: examples and software. *Ecological Applications*
438 17: 281-290.
- 439 15. MacKenzie DI, Royle JA (2005) Designing occupancy studies: general advice and
440 allocating survey effort. *Journal of Applied Ecology* 42: 1105-1114.
- 441 16. Mackenzie DI, Nichols JD, Royle JA, Pollock KH, Bailey LL, et al. (2006) *Occupancy*
442 *estimation and modeling: inferring patterns and dynamics of species occurrence*. Burlington,
443 MA: Elsevier Academic Press.
- 444 17. McDonald PJ, Pavey CR, Fyfe G (2012) The lizard fauna of litter mats in the stony desert
445 of the southern Northern Territory. *Australian Journal of Zoology* 60: 166-172.
- 446 18. Heyer WR, Donnelly MA, McDiarmid RW, Hayek L-AC, Foster MS (1994) *Measuring*
447 *and monitoring biological diversity: standard methods for amphibians*. Washington, D.C.:
448 Smithsonian Institution Press.
- 449 19. Otto CR, Bailey LL, Roloff GJ (2013) Improving species occupancy estimation when
450 sampling violates the closure assumption. *Ecography* 36: 1299-1309.

- 451 20. Basset Y, Springate N, Aberlenc H, Delvare G (1996) A review of methods for sampling
452 arthropods in tree canopies. In: Stork NE, Adis J, Didham RK, editors. Canopy arthropods.
453 London: Chapman & Hall. pp. 27-52.
- 454 21. Kubečka J, Godø OR, Hickley P, Prchalová M, Říha M, et al. (2012) Fish sampling with
455 active methods. Fisheries Research 123: 1-3.
- 456 22. Cogger H (2000) Reptiles and Amphibians of Australia. Reed New Holland, Sydney.
457 New South Wales, Australia.
- 458 23. Nimmo DG, Spence-Bailey LM, Kenny S (2008) Range extension of the Millewa Skink
459 *Hemiergis millewae* in the Murray-Sunset National Park, Victoria. The Victorian Naturalist
460 125: 110-113.
- 461 24. Robertson P, Coventry P, Sluiter IRK (2011) Survey for the threatened Millewa Skink
462 (*Hemiergis millewae*) in Murray-Sunset National Park, April 2011. Melbourne: Unpublished
463 report to the Mallee Catchment Management Authority.
- 464 25. Parris KM, Norton TW, Cunningham RB (1999) A comparison of techniques for
465 sampling amphibians in the forests of south-east Queensland, Australia. Herpetologica: 271-
466 283.
- 467 26. Spiegelhalter DJ, Best NG, Carlin BP, van der Linde A (2002) Bayesian measures of
468 model complexity and fit (with discussion). Journal of the Royal Statistical Society, Series B
469 (Statistical Methodology) 64: 583-639.
- 470 27. Plummer M (2005) JAGS: just another Gibbs sampler. Proceedings of the 3rd
471 International Workshop on Distributed Statistical Computing (DSC 2003), Vienna, Austria.

- 472 28. Kendall WL, White GC (2009) A cautionary note on substituting spatial subunits for
473 repeated temporal sampling in studies of site occupancy. *Journal of Applied Ecology* 46:
474 1182-1188.
- 475 29. Goode MJ, Horrace WC, Sredl MJ, Howland JM (2005) Habitat destruction by collectors
476 associated with decreased abundance of rock-dwelling lizards. *Biological Conservation* 125:
477 47-54.
- 478 30. McCarthy MA, Possingham HP (2007) Active adaptive management for conservation.
479 *Conservation Biology* 21: 956-963.
- 480 31. Brown S, Clarke MF, Clarke R (2009) Fire is a key element in the landscape-scale habitat
481 requirements and global population status of a threatened bird: The Mallee Emu-wren
482 (*Stipiturus mallee*). *Biological Conservation* 142: 432-445.
- 483 32. Kelly LT, Nimmo DG, Spence-Bailey LM, Haslem A, Watson SJ, et al. (2011) Influence
484 of fire history on small mammal distributions: insights from a 100-year post-fire
485 chronosequence. *Diversity and Distributions* 17: 462-473.
- 486 33. Nimmo DG, Kelly LT, Spence-Bailey LM, Watson SJ, Haslem A, et al. (2012) Predicting
487 the century-long post-fire responses of reptiles. *Global Ecology and Biogeography* 21: 1062-
488 1073.
- 489
- 490

491 **Supporting Information**

492

493 **S1 Code.** JAGS code for the detection model for *Hemiergis millewae*.

494 **S2 Dataset.** Data for the detection model.

495 **S3 Spreadsheet.** Spreadsheet for optimisation of search strategies.