Towards meaningful monitoring: a case study of a threatened rodent

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Abstract

Detecting trends in species' distribution and abundance is essential for conserving threatened species, and depends upon effective monitoring programs. Despite this, monitoring programs are often designed without explicit consideration of their ability to deliver the information required by managers, such as their power to detect population changes. Here, we demonstrate the use of existing data to support the design of monitoring programs aimed at detecting

24 declines in species occupancy. We used single–season occupancy models and baseline data to

25 gain information on variables affecting the occupancy and detectability of the threatened brush-

26 tailed rabbit-rat *Conilurus penicillatus* (Gould 1842) on the Tiwi Islands, Australia. This

27 information was then used to estimate the survey effort required to achieve sufficient power to

28 detect changes in occupancy of different magnitudes. We found that occupancy varied

29 spatially, driven primarily by habitat (canopy height and cover, distance to water) and fire

30 history across the landscape. Detectability varied strongly among seasons, and was three times

31 higher in the late dry season (July–September), compared to the early dry (April–June).

32 Evaluation of three monitoring scenarios showed that conducting surveys at times when

33 detectability is highest can achieve a substantial improvement in the ability to detect declines,

34 thus reducing the survey effort and costs. Our study highlights the need for careful

35 consideration of survey design related to the ecology of a species, as it can lead to substantial

36 cost savings and improved insight into species population change via monitoring.

Keywords

Introduction

41 The loss and fragmentation of natural habitats, introduction of non-native species and global

42 climate change are driving declines in species distribution and abundance worldwide (Chapin

43 III *et al.* 2000; Butchart *et al.* 2010; Barnosky *et al.* 2011). Effective conservation depends on

44 the ability to detect population trends through reliable, effective and efficient monitoring

45 programs (Reynolds *et al.* 2011). Ecological monitoring refers to the process of gathering

46 information about an ecological variable (e.g. species distribution) at different points in time

47 and space to assess change (Yoccoz *et al.* 2001). Despite their importance, monitoring

48 programs are often designed without regard for their ability to deliver the types of information

49 required by land managers (Legg & Nagy 2006; Guillera-Arroita *et al.* 2010; Peel *et al.* 2015).

50 Disregarding imperfect detection (when a given method does not detect a species where it

51 occurs) can reduce the reliability of estimates of population trends, particularly when detection

52 varies in space or time (MacKenzie *et al.* 2002; Field *et al.* 2005; Wintle *et al.* 2004). The

53 purpose of monitoring programs differs from that of baseline surveys, which are largely

54 designed to collect information on species distribution and richness (i.e. the number of distinct

55 species that occur within a region). Baseline surveys may not be suitable for collecting the

56 types of data required to infer population trends in some or all of the species they report on, but

57 they do provide valuable data that can be used to inform monitoring programs.

58 A useful variable in ecological monitoring is species occupancy (Holt *et al.* 2002), that

59 is, the proportion of sites occupied by a species. Monitoring occupancy is typically cheaper

60 and less technically demanding than measuring population abundance or density, which can be

61 expensive to implement on large scales (Nimmo *et al.* 2015); consequently monitoring

62 abundance may suffer from limited statistical power to detect change (Field *et al.* 2005), despite

63 the available statistical methods to account for detectability (Borchers *et al.* 2012; Buckland *et*

64 *al.* 1993; Royle 2004). Change in occupancy is considered an important measure of extinction

65 risk, for example in the International Union for the Conservation of Nature (IUCN) Red List

66 of Threatened Species (IUCN 2017). Occupancy methods that account for imperfect detection

67 (MacKenzie *et al.* 2002) have been used for many large-scale monitoring programs, and

68 applied across diverse taxa including mammals (Wibisono *et al.* 2011), birds (Royle and Kéry

69 2007), reptiles (McGrath *et al.* 2015), amphibians (Petitot *et al.* 2014) and invertebrates

70 (MacKenzie 2003).

71 Inadequate survey design can lead to low statistical power to detect trends of interest

72 (Guillera-Arroita & Lahoz-Monfort 2012). Key decisions in the design of occupancy surveys

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include the total survey effort required to detect effect sizes of ecological relevance with confidence, when and where to monitor and how to allocate a survey budget, given the recognised trade-off between the effort applied at each given site (and thus the quality of site-level data) (Mackenzie & Royle 2005; Bailey *et al.* 2007). One way to guide monitoring design decisions is to use existing data to inform the likely values of relevant system parameters. Based on these, the expected performance of alternative monitoring strategies in meeting the objectives of the monitoring program can be explored.

In this study, we use existing baseline survey data and occupancy models to examine alternative monitoring strategies for a threatened species, the brush-tailed rabbit-rat *Conilurus penicillatus* (Gould 1842), in one of its last remaining safe–havens, the Tiwi Islands in northern Australia. Australia has suffered a remarkably high rate of mammal extinctions over the past two centuries (Woinarski *et al.* 2015), amounting to loss of at least 30 terrestrial mammals (Fisher *et al.* 2014). The Tiwi Islands are now one of the few areas in Australia to retain a complete pre-European assemblage of mammals, but recent evidence suggests that small mammal populations, including *C. penicillatus*, are in decline (Firth *et al.* 2006; Davies *et al.* 2016). The distinct Tiwi Islands subspecies (*C. penicillatus melibius)* has also been highlighted as one of the 20 mammals most likely to go extinct in the next two decades (Geyle *et al.* 2018), suggesting that emergency action must be taken to improve its conservation status.

We estimated the occupancy and detectability of *C. penicillatus* using a baseline dataset collected across the Tiwi Islands in 2000–2002. We then used this information to examine the statistical power of different monitoring strategies for detecting declines of relevance to IUCN Red Listing. We note here that the aim of this paper is not to make recommendations to the IUCN for listing or assessment, but to advise on how much monitoring effort is required to confidently detect a decline when one occurs. With this, we address in part the priority need to establish an appropriate monitoring program for this species (see Woinarski *et al.* 2017).

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Methods

Study area

The Tiwi Islands comprise Melville (5788 km^2) and Bathurst (1693 km^2) islands, and are ~20 km north of mainland northern Australia. Both islands have similar environments and experience a highly seasonal (wet–dry tropical monsoonal) climate (average rainfall of 1,860 mm and 146 mm in the wet and dry seasons respectively) (Australian Bureau of Meteorology 2015). Vegetation includes savanna woodland and open forest dominated by eucalypts *Eucalyptus* and *Corymbia* spp., with smaller areas of *Melaleuca* woodland, sedgeland, grassland, rainforest, mangrove and coastal dunes. Approximately 5% of the islands are covered in short–rotation *Acacia mangium* forestry plantations, mineral sand mining and urban areas (Richards *et al.* 2012).

Study species

Conilurus penicillatus is a semi–colonial, medium–sized (150 g) native rodent with a now patchy distribution in northern Australia and southern New Guinea (Firth *et al.* 2010). It is listed as Vulnerable under the IUCN Red List (Burbidge & Woinarski 2016), and under Australian (Environment Protection and Biodiversity Conservation Act, 1999) legislation. It is listed as Endangered under Northern Territory legislation (Northern Territory Parks & Wildlife Conservation Act, 2012). The species has suffered a dramatic range contraction, most likely in response to increases in the frequency, intensity and size of landscape fires, and a consequent simplification of vegetation structure (Firth *et al.* 2010), which may make them more susceptible to predation by feral cats and other predators (Davies *et al.* 2016; Woinarski *et al.* 2011). *Conilurus penicillatus* mostly occurs in tall open eucalypt forests and woodlands that burn infrequently, with a sparse to moderate mid-storey and an under-storey of perennial grasses (of which the seeds and stems are primary diet items, Firth *et al.* 2005; Firth *et al.* 2010). Breeding in *C. penicillatus* is seasonal, occurring over at least four months with

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123   juveniles predominantly entering populations in the mid to late dry season (June–September)

124   (Taylor and Horner 1971; Firth 2007).

125   *Survey data*

126   We used data collected as part of a larger baseline wildlife survey conducted in the early

127   2000s (Firth *et al.* 2006). A total of 338 sites were sampled in native vegetation across the Tiwi

128   Islands (223 sites on Melville Island and 115 on Bathurst Island) (Fig. 1). Each site was visited

129   only once between 2000 and 2002. Approximately 53% of sites were sampled during the early

130   dry (Apr–Jun) season, while 33% and 14% of sites were sampled during the late dry (Jul–Sep)

131   and late wet (Jan–Mar) seasons respectively. No sampling took place during the early wet (Oct–

132   Dec) season. Sampling followed a protocol widely used across northern Australia (Woinarski

133   & Ash 2002); each site consisted of a 50 × 50 m quadrat, and included twenty Elliott traps (33

134   × 10 × 9 cm) distributed evenly around the perimeter, and one large cage trap (56 × 20 × 20

135   cm) located at each corner (four in total), set for three consecutive nights and checked early

136   each day. All individuals caught were released unmarked at the site of capture. The total

137   number of individuals captured was recorded for each trapping night. Note that this sampling

138   encompassed the entire known range of the subspecies *C. p. melibius.*

139   *Predictor variables*

140   We selected covariates for inclusion in our occupancy models based on environmental

141   and other variables considered important for *C. penicillatus*, taken from published peer-

142   reviewed literature (in particular Firth *et al.* 2006a) (see Table 1 for a detailed description

143   justifying the inclusion of each covariate). These included field-measured site characteristics

144   and remotely-sensed variables (i.e. geospatial layers). We had reason to suspect that *C.*

145   *penicillatus* detectability may vary seasonally (based on expert knowledge), and thus explored

146   this by including "season" as a survey–specific covariate. We tested for collinearity between

147   each of the predictor variables, finding no correlation coefficients larger than 0.7.

Occupancy–detectability analysis

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149   Single–species, single–season occupancy models (MacKenzie *et al.* 2002) were used to

150   estimate occupancy and detection probabilities of *C. penicillatus* across the Tiwi Islands. We

151   summarised survey data as binary detection/non-detection histories at each sampling site,

152   considering each trapping night (here meaning the entire set of traps deployed at each site on

153   each night) as one detection attempt. For reference, we first calculated the species' "naïve

154   occupancy" – the estimate of site occupancy disregarding imperfect detection (i.e. the

155   proportion of sites with at least one detection across three trapping nights). We then fitted

156   models (MacKenzie *et al.* 2002), which are formulated in terms of parameters ψ_i and p_{ij}, where

157   ψ_i (occupancy) is the probability that sampling site i is occupied by the species and p_{ij}

158   (detectability) is the probability of detecting the species at sampling site i during survey j,

159   *conditional* upon its presence. In its basic formulation, the model structure assumes

160   independence among sites and detections, no changes in the occupancy status of sites (i.e. a

161   site is either occupied or empty across the whole survey period) and no false positive records.

162   We first fitted a model assuming constant detection and occupancy probabilities (null model)

163   to the dataset. From the estimated detection probability and assuming independence, we

164   calculated the probability of detecting the species at a presence site in at least one of the k

165   visits, as follows $p^* = 1 - (1 - p)^k$. This quantity therefore reflects species detectability

166   given the *cumulative* effort applied to the site (Kéry 2002). We then extended our models to

167   incorporate covariates (MacKenzie *et al.* 2002; 2006) for occupancy and detectability (Table

168   1), to explore how these probabilities vary in response to different site characteristics.

169   Covariates were related to these probabilities via a logit-link function; this way, the resulting

170   models are effectively an extension of the traditional logistic regression model to account for

171   imperfect detection.

172   We ran preliminary models to determine which covariates were likely to be good

173   predictors of occupancy and detectability using a step-wise approach, where individual

174   variables were dropped if considered unimportant (i.e. where confidence intervals overlapped

175   zero), finding only two important predictors of detectability (season and fire frequency). We

176   then fitted all possible models resulting from combinations of our chosen covariates: (two for

177   detectability and 10 for occupancy, leading to 4,096 models in total). We tested for non–linear

178   relationships for two covariates, foliage projection cover (FPC) (in occupancy) and fire

179   frequency (in occupancy and detectability). Preliminary results showed very little evidence of

180   a non-linear relationship, so all models were fit with linear relationships.

181   We used the Akaike Information Criterion (AIC) to rank and identify the best performing

182   models for the observed dataset (Burnham and Anderson 2002). The fit of the most saturated

183   model was assessed with a goodness-of-fit test based on parametric bootstrapping and three

184   test statistics: Pearson's chi-square, the sum of squared residuals (SSE) and the Freeman-Tukey

185   chi-square. This method simulates datasets based upon a fitted model, refits the model and

186   evaluates whether the observed frequency of histories has a reasonable chance of happening if

187   the model assessed is assumed to be correct. We calculated Akaike weights (w_i,) for each

188   model and summed the contributions of each covariate (i.e. the sum of the Akaike weights

189    $\sum w_i$) to provide an indication of which covariates had substantial support for explaining the

190   observed data (but see Cade 2015). We conducted all analyses in R (R Development Core

191   Team, 2014), fitting models within the maximum-likelihood framework of inference using the

192   R-package 'Unmarked' (Fiske *et al.* 2010).

193   *Power analysis*

194   Using the methods outlined in Guillera-Arroita and Lahoz-Monfort (2012), we identified

195   the survey effort requirements to detect *C. penicillatus* occupancy declines of different

196   magnitudes with a given statistical power. These methods provide approximations (equation 1)

197 to calculate how the power of a given occupancy–detection study changes depending on the

198 allocation of survey effort (i.e. number of sites and replicate visits), assuming a standard

199 sampling design with k replicate surveys (here trap nights) carried out at S sampling sites, and

200 constant probabilities of occupancy and detectability. The calculations assume that two datasets

201 are collected (one at time 1 and one at time 2), analysed, and their estimated occupancy

202 probabilities with associated uncertainties compared to assess whether there is evidence of a

203 decline between these two times. The probability of observing a significant difference in

204 occupancy (i.e. power), given a significance level α, is

205 $$G = 1 - \beta = \left\{ 1 - \Phi \left(\frac{z_{\alpha/2} \sqrt{\sigma_1^2 + \sigma_2^2} - (\psi_1 - \psi_2)}{\sqrt{\sigma_1^2 + \sigma_2^2}} \right) \right\} + \Phi \left(\frac{-z_{\alpha/2} \sqrt{\sigma_1^2 + \sigma_2^2} - (\psi_1 - \psi_2)}{\sqrt{\sigma_1^2 + \sigma_2^2}} \right)$$

206   **Equation 1**

207 where ψ_1 and ψ_2 are the true underlying occupancy probabilities in the two times, $\Phi(x)$ is the

208 cumulative distribution function for the standard normal distribution, $z_{\alpha/2}$ is the upper $100\alpha/2$-

209 percentage point for the standard normal distribution (e.g. 1.96 for α = 0.05), $\sigma_i^2 =$

210 $\psi_i(1 - \psi_i + F_i)/S_i$ is the variance of the occupancy estimator, and $F = (1 - p *$

211 $)/\{p * -kp(1 - p)^{k-1}\}$. For convenience, hereafter we defined R to be the proportional

212 difference in occupancy, so that $\psi_2 = \psi_1 (1 - R)$, with $R > 0$ representing a decline. For a

213 given R, the power to detect the decline increases both as the number of sampling sites (S) and

214 the number of repeat visits (k) increases.

215   We applied equation 1 using the fitted estimates obtained for occupancy and detectability

216 to explore the number of sampling sites required to achieve a given power for detecting changes

217 in $C.$ $penicillatus$ occupancy. We set ψ_1 to the occupancy estimated as part of our analysis

218 described above, and set ψ_2 to reflect three different magnitudes of decline (i.e. effect size)

219 corresponding to IUCN Red List decline thresholds for threatened species based on rule A2c

220 (a decline in the area of occupancy where the cause may not have ceased): 80%, 50% and 30%

221 declines over relevant time periods (in the case of *C. penicillatus*, 10 years, which is greater

222 than three generations) (Burbidge & Woinarski 2016). We did not consider criterion A1

223 (declines in area of occupancy where the cause of decline has ceased) because there is evidence

224 to suggest some threatening processes are ongoing and could cause rapid declines in this

225 species (Davies *et al.*2016; Woinarski *et al.* 2017).

226   The calculations above assume the species is monitored twice: once at the beginning and

227 once at the end of the period over which change is considered. More frequent monitoring will

228 yield greater statistical power to detect the same decline, and simulations can be run to compute

229 power for different survey designs (e.g. see Table 1 in Guillera-Arroita & Lahoz-Monfort

230 2012). The calculations also assume independence in the occupancy status of sites across time

231 steps. Accounting for dependence may lead to increased power to detect declines. Thus, by

232 assuming independence, we are being conservative in our evaluation (i.e. power will be as

233 indicated or greater; Appendix S2 in Guillera-Arroita & Lahoz-Monfort 2012). Where survey

234 data across multiple seasons are available from the same sites (not the case in this study), multi-

235 season models can be fitted to parameterise probabilities of extinction and colonization that

236 reflect the dependence in occupancy status of sites across time, and the information accounted

237 for in sample size assessments (Popescu *et al.* 2012). This implies that future monitoring should

238 continue sampling the same sites, which is unlikely to be the case here.

239   For all of our analyses, we set alpha (α) to 0.2 and beta (β) to 0.8. Our rationale behind

240 this choice is that it better reflects the ratio of Type I and Type II costs in threatened species

241 conservation, where committing a Type II error (i.e. not detecting a decline when one has

242 occurred) could have implications that ultimately lead to extinction. In contrast, the general

243 0.05:0.8 convention assumes that the cost of making a Type I error is four times more important

244 than the cost of making a type II error (for detailed reviews on setting alpha and beta values

245 see Di Stefano 2003). Sample code for the power analysis conducted in this study is available

246 online as supplementary material in Guillera-Arroita & Lahoz-Monfort (2012).

247 *Monitoring scenarios*

248   We considered three different monitoring scenarios:

249   In "Scenario A" the assumption is that monitoring will target *C. penicillatus* likely habitat,

250 excluding the more marginal sites. To calculate average occupancy to inform survey design,

251 we took the 200 sites with the highest probability of occupancy as determined by our best

252 model (Table 1). This eliminated low probability sites (< 0.07 probability) that largely reflected

253 habitats unlikely to be suitable for *C. penicillatus*; for example, treeless plains and mangrove

254 forests (Firth *et al.* 2006a). This monitoring regime also assumes that surveys are conducted

255 during the late dry season (July–September) when *C. penicillatus* detectability is highest, and

256 therefore assumes a sampling effort of two repeat visits to each site (as this is sufficient for

257 detecting *C. penicillatus* with >95% confidence, as discussed in the results section below). This

258 is the monitoring regime that takes greatest account of the model results. Scenario B targets the

259 same type of sites, but assumes surveys are conducted year round (i.e. the design assumes a

260 level of detectability as averaged throughout the year, and thus assumes a sampling effort of

261 four repeat visits to each site. Scenario C takes what may be considered a naïve approach in

262 targeting a random selection of sites and conducting surveys all year round (i.e. detectability

263 averaged throughout the year), effectively ignoring knowledge gained through the modelling

264 process. Like Scenario B, Scenario C too assumes a sampling effort of four repeat visits to each

265 site. Four nights were chosen as this reflects the current standards for sampling of small

266 mammals across the Northern Territory (Gillespie *et al.* 2015), and thus would realistically be

267 applied if one had not modelled pilot data to better inform monitoring (i.e. the conditions under

268 Scenario A).

269   For these monitoring scenarios, we considered the extent of sampling required to detect

270   changes relevant to IUCN conservation status categories (i.e. 30%, 50%, 80%) across two

271   monitoring episodes, here assumed to be 10 years apart (i.e. matching the time period relevant

272   to IUCN Criterion A).

273   *Monitoring costs*

274   We calculated the costs associated with conducting monitoring to detect declines in

275   occupancy of differing magnitudes (corresponding to IUCN Red List Criteria) under each of

276   the three monitoring scenarios described above. This includes the costs associated with

277   equipment, bait for traps, travel and field assistant salaries (De Bondi *et al.* 2010; Garden *et al.*

278   2007) (details of estimated expenditure can be found in Appendix S1). While we provide an

279   estimate of equipment expenses, we focus on the costs required to implement *ongoing*

280   monitoring under each scenario, including in our calculations only 10% of the initial equipment

281   costs. This was considered appropriate to account for minor repairs and replacement associated

282   with the ongoing use of equipment.

283   **Results**

284   Naïve occupancy (the proportion of sites with *C. penicillatus* detections) was 0.15. The

285   null model (containing no covariates) estimated an occupancy of 0.18 (SE ± 0.02) and a

286   detectability of 0.47 (SE ± 0.05) (per trapping night). No single model was clearly superior in

287   explaining patterns of occupancy and detectability (Table 2). Island, canopy height, canopy

288   cover, fire impact, distance to nearest watercourse, mean rainfall and foliage projection cover

289   were all important predictors (Table 2), featuring in all the top candidate models (those within

290   4 AIC units of the best fitting model); the only exception was fire impact which was absent

291   from the last top ranked model. All the variables considered important predictors of occupancy

292   had a summed Akaike weight ≥93% (Appendix S2). Basal area of large trees, fire frequency

293   and total grass cover only featured in some of the competing models as explanatory variables

294 for the variation in observed occupancy, but had little support (summed Akaike weights ≤36%,

295 Appendix S2). Both season and fire frequency had high support for explaining variation in

296 detectability, featuring in all top ranked models (Table 2) and with summed Akaike weights

297 >99% (Appendix S2). The overall direction and effect size of the estimated relationships

298 (regression coefficients) remained similar for each of the covariates across all top ranked

299 models (Appendix S3). Therefore, we focus on the top ranked model as an explanation for the

300 observed data. The model suggests that the probability of *C. penicillatus* occupying a site

301 increases with canopy height, distance from nearest watercourse, foliage projection cover and

302 mean annual rainfall, and decreases with canopy cover, increasing fire impact and Island (with

303 occupancy lower on Bathurst Island) (Fig. 2a).

304 We found that detectability varied seasonally (Fig. 2b), with nightly detection probabilities

305 much higher in the late dry season (July–September), 0.78 (SE±0.02), compared to the early

306 dry (Apr–June), 0.26 (SE±0.08), or late wet (January–March), 0.31 (SE±0.08). This suggests

307 that surveys conducted in the late dry season would require far less effort (i.e. fewer repeat

308 visits) to ensure high certainty that *C. penicillatus* is detected when present (Fig. 3).

309 We calculated the number of survey sites required for detecting declines of 30, 50 and

310 80% in *C. penicillatus* occupancy under each monitoring scenario (Fig. 4). Our results show

311 that fewer sites and visits were required under Scenario A compared with Scenario B, and less

312 than half the number of sites were required under Scenario A compared with Scenario C to

313 detect declines corresponding to each IUCN threatened category (Vulnerable, Endangered and

314 Critically Endangered) (see Fig. 4 and Appendix S4).

315 The relative costs associated with the ability to detect declines corresponding to each

316 IUCN threatened category (Vulnerable, Endangered and Critically Endangered) for all

317 monitoring scenarios are outlined in Table 3. Scenario A is the most cost-effective method for

318 detecting declines of a magnitude great enough to nominally qualify *C. penicillatus* for a

319   threatened (or more threatened) status, saving approximately $11 700, $40 500 and $123 200

320   compared with Scenario B and approximately $46 800, $150 200 and $467 800 compared with

321   Scenario C (for allocation of Critically Endangered, Endangered and Vulnerable threat

322   categories respectively) (Table 3).

Discussion

324   Monitoring is a critical component of threatened species conservation, but requires

325   sufficient power to detect and reliably estimate population trends (Guillera-Arroita and Lahoz-

326   Monfort 2012). We show how a quantitative assessment of statistical power based on existing

327   data can inform the design of monitoring to ultimately improve our ability to detect policy–

328   relevant species' declines.

329   We found that detectability for *C. penicillatus* is reasonably high (0.45 on average per

330   trapping night), but varies greatly throughout the year: detection rates in the late dry season

331   were three times higher than in the early dry (0.78 compared to 0.26). Although seasonal

332   variability in detection of wildlife is well known for other taxa and generally considered in the

333   timing of surveys, for example in butterflies (Pellet 2008), burrowing owls (Latif *et al.* 2012),

334   bats in maternity caves (Baudinette *et al.*1994), and amphibians (Sewell *et al.* 2010), there is

335   little evidence in the literature to suggest that such variability has been considered when

336   monitoring mammals in a tropical climate. In highly seasonal environments (i.e. those closer

337   to the poles), seasonal changes (and subsequent changes in detectability) are more obvious,

338   particularly for species that hibernate (i.e. mountain pygmy possums, Geiser & Broome 1991)

339   or go into torpor (i.e. bats, Geiser & Brigham 2000). Here we show that explicit consideration

340   of monitoring design, based on seasonal variability, can be critical, even in contexts where

341   seasonality and changes in temperature are less apparent (i.e. in areas closer to the equator).

342   Our findings have strong implications for the cost–effectiveness of monitoring and

343   management of *C. penicillatus*, and potentially other threatened taxa with similar ecologies and

344   life history characteristics in seasonal environments. They also demonstrate the need to account

345   for imperfect detection when analysing survey data, as otherwise, declines may be masked or

346   exaggerated by seasonal inconsistency in sampling and seasonal variation in detectability.

347   Several factors could explain the higher probability of detection during the late dry

348   season compared with the early dry season. Food resources are more abundant during the early

349   dry season (related to plant productivity following wet conditions), potentially reducing the

350   chance of an individual entering a trap in search of bait. Seasonal variation may also relate to

351   *C. penicillatus* breeding patterns; high numbers of juveniles at the end of the dry season may

352   result in higher trap success due to increased relative abundance and/or inexperienced, less

353   cautious individuals. *Conilurus penicillatus* is just one example of a species displaying strong

354   seasonal breeding cycles – it can be expected of other rodents and some dasyurids (i.e. the

355   northern quoll *Dasyurus hallucatus*) – highlighting the importance of accounting for this when

356   examining population trends.

357   The most important variables driving occupancy of *C. penicillatus* (canopy height,

358   canopy cover, fire impact and distance to nearest watercourse) were consistent with a previous

359   analysis of this dataset (Firth *et al.* 2006a). This species shows a preference for eucalypt forests

360   with taller trees, less intense fire and drier upland areas. While fire is thought to influence the

361   occupancy of *C. penicillatus*, the results of this study were somewhat equivocal. Fire frequency

362   was not a strong predictor for occupancy, while fire impact – a field-based measure of the

363   apparent severity of fire – had greater support, and was negatively correlated with occupancy.

364   Firth *et. al.* (2010) found that late dry season fires contribute to a reduction in both juvenile and

365   adult survival probabilities in *C. penicillatus* due to a greater impact on vegetation cover and

366   the loss of important resources such as den sites (i.e. logs). Similarly, McDonald *et al.* (2016)

367   concluded that fire is an important driver of grass cover, which influences the occupancy

368   patterns of another rare rodent (the critically endangered central rock-rat *Zyzomys*

369   *pedunculatus*). This outcome suggests recent severe fire events are shaping *C. penicillatus*

370   occupancy rather than the number of fires that have occurred over time. More intense fire may

371   lead to lower perennial grass species diversity, and thus a reduction in the availability and

372   variety of seed (Russell-Smith *et al.* 2000). Fire impacts may also be synergistic with other

373   potential causes of declines, such as predation by feral cats, with cat abundance and hunting

374   efficiency shown to increase in areas that have been subject to recent intensive fires in other

375   comparable environments in northern Australia (McGregor *et al.* 2014; Leahy *et al.* 2015;

376   Davies *et al.* 2016).

377   The power to detect population trends can be improved by increasing sampling effort,

378   but there are always financial and logistical constraints limiting the effort that can be applied

379   to a particular monitoring program. Alternative methods have been proposed for improving

380   power; one example is excluding sites with a low probability of occupancy (Rhodes *et al.*

381   2006). This approach is explored in this study, where we considered a strategy that targeted

382   sites with a probability of *C. penicillatus* occupancy greater than 7%, therefore focusing our

383   inference on declines in its core distribution. Our results show that to detect smaller

384   proportional changes in occupancy (<50%), a substantial improvement in power can be

385   achieved by targeting suitable habitats, reducing the survey effort (and thus costs) required to

386   detect declines. Conducting sampling when detectability is highest improves power and

387   reduces costs further. Species' presence can be inferred with high confidence in two repeat

388   visits when monitoring is conducted during the late dry season, while four times as many visits

389   are necessary to infer the same level of confidence in the early dry season.

390   One note of caution is that, in assessing the power to detect a decline, we are identifying

391   the ability to detect that *there is* a decline, but this does not necessarily imply that the true

392   magnitude of that decline is estimated. For example, a power of 0.8 for detecting a decline of

393   30% between two sampling times indicates that, given there is a true decline of 30%, there is

394   80% chance that the statistical analysis of the data identifies a decline greater than 0. The

395   estimated decline may be smaller than the true decline, and may be insufficient to allocate to a

396   threatened category. One can formulate a more stringent null hypothesis to guide the survey

397   design. For example, we could design the sampling to ensure there is high power to estimate a

398   decline greater than X, when the true decline is Y, but this naturally leads to greater sample

399   size requirements (Guillera-Arroita and Lahoz-Monfort 2012). Note however that one cannot

400   set X=Y, as this would require an infinite sample size (to obtain an estimate of the truth with

401   no uncertainty).

402   Another important consideration is that as a species declines, its detectability may also

403   decline, thus leading to greater difficulty in detecting a change between sampling occasions.

404   *Conilurus penicillatus* has declined on the Tiwi Islands in the last 15 years, attributed primarily

405   to predation by feral cats (most likely a consequent result of changing fire regimes and

406   associated impacts on vegetation cover). On Melville Island, it is now restricted to areas with

407   low probabilities of cat occupancy and high shrub density, where predation effects are thought

408   to be effectively diminished (Davies *et al.* 2016). Trap success in 2015 was less than a third of

409   that reported in monitoring conducted in 2000–2002 (Davies *et al.* 2016), suggesting that the

410   species is likely to have lower probabilities of both occupancy and detectability across the

411   Island. In light of new data we must recognise that there is a possibility that two trap nights,

412   sampled during the late dry season when detectability of this species is highest, may now be

413   insufficient for obtaining high (>95%) confidence in detection.

414   If one has reason to suspect that a decline has occurred between two samples, then

415   sampling design may benefit from calculating power against different levels of detectability

416   during the early stages of survey design. This would allow for a more conservative approach

417   to be developed that can meet the project objectives in the event of a decrease in detectability

418   between sampling occasions. In the context of *C. penicillatus*, implementing alternative trap

methods could overcome limitations associated with decreasing detectability through time. Motion-sensor cameras are a non-invasive survey tool that have been successfully used for several mammals of varying sizes (Rendell *et al.* 2014; Mcdonald *et al.* 2015; Welbourne *et al.* 2015), including *C. penicillatus* (Davies *et al.* 2016). Once deployed, cameras may be left in the field for long durations of time, thus collecting data across a greater temporal scale with fewer resources (DeBondi *et al.* 2011). The data obtained from cameras can be analysed in a similar way to provide insights into survey design and power to detect change (Davies *et al.* 2016).

Designing an effective monitoring program will depend upon the objectives of the study, however, if practitioners are interested in detecting a decline of magnitude great enough for allocation to a "threatened" category (Vulnerable, Endangered, Critically Endangered), then implementing a monitoring regime capable of detecting smaller declines (i.e. ≤30%) within an allocated budget would be ideal. As we have shown here, detecting a larger decline requires less resources than detecting a small decline, so designing a monitoring regime that is capable of detecting smaller declines will lead to increased confidence in our ability to detect more catastrophic declines (i.e. >50%).

However, land practitioners must also consider the scale and frequency at which monitoring takes place. The IUCN Red List Criteria applies to declines across a species' entire distribution, and is generally applied at the species level. Though the population of *C. penicillatus* on the Tiwi Islands is considered a distinct subspecies (*C. p. melibius,* Thomas 1921; Kemper and Schmitt 1992), a reported decline in this population alone would not be sufficient to upgrade its' conservation status at the species level. A recent study (Geyle *et al.* 2018) identifying the Australian mammals most likely to go extinct in the next two decades, placed both Australian subspecies (*C. p. melibius* and the mainland *C. p. penicillatus*) in the top 20 mammals most at risk. This suggests that each may require emergency intervention to

444 ensure their ongoing survival. Gaining an understanding of population trends for both

445 subspecies is thus crucial if we're to improve the conservation outlook for these species.

446   The frequency in which monitoring occurs is also important. In this case, we have used

447 a 10-year interval, as it is related to the generation time for which a decline must occur for a

448 species to be eligible for conservation status assessment. However, in practise, if monitoring

449 occurs more frequently, there is more likelihood of detecting a decline in a time-sensitive

450 manner, and subsequently managers will be able to respond more effectively and rapidly to the

451 threats driving such declines.

452   Despite some limitations of our approach, power analyses provide important insight into

453 whether a study is worth conducting by identifying if the change considered meaningful can

454 be detected with reasonable probability using an affordable sample size. Power analysis is an

455 important tool in the development of effective monitoring regimes capable of achieving the

456 desired study outcomes (Guillera-Arroita & Lahoz-Monfort 2012). We show how existing data

457 can be used to estimate parameters required to determine sample sizes and monitoring design,

458 and thus provide powerful insights into the effectiveness of existing monitoring methods at

459 achieving different research and management goals. Our findings demonstrate that a targeted

460 single–species monitoring protocol has greater power to detect declines for *C. penicillatus* than

461 a design targeted at multiple species. However, we recognise that in many cases, particularly

462 at large spatial scales, single–species monitoring is often impractical and may be inefficient.

463 For example, the Tiwi Islands are home to many threatened species that have suffered

464 widespread declines across northern Australia. Future research should explore ways to optimise

465 power for detecting simultaneous declines in multiple threatened species to ensure better use

466 of resources, especially given the sudden collapse of a wide range of small mammal species in

467 Kakadu National Park on the adjacent mainland in recent decades (Woinarski *et al.* 2010). We

468 suggest targeting several species with similar ecological needs, habitat preferences and life

469 history characteristics, as this study highlights the importance of targeting particular sites based

470 upon the local habitat characteristics present and seasonal fluctuations in detectability.

471   Monitoring programs that detect a change in abundance or occupancy, while of great

472 importance, simply identify the problem, which is only one of the steps contributing to

473 threatened species conservation. Ideally, monitoring programs should provide some insight

474 into the potential causes of such change, and designs should thus synchronously include site

475 level consideration of the putative threatening factors (Lindenmayer *et al.* 2012). As

476 demonstrated here, good sampling design can provide information not only on trends but also

477 on factors influencing those trends. In this case, our analysis indicates that fire regimes are

478 associated with variation among site occupancy, and hence may be contributing to the observed

479 pattern of decline. Such careful consideration of survey design will ultimately lead to a far

480 greater level of confidence in our ability to detect declines, and understand the reasons for

481 them, which in turn may lead to more informed and better conservation outcomes.

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700   **Table 1.** Occupancy predictors considered for inclusion in single–season, single–species

701   occupancy models of *Conilurus penicillatus* on the Tiwi Islands.

Predictor	Justification for inclusion	Measurement	Reference(s)
Canopy height	An indicator of habitat suitability	Height of tallest woody plants	Firth *et al*. 2006a
Canopy cover	An indicator of habitat suitability	Percentage foliage cover of canopy	Firth *et al*. 2006a
Mean annual rainfall	An indicator of productivity	Mean average rainfall in 10 years preceding survey, derived for BOM gridded data	J. Woinarski, pers obs
Total grass cover	An indicator of potential food availability	Percentage ground cover of grass (annual and perennial)	Firth *et. al.* 2005; Firth *et al.* 2006a; Firth *et al.* 2010
Fire impact	Fire impact may have a strong influence on critical resources required for species survival (i.e. food availability, hollow logs)	Five-point scale measuring the apparent severity of fire impact, from 1 (no sign of fire) to 5 (evidence of severe crown fire)	Firth *et al.* 2010; Firth *et al.* 2006b; Woinarski *et al.* 2011; Yates *et al.* 2008
Fire frequency	See above	The number of times a site has burnt in the four years preceding survey. Derived from Landsat satellite imagery	See above
Distance to nearest watercourse	A highly significant finding in previous analysis across all quadrats, indicative of variation in habitat	Measure in metres. Derived from a digital elevation model	Firth *et. al.* 2006a
Foliage projection cover	An indicator of habitat suitability	The percentage of the site occupied by the vertical projection of foliage or measure of green vegetation on the ground. Derived from Landsat TM satellite imagery	Walker and Hopkins 1990
Basal area of large trees	An indicator of a critical resource (i.e. hollows –	Total basal area ($m^2 ha^{-1}$) of trees with diameter at breast height > 50 cm	Firth *et. al.* 2006a & b; Bennett *et al.*

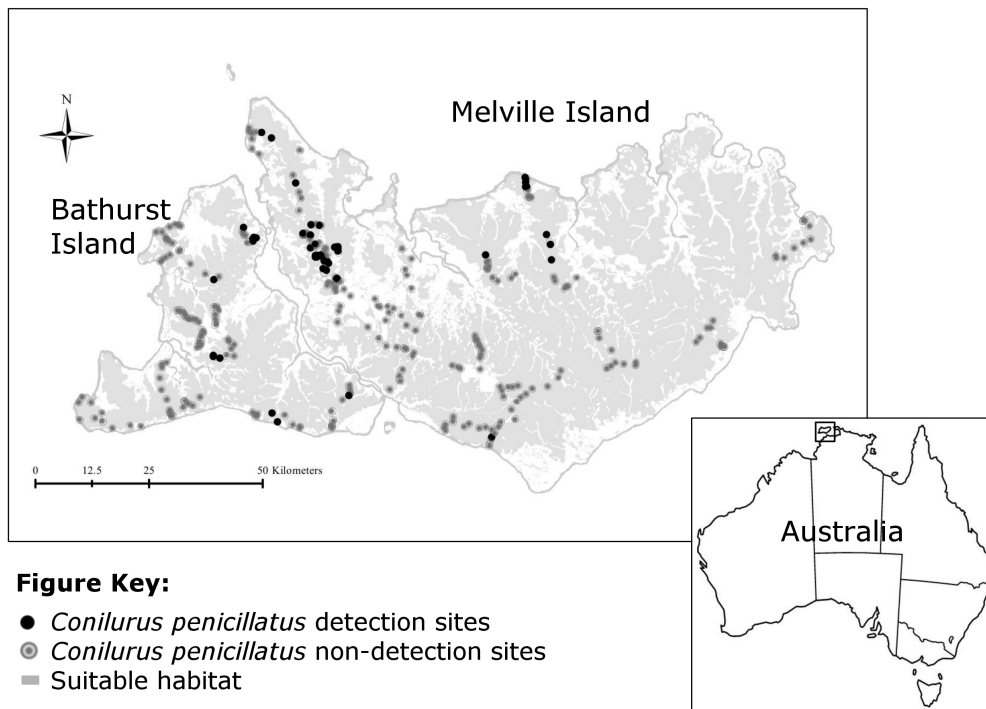|	more likely to be present in larger trees)	Derived from two sweeps of bitterlich gauge	1993; Whitford 2002; Woolley *et al.* 2018
Island	A surrogate for the overall population size (due to area of habitat) and related meta-population dynamics, differences between disturbance histories, predator densities and composition of vegetation	155 sites on Bathurst Island and 223 on Melville Island. Modelled as a binary predictor	

702

703 **Table 2.** Akaike information criterion, mean occupancy and mean detectability estimates for the candidate set of single–season occupancy models

704 for *Conilurus penicillatus* on the Tiwi Islands of the Northern Territory. The null model outputs are provided for comparison.

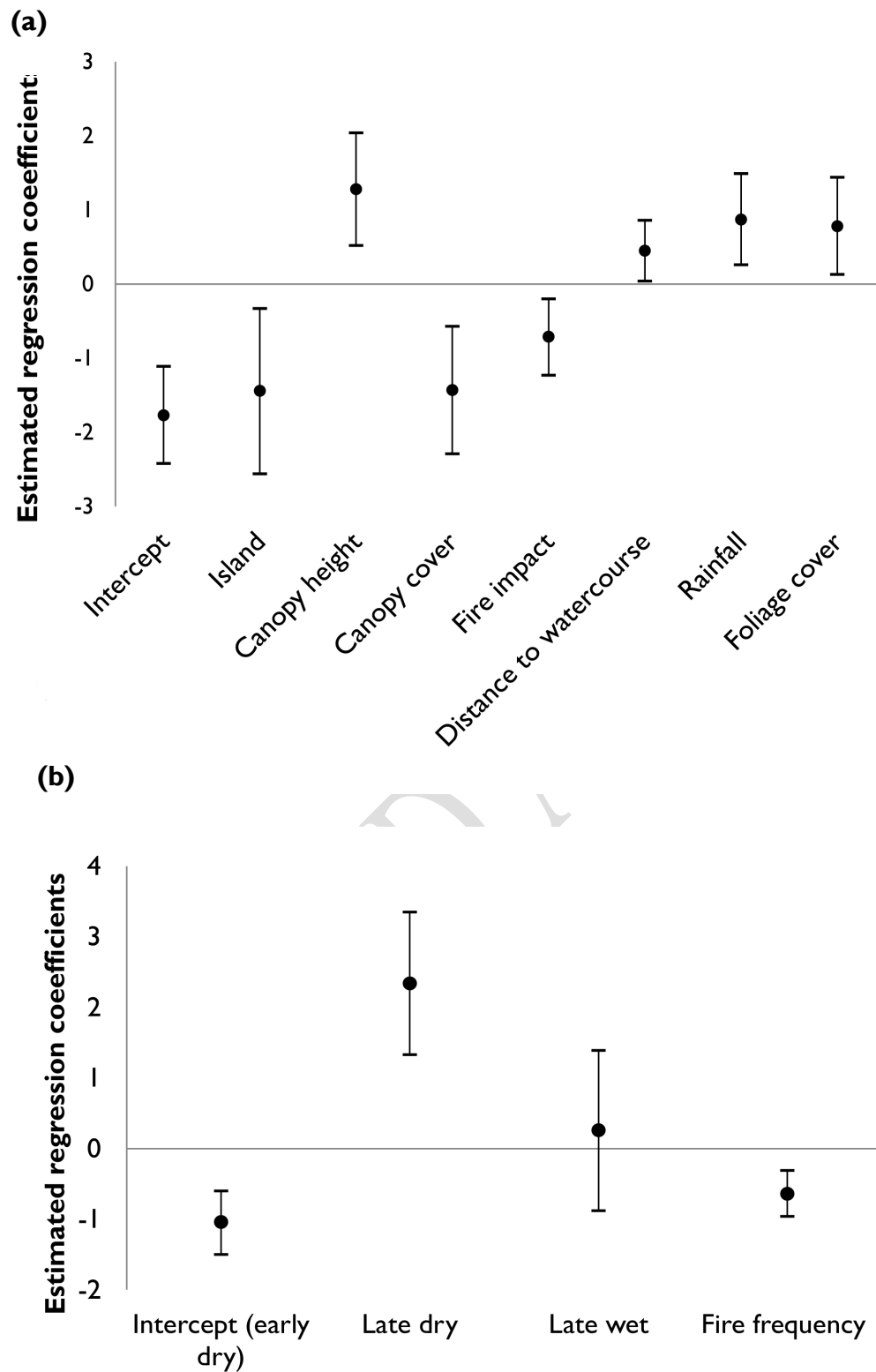|					Occupancy			Detectability		
ID	**Candidate models**	**AIC**	**ΔAIC**	**Wi**	**ψ (±SE)**	**CI**		**p (±SE)**	**CI**	
1	*p* (S+FF) Ψ (IS+CH+CC+FI+DW+RF+FC)	426.38	0.00	0.22	0.24 (0.07)	0.13	0.34	0.45 (0.07)	0.31	0.59
2	*p* (S+FF) Ψ (IS+CH+CC+FI+DW+ RF+GC+FC)	426.48	0.01	0.21	0.25 (0.07)	0.13	0.41	0.44 (0.07)	0.30	0.58
3	*p* (S+FF) Ψ (BA+IS+CH+CC+FI+DW+RF+GC+FC)	427.77	1.40	0.11	0.25 (0.07)	0.12	0.42	0.44 (0.07)	0.30	0.58
4	*p* (S+FF) Ψ (BA+IS+CH+CC+FI+DW+RF+FC)	427.82	1.44	0.11	0.24 (0.07)	0.13	0.40	0.45 (0.07)	0.31	0.59
5	*p* (S+FF) Ψ (IS+CH+CC+FI+FF+DW+RF+FC)	428.28	1.90	0.08	0.24 (0.07)	0.12	0.40	0.45 (0.08)	0.31	0.59
6	*p* (S+FF) Ψ (IS+CH+CC+FI+FF+DW+RF+TC+FC)	428.40	2.09	0.08	0.25 (0.08)	0.12	0.42	0.44 (0.08)	0.30	0.58
7	*p* (S+FF) Ψ (IS+CH+CC+FI+DW+RF+TC)	429.25	2.87	0.05	0.25 (0.07)	0.13	0.40	0.44 (0.08)	0.29	0.58
8	*p* (S+FF) Ψ (BA+IS+CH+CC+FI+FF+DW+RF+TC+FC)	429.77	3.39	0.04	0.25 (0.08)	0.11	0.43	0.44 (0.08)	0.30	0.58
9	*p* (S+FF) Ψ (BA+IS+CH+CC+FI+FF+DW+RF+FC)	429.81	3.42	0.04	0.24 (0.07)	0.11	0.41	0.45 (0.07)	0.30	0.59
10	*p* (S+FF) Ψ (IS+BA+CH+CC+FI+FF+DW+RF+GC)	429.84	3.45	0.04	0.25 (0.07)	0.13	0.41	0.44 (0.08)	0.29	0.58
11	*p* (S+FF) Ψ (IS+CH+CC+DW+RF+TC+FC)	430.12	3.74	0.03	0.26 (0.08)	0.13	0.43	0.42 (0.07)	0.29	0.56
Null	*P* (.) Ψ (.)	496.20	NA	NA	0.18 (0.02)	0.14	0.23	0.47 (0.05)	0.37	0.57

705 AIC = Akaike Information Criterion, ΔAIC = Akaike unit difference, Wi = Akaike weight, ψ = mean probability of occupancy, p = mean probability of detection, SE = standard

706 error, CI = confidence intervals, S = season, FF = fire frequency, BA = basal area of large trees, IS = island, CH = canopy height, CC = canopy cover, FI = fire impact, DW =

707 distance to watercourse, RF = mean rainfall, GC = total grass cover and FC = foliar projection cover.

708   **Table 3.** Costs associated with our ability to detect declines of varying magnitude in *Conilurus*

709   *penicillatus* occupancy under the three differing monitoring Scenarios: (A) core sites surveyed

710   when detectability is highest (late dry season), assuming two repeat visits to a trap site; (B)

711   core sites surveyed across the year (i.e. average detectability), assuming four repeat visits to a

712   trap site; and (C) random selection of sites sampled across the year, assuming four repeat visits

713   to a trap site. Scenario C takes no account of the information provided by the model. Costs are

714   based on the estimated expenditure described in Appendix S1, and the number of sites required

715   for allocation of each threatened category (Appendix S4).

Proportional decline in occupancy	Costs (AU$)		
	A	B	C
30%	265,356	388,515	733,130
50%	86,814	127,310	237,060
80%	27,846	39,510	74,630

Figure Key:

- ● *Conilurus penicillatus* detection sites
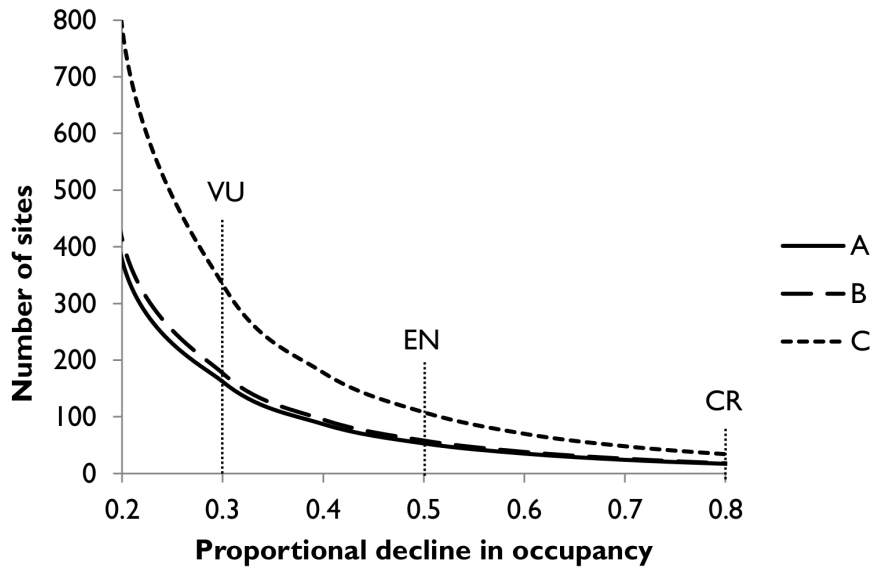- ◉ *Conilurus penicillatus* non-detection sites
- ▬ Suitable habitat

716   **Figure 1.** The location of the Tiwi Islands and all sites sampled during 2000–2002 across

717   Bathurst and Melville Islands.

(a)

(b)

718   **Figure 2.** Standardised regression coefficients (with 95% confidence intervals) for the best

719   model predictors of *Conilurus penicillatus* (a) occupancy and (b) detectability.
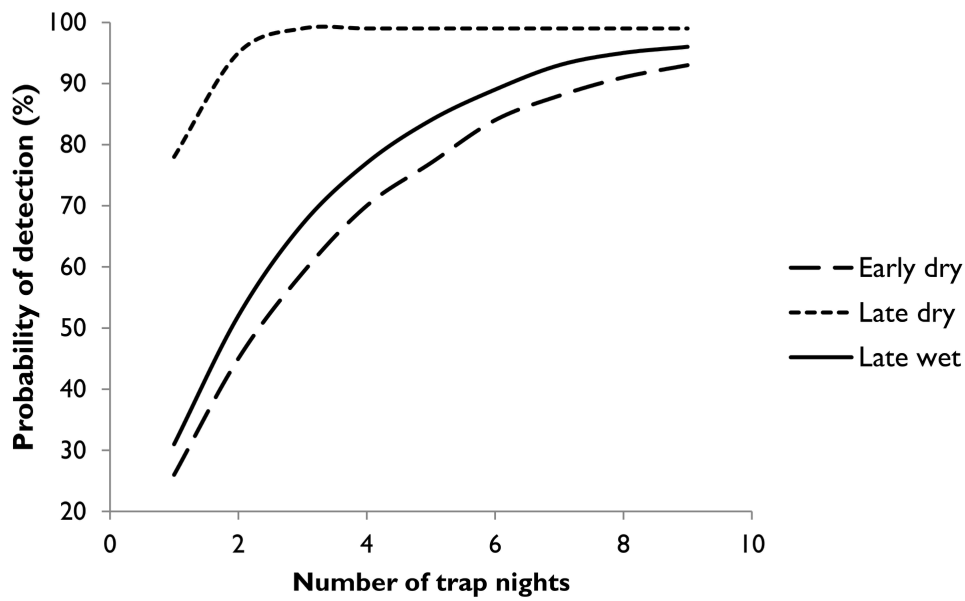
720 **Figure 3.** The probability of detecting *Conilurus penicillatus* in the early dry season, late dry

721 season and late wet season, assuming a mean value of fire frequency.

722 **Figure 4.** The number of sampling sites required to achieve a statistical power of 0.8 to detect

723 change when *Conilurus penicillatus* occupancy has declined by 30, 50 or 80%. These

724 declines correspond to IUCN Red List criteria for allocation of Vulnerable (VU), Endangered

725 (EN) and Critically Endangered (CR) conservation status. Three monitoring scenarios are

726   considered: (A) core sites surveyed when detectability is highest (late dry season), given two

727   repeat visits to a trap site; (B) core sites surveyed across the year (i.e. average detectability),

728   given four repeat visits to a trap site; and (C) random selection of sites sampled across the

729   year, given four repeat visits to a trap site. Scenario C takes no account of the information

730   provided by the model.

Appendices

Appendix S1. Estimated costs associated with monitoring *Conilurus penicillatus* on the Tiwi Islands. Total cost per site is estimated based on ongoing monitoring costs (i.e. 10% of expenditure for initial purchase of equipment) bait, travel and personnel expenses. The totals in the far right column represent costs associated with visiting a site for four consecutive nights – or 8 trips in total (required of Scenarios B and C). The total cost per site for Scenario A takes 100% of ongoing monitoring costs and 50% of bait, travel and personnel costs (i.e. the costs associated with visiting a site for two consecutive nights – or 4 trips in total). Note: all values are rounded to the nearest whole number.

Item description		Quantity	Unit cost	Total cost ($AU)
Vehicle transport by barge		4 x trips	$600	$2,400
Elliott traps		200	$40	$8,000
Cage traps		40	$70	$2,800
Ongoing monitoring costs (10%)				**$1,080**
Bait	Oats	2,000 g	$1 (750 g)	**$18**
	Honey	500 g	$36 (3 kg)	
	Peanut butter	500 g	$36 (2 kg)	
Travel	University car hire	Average distance (41 km) x 8 trips	$60 per 100 km	**$197**
Personnel	Wages	7.5 hrs × 2 staff	$60 per hour (including on-costs)	**$900**
Total cost per site (Scenario A)				**$1,638**
Total cost per site (Scenario B & C)				**$2,195**

Appendix S2. The summed Akaike weights for each occupancy and detectability covariate corresponding to the candidate set of single–season occupancy models in Table 1.

Occupancy (ψ)	
Island	> 99%
Basal area of large trees	30%
Canopy height	> 99%
Canopy cover	> 99%
Fire frequency	28%
Fire impact	98%
Distance to watercourse	>99%%
Mean annual rainfall	> 99%
Total grass cover	36%
Foliage projection cover	93%
Detectability (p)	
Season	> 99%
Fire frequency	> 99%

Appendix S3. Standardised coefficient and confidence interval graphs for the first 5 candidate models (i.e. within 2 Akaike unit difference) (Table 2), demonstrating that the overall direction and effect size of estimated relationships remained similar across all top ranked models.
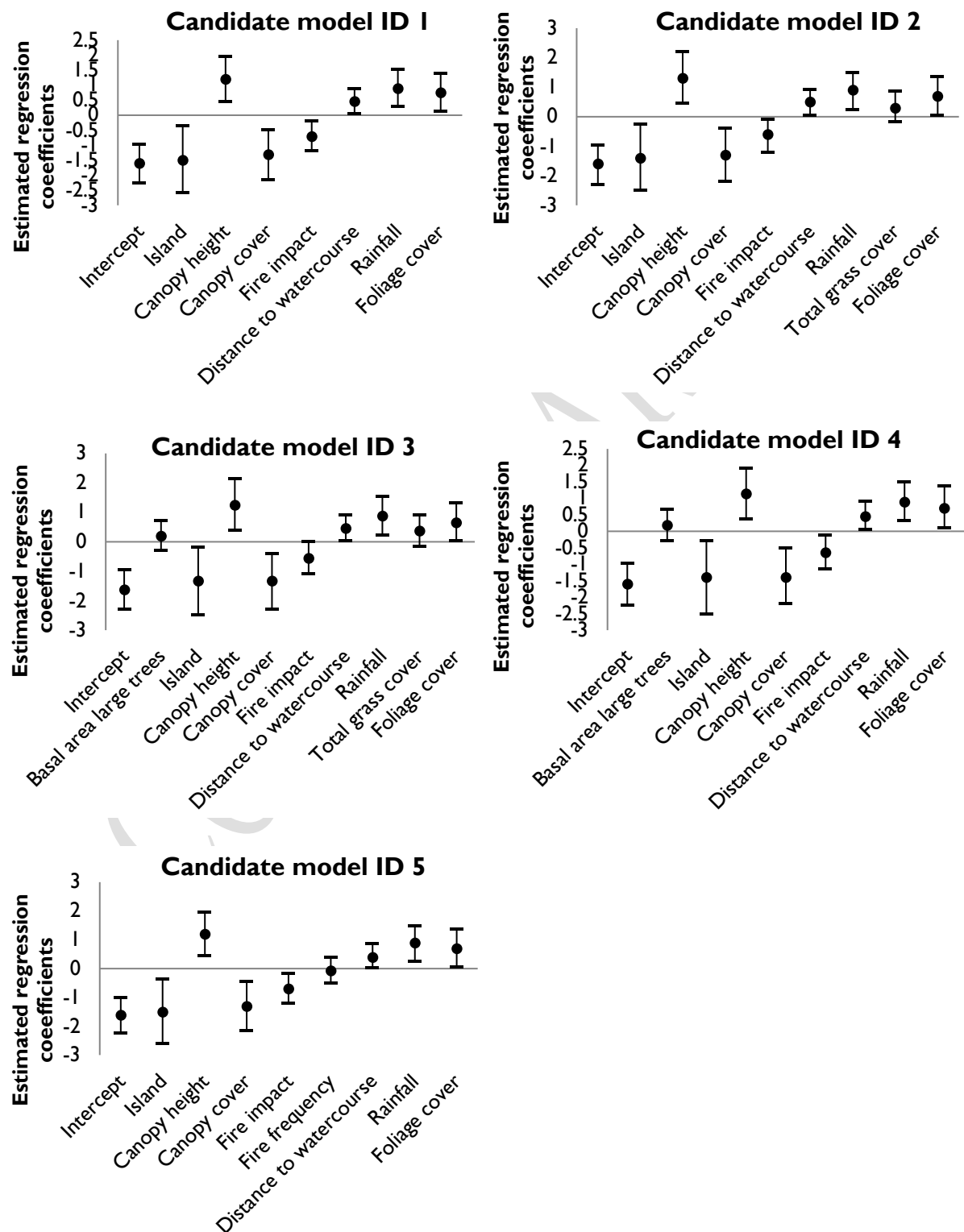
Appendix S4. The number of sites required to detect declines of varying magnitudes (30, 50 and 80%), corresponding to IUCN Red List criteria for allocation of Vulnerable, Endangered and Critically Endangered threat status under each of the three Scenarios (A, B and C, detailed in the main text), given two repeat visits to each site for Scenario A and four repeat visits to each site for Scenarios B and C. Power (β) = 0.8 and alpha (α) = 0.2.

Proportional decline in occupancy	Number of Sites		
	A	B	C
30%	162	177	334
50%	53	58	108
80%	17	18	34