

1 **Landholder participation in regional-scale control of invasive predators: a spatial**
2 **model for an agro-ecosystem**

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18 Running title: Landowner participation and invasive predator control

19 **Abstract**

20 Control of invasive predators is necessary for persistence of many endemic species. Invasive
21 predator management tends to focus on priority sites – often only a small fraction of the
22 impacted area. Landscape-scale ecological recovery requires threatening processes to be
23 managed not only in these priority areas, but also in the matrix between them. However,
24 wide-scale control of invasive species can be logistically, economically and socially
25 challenging. We used a spatially explicit model to estimate the effects of varying levels of
26 landholder participation in a landscape-scale program to control invasive predators in the
27 North Island of New Zealand. Under various scenarios for landholder participation, we
28 estimated how the participation rate, as well as size and location of non-participating
29 properties, would influence effectiveness of trapping predators. We also modelled how trap
30 deployment could be spatially optimised to limit reinvasion. Under all modelled scenarios,
31 predator populations remained below pre-control levels for six years. Non-participation by
32 owners of small properties (≤ 25 ha) had a negligible effect on the success of predator
33 control. If owners of large properties (> 800 ha) failed to participate, reinvasion by predators
34 from these properties reduced the effectiveness of control; however, this could be largely
35 offset by placing additional traps on the nearest participating properties. Our results indicate
36 that predator control will be effective even if some landholders choose not to participate. Our
37 model can be readily adapted to other invasive species and landscapes worldwide.

38

39 **Keywords** agro-ecosystem · community support · feral cat · ferret · social-ecological models
40 · stoat

41

42 **Introduction**

43 Control of invasive predators is one of the most important tools for conserving native fauna
44 in island ecosystems, including Australia and New Zealand where endemic species are highly
45 vulnerable to decline and extinction through predation (Dickman 1996; Salo et al. 2007;
46 Innes et al. 2010; Simberloff 2010). Control of invasive predators is often restricted to
47 priority sites such as wildlife sanctuaries, designated conservation areas or relict patches of
48 habitat (e.g. Kinnear et al. 1988; Norbury et al. 2013), which may represent a small
49 proportion of the impacted landscape. If impacted faunal assemblages and ecological
50 processes are to be restored at the landscape scale, invasive predators must also be controlled
51 in the matrix between these areas (Glen et al. 2013). However, controlling invasive predators
52 across entire landscapes is challenging not only due to the resources required, but also due to
53 variation in land tenure and the need for a cohesive approach among many landholders who
54 may have diverse views on conservation and invasive species management.

55

56 Increasingly, the role of the general public in invasive species management has been
57 recognised worldwide, particularly in areas with a high diversity of land uses (Epanchin-Niell
58 et al. 2010). Landholders' decisions to engage in control efforts may be influenced by the
59 perceived value of reducing invasive species populations, the perceived difficulty and cost of
60 engaging in control actions, their personal ability to take effective action, and the perceived
61 likelihood that widespread control efforts will be successful (Aslan et al. 2009; Corbett 2002;
62 McLeod et al. 2015; Prinbeck et al. 2011). Landowners may especially be influenced by their
63 neighbours' invasive species control actions, as normative influences are important predictors
64 of pro-environmental behavior (Cialdini et al. 1990). The actions of neighbours may
65 influence behaviour by indicating the potential for social rewards for engaging, or penalties
66 for not engaging, in invasive predator control (Cialdini et al. 1990).

67

68 New approaches are needed that link environmental decision making, societal participation in
69 environmental management, and biophysical requirements for intervention. Recent
70 developments in modelling coupled social-ecological systems (e.g. Rebaudo and Dangles
71 2013) provide an approach for improving environmental management, both in case studies
72 with specific characteristics, and for establishing generic principles and ‘rules of thumb’ that
73 can be applied to guide policy at regional and national scales.

74

75 Successful environmental management depends on societal cooperation and commitment as
76 well as ecological responses to intervention (Lade et al. 2013). For instance, pest
77 management needs to take into account the dynamics (increase and spread) of invasive
78 species, the cost of control per unit area, the number of participating landholders, the size and
79 spatial context of their properties, and the efficiency of control. When there are few
80 participants there can be rapid reinvasion of pests from surrounding unmanaged properties
81 and the result can be a reduced efficiency of control at a landscape scale (Gentle et al. 2007;
82 Cumming et al. 2013). Control efficiency is predicted to increase as more landholders
83 participate until efficiency reaches a maximum, which is set by the technology used.
84 However, this scenario has not been tested at a regional scale in New Zealand production
85 ecosystems.

86

87 In the North Island of New Zealand, Hawke’s Bay Regional Council plans to control invasive
88 predators (feral cats *Felis catus*, stoats *Mustela erminea* and ferrets *M. furo*) across 26,000 ha
89 of rural and peri-urban land under the proposed *Cape to City* program
90 (<http://capetocity.co.nz/>). Most of the land in the *Cape to City* area is privately owned, and
91 participation of landholders will be voluntary. There is a risk that non-participation by some

92 landholders could create safe havens for predators, which might reinvade surrounding areas
93 and undermine the effectiveness of the program. Here we develop and apply a spatially
94 explicit simulation model to predict how different levels of landholder participation would
95 influence the effectiveness of predator control across the whole *Cape to City* area. We aim to
96 estimate (1) the impact of varying levels of landholder participation; (2) how size and
97 location of non-participating properties might influence the effectiveness of predator control,
98 and; (3) how trap deployment might be adjusted to limit reinvasion. Our model is broadly
99 applicable to scenarios in which invasive species are managed across multi-tenured
100 landscapes.

101

102 **Methods**

103 *Study area*

104 *Cape to City* covers 26,000 ha of rural and residential land in Hawke’s Bay, North Island
105 New Zealand (39° 47’ S; 176° 57’ E; Fig. 1). The north-eastern boundary is adjacent to Cape
106 Sanctuary, a privately owned wildlife reserve protected by a predator-proof fence. Invasive
107 predators are controlled to low densities in Cape Sanctuary, which has allowed population
108 recovery and/or reintroduction of numerous threatened native species (Ward-Smith 2011;
109 Innes et al. 2015). Ten kilometres west of Cape Sanctuary is the city of Havelock North
110 (hence ‘*Cape to City*’). The aim of *Cape to City* is to allow native biodiversity, including rare
111 and threatened species, to spread from Cape Sanctuary and coexist with people in residential,
112 rural and recreational areas.

113

114 [Figure 1 hereabouts]

115

116 The *Cape to City* area comprises 163 properties ranging in size from 1.5 – 2033 ha (mean =
117 189 ha). These include sheep and cattle farms, orchards, vineyards and residential ‘lifestyle’
118 properties. There are also fragments of native vegetation, exotic timber plantations and some
119 small conservation reserves; collectively these cover ~8% of the *Cape to City* area.

120

121 *Invasive predator control*

122 Control of invasive predators is planned to begin in the austral summer of 2016 (March), and
123 continued suppression of these predators will be maintained for at least five years. Invasive
124 predators will initially be controlled by intensive trapping using a combination of trap types.
125 After this initial knock-down phase, on-going control will involve a network of 1460 humane
126 kill-traps set ~200 m apart alongside roads and farm tracks on predefined routes within *Cape*
127 *to City* (Fig. 1). Easy access is required to make trapping affordable over this extensive area.
128 Traps will be left in place year-round, and set for active trapping sessions over seven
129 consecutive nights every 1.5 months. Additional trapping may be conducted where and when
130 required to maintain low densities of invasive predators.

131

132 *Model design*

133 A spatial model written in R version 3.1.3 (R Development Core Team 2015) was used to
134 estimate predator population size over time under each of four landholder participation
135 scenarios (see below). Each invasive predator species (feral cat, ferret, stoat) was modelled
136 separately. The R code is provided in Appendix S1.

137

138 The first step was to specify which properties participated in the trapping program, which
139 conditioned the trap layout to include only traps that fell within those properties. The model
140 was then initiated by creating a regular grid of available home range centres across *Cape to*

141 *City*. Post-knock-down populations of predators (details below) were then randomly
142 distributed across this grid. An occupied home-range-centre grid point remained occupied for
143 the entire simulation unless the predator was captured by a trap, in which case it was removed
144 from the population and that location became available to *in-situ* dispersers or invaders. The
145 resolution of the grid of home range centres (500 m) was set so that each grid cell was
146 occupied by a single animal and the local density of predators did not exceed the maximum
147 allowed (4 per km²). The carrying capacity of the predator population was based on typical
148 population densities for feral cats, ferrets and stoats in New Zealand (King 2005); initial
149 populations (pre-knock-down) were based on population densities estimated specifically for
150 the study area, and the percent kill achieved during the knock-down phase was determined
151 from data obtained from a pilot study at nearby Waitere Station (Table 1). Three levels of
152 knock-down were simulated for each of the three predator species: a ‘minimum’ ‘mean’ and
153 ‘maximum’ % kill (Table 1).

154

155 We then quantified the probability that each individual predator would be removed by the
156 network of traps. The probability of capture of an individual ($P(\text{capture})_{ijt}$) with a home-
157 range centre at location i by trap j during night t was:

158
$$P(\text{capture})_{ijt} = g_0 \exp\left(\frac{-d_{ij}^2}{2\sigma^2}\right)$$

159 where d_{ij} was the distance between home-range centre i and trap j , g_0 was the probability of
160 capture of an individual by a trap placed at the animal’s home-range centre and σ was the
161 spatial decay parameter for a half-normal home-range kernel (Efford 2004). Values for g_0 and
162 σ were randomly drawn from Program Evaluation and Review Technique (PERT)
163 distributions (Herrerias et al. 2003) with parameters described in Table 1. These parameters
164 were determined through a review of the literature on home ranges, movements and capture
165 probabilities for each species in New Zealand (Glen and Byrom 2014). Each animal retained

166 the same g_0 and σ values across all trapping sessions, i.e., we assumed that these are traits
167 that characterise the behaviour of an animal from birth to death. The probability that each
168 individual would be captured by any one of the j traps in the *Cape to City* area over the seven
169 nights of a trapping session was calculated as:

$$170 \quad P(\text{capture})_i = 1 - \prod_{j=1}^j (1 - P(\text{capture})_{ijt}^7)$$

171 Each individual was then either captured (and thus removed from the population) or left
172 untrapped based on a random draw (1 or 0) from a binomial distribution with $p_i =$
173 $P(\text{capture})_i$. In the model we did not close the specific trap that caught an individual, which is
174 equivalent to assuming that trap saturation was not a problem (due to a high ratio of traps to
175 predators in the *Cape to City* area and the protocol for re-setting all traps at least once every 6
176 or 7 weeks), and we did not adjust trap availability in the calculation of $P(\text{capture})_i$ for
177 subsequent individuals.

178
179 The simulation continued the trapping described above for the remaining population with
180 eight trapping sessions per year over six years to ensure complete coverage of the
181 maintenance phase of the *Cape to City* program. Before the start of each trapping session
182 (except for the first session), immigration from outside the western boundary of *Cape to City*
183 was allowed to occur (the eastern boundary is ocean). The number of invaders was
184 determined as a random draw from a Poisson distribution with parameter lambda (λ ; Table 1).
185 These values were based on estimated rates of reinvasion from other predator control
186 programs in New Zealand. Following the addition of *in-situ* recruits, the randomly drawn
187 number of invaders was adjusted so that residents plus invaders did not exceed local carrying
188 capacity. Adjusted invaders were then randomly placed on home range centres unoccupied by
189 residents; in this case we assumed that all available home range centres were equally likely to

190 receive an invader irrespective of their distance from the invasion front. This was a realistic
191 assumption in the *Cape to City* area given that it is only ~10 km wide, i.e. well within the
192 range of dispersal distances for all three predator species. Settled invaders were then added to
193 the resident population and trapped following the steps described in the previous paragraph.

194

195 Each year before the start of the seventh trapping session, the modelled population was
196 allowed to grow according to a *per-capita* annual growth rate. The number of offspring for
197 each adult was randomly drawn from a PERT distribution with biological parameters (Table
198 1) that were based information from previous studies of invasive predators in New Zealand.
199 The drawn number of offspring per adult was adjusted so that adults plus offspring did not
200 exceed the carrying capacity. This was done by first removing one offspring from adults
201 having ≥ 2 offspring, or by randomly removing offspring from any of the adults. The adjusted
202 number of juveniles then dispersed from the maternal home range centre to an unoccupied
203 home range centre which was bounded by the maximum dispersal distance for the species (m ;
204 Table 1). From the pool of H remaining unoccupied home range centres, the destination of a
205 juvenile was determined by a random draw from a multinomial distribution. The multinomial
206 probability for a dispersing juvenile from maternal location i to available location k was
207 calculated as:

208

$$209 \quad P(\text{disp})_{ik} = \frac{\Phi(d_{ik} | \ln(\mu), \ln(\varepsilon))}{\sum_{k=1}^K \Phi(d_{ik} | \ln(\mu), \ln(\varepsilon))}$$

210

211 where Φ was a log-normal probability density function, d_{ik} was the distance between the
212 maternal (i) and available (k) locations, and μ and ε were the mean and standard deviations of
213 dispersal distances (Table 1). The juvenile was then placed in the selected home range centre,

214 which became unavailable for the remaining juveniles. After moving the offspring and
215 adding them to the resident population, invaders were allowed to enter the study area
216 following the steps described in the previous paragraph. It is important to note that the model
217 only trapped animals once they had settled into a home range centre, and not during the
218 dispersal or invasion stages.

219

220 Population size was recorded at the end of each trapping session. Uncertainty was
221 incorporated into the model and propagated through to the estimates of population size by
222 repeating the simulation 10,000 times. For each iteration, new regular grids of home range
223 centres and parameter values were drawn for each animal. The resulting uncertainty in
224 predictions was assessed with 95% Bayesian credible intervals. Natural mortality was not
225 incorporated in the model as this was assumed to be trivial in comparison to mortality from
226 the trapping program (Byrom 2002).

227

228 *Simulated scenarios*

229 1. *Status quo*. Although most landholders in *Cape to City* have agreed to participate in the
230 predator control program, there are two with properties of ~900 ha adjacent to Cape
231 Sanctuary whose participation has not been confirmed. We ran the model removing traps
232 only from within these two large properties. Also, for comparison, we ran the model with
233 100% participation by landholders.

234

235 2. *Failure of landholders with large properties to participate*. There are seven landholders
236 with large properties (>800 ha). If they choose not to participate, this might reduce trapping
237 effectiveness more than if landholders with small properties opt out. The model was run for

238 four levels of large landholder participation by randomly excluding 1, 2, 3, or 4 of these large
239 properties.

240

241 *3. Limited participation by lifestyle landholders.* If landholders are influenced by neighbours'
242 actions, then small clusters of adjacent properties may decline to participate, rather than
243 scattered individual ones. In *Cape to City*, these clusters are expected to occur mostly in
244 areas dominated by lifestyle properties (i.e. properties of ≤ 25 ha; Sanson et al. 2004). We
245 identified five clusters of lifestyle properties, each composed of an average of 12 properties
246 (range: 5 – 19) and with an average cluster size of 110 ha (range: 33 – 208). The model was
247 run for three levels of lifestyle landholder participation by randomly excluding 1, 2, or 3 of
248 the clusters.

249

250 *4. Traps allocated to the properties of non-participants relocated on neighbouring*
251 *properties.* If a large landholder in the middle of the study area fails to participate in the
252 trapping program, this could provide a refuge from which surviving predators reinvade
253 adjacent areas. This could be mitigated with a buffer of traps around the non-participating
254 property. To simulate this, we removed traps from randomly selected large properties, but an
255 equivalent number of traps were then placed on adjacent participating properties. These were
256 intended to intercept predators whose home ranges extend beyond non-participating
257 properties, and juvenile predators dispersing from these properties. The additional traps were
258 accommodated by placing traps more closely along the routes already identified. The model
259 was run for four levels of large landholder participation by randomly excluding 1, 2, 3, or 4
260 of these large properties (as in scenario 2).

261

262 **Results**

263 Abundance of all three predator species was predicted to decline rapidly after the initial
264 knock-down (Table 1). However, the predicted rate of population recovery varied between
265 scenarios, and according to participation rate. Results for the mean initial knockdown are
266 shown in Fig. 2. Varying the level of initial knock-down had minimal effect on predicted
267 predator abundance after six years (Appendix S2).

268

269 [Figure 2 hereabouts]

270

271 Under Scenario 1 (*Status quo*), 1332 traps (91% of the planned total) fell within participating
272 properties. Predator populations recovered slowly after initial knock-down; after 6 years,
273 abundance of all three predator species was much lower than before the initial knock-down
274 (Fig. 2).

275

276 Under Scenario 2 (*Failure of landholders with large properties to participate*), the proportion
277 of the study area participating in trapping ranged from 77–91%. For all three predator
278 species, participation rate had a substantial effect on the predicted abundance (Fig. 2).

279 However, even at the lowest participation rate the model predicted predators would remain
280 well below their initial abundance after six years.

281

282 The *degree of participation of lifestyle landholders* (Scenario 3) had no noticeable effect on
283 predator population trends (Fig. 2). Only 3% of the *Cape to City* area is occupied by lifestyle
284 properties. Thus, even if all lifestyle landholders decided not to participate, only 34 traps
285 (2%) would be lost from the trapping network.

286

287 *Relocating traps* from non-participating properties to neighbouring ones (Scenario 4)
288 increased the effectiveness of predator control. Predator populations were lower for this
289 scenario than for Scenario 2, in which the total number of traps was reduced by non-
290 participation (Fig. 2).

291

292 **Discussion**

293 Using a spatially explicit population model, we have shown that the control of invasive
294 predators proposed in the *Cape to City* conservation initiative is likely to reduce the
295 abundance of feral cats, stoats and ferrets under a range of plausible scenarios for landowner
296 participation. Under the most likely *status quo* scenario, numbers of all three predators are
297 predicted to remain substantially below starting levels for at least six years.

298

299 Predator control could be less effective if one or more large properties opt out of the trapping
300 program. However, the effects of non-participation by some landholders can be largely
301 negated if the traps intended for their properties are shifted to neighbouring properties, as in
302 Scenario 4. In addition, we note that many of the proposed trap lines run along property
303 boundaries. In these cases, landholders on both sides of the boundary would presumably have
304 to opt out in order to influence the proposed layout of traps. However, for modelling
305 Scenarios 1–3, if a property is excised from the program all traps within it are removed. In
306 reality these traps may simply be able to be set a few metres away across the property
307 boundary. Thus, the model’s predictions are likely to be pessimistic when predicting the
308 influence of individual properties opting out of the trapping effort. Our model also predicts
309 that non-participation by owners of small properties would have a negligible effect. These
310 results give a high level of confidence that predator control in the *Cape to City* area will be
311 effective even if some landholders choose not to participate.

312

313 Based on the 6-year end points of simulated population trajectories, Scenarios 1 (*Status quo*)
314 and 3 (*Limited participation by lifestyle landholders*) outperformed all other scenarios (Fig.
315 2). Comparison of trajectory endpoints for Scenarios 2 (*Failure of landholders with large*
316 *properties to participate*) and 4 (*Traps allocated to the properties of non-participants*
317 *relocated on neighbouring properties*) indicated that when large properties were not included,
318 redeployment of traps onto neighbouring properties could compensate, resulting in better
319 suppression of all predator populations.

320

321 Participants in environmental decision making and management can have differing
322 expectations depending on cultural backgrounds (e.g. indigenous cf. non-indigenous
323 peoples), occupation (e.g. farmers, horticulturalists) and location (urban, peri-urban or rural)
324 (Karali et al. 2014). Landholder participation in pest management programs can depend on
325 the cost of intervention, the type of management technique (e.g. poison vs. traps), each
326 person's or group's interest in the desired outcome, and the number and characteristics of
327 participating landholders (Fowler and Christakis 2010; Montanari and Saberi 2010). This last
328 variable may influence engagement by altering landholder perceptions of normal or socially
329 approved behavior relating to invasive species control (Cialdini et al. 1990; McLeod et al.
330 2015) or by changing landholder's self or collective efficacy beliefs towards achieving the
331 desired outcomes (Bandura 1998). For example, if individual landholders perceive that not
332 enough large landholders are participating, they may believe that reduction in predator
333 numbers and subsequent recovery of native species will never be achieved, and thus their
334 own control efforts will be futile.

335

336 Further, the number and characteristics of potential participants may determine the period of
337 greatest need for investment in public engagement; for example, investing early to draw in a
338 number of key social ‘hubs’ may allow for a baseline number of individuals to be recruited
339 initially to establish social norms and enhance efficacy beliefs, which may then attract others
340 to the program (Fowler and Christakis 2010). Conversely, landholders might drop out of a
341 pest control program due to ‘burn out’ (which may be reduced by employing contractors to
342 do the control), a change in land use (e.g. a change to production unaffected by pest animals)
343 or if control is very efficient and pests are no longer perceived to be a problem (Russell et al.
344 2015).

345

346 Results from our spatial model suggest that support for the predator control program by
347 owners of large properties will be important. Also, our modelling demonstrates that, with the
348 exception of very small properties, continued high levels of landholder participation will be
349 needed to capitalise on gains achieved through the initial broad-scale knock-down of
350 predators. Further social data are needed to determine landholders’ attitudes towards pest
351 mammals and to pest control, and the factors that might influence the likelihood that a
352 landholder will support and/or participate in broad-scale predator control. Behavioral theories
353 from social psychology research can help inform what these factors may be (McLeod et al.
354 2015).

355

356 Finally, models can be designed to address more general questions such as: How do new
357 perceptions of pest control, or of the value of native biodiversity, spread through and persist
358 in communities? (See, for example, Kendal and Laland 2000; Fowler and Christakis 2010;
359 Montanari and Saberi 2010). This might generate insights into how communities both in New
360 Zealand and internationally might learn from the *Cape to City* experience. Furthermore,

361 generic models can be particularly useful for identifying the key social or biophysical drivers
362 that can lead to unexpected regime shifts or ‘tipping points’ (Lade et al. 2013).

363

364 Although our model predicts reduced predator abundances as a result of trapping in *Cape to*
365 *City*, it remains to be seen whether these reductions will be sufficient to allow recovery of
366 native species and ecological processes. It is essential that long-term monitoring measures
367 both the *results* of predator removal (changes in predator numbers) and the *outcomes* (e.g.
368 changes in abundance or distribution of native prey species) (Clayton and Cowan 2010) that
369 might, in turn, influence landholders attitudes about participation in *Cape to City*. As more
370 information becomes available (e.g. confirmation of participating properties and information
371 on the drivers and motivations for participation by landowners), our model could be adapted
372 to predict more accurately the likelihood of success in terms of the desired outcomes for
373 native species. Given appropriate data on species biology, property boundaries, and
374 willingness of landholders to participate in efforts to control invasive species, our model
375 could easily be adapted to simulate the results of managing other invasive species, or to other
376 landscapes, worldwide.

377

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381

382 **References**

383 Aslan CE, Hufford MB, Epanchin-Niell RS, Port JD, Sexton JP, Waring TM (2009) Practical
384 challenges in private stewardship of rangeland ecosystems: yellow starthistle control
385 in Sierra Nevadan foothills. *Rangeland Ecology & Management* 62:28-37

386 Bandura A (1998) Personal and collective efficacy in human adaptation and change.
387 Advances in Psychological Science 1:51-71

388 Byrom AE (2002) Dispersal and survival of juvenile ferrets *Mustela furo* in New Zealand.
389 Journal of Applied Ecology 39:67-78

390 Cialdini EB, Reno RR, Kallgren CA (1990) A focus theory of normative conduct: recycling
391 the concept of norms to reduce littering in public places. Journal of Personality &
392 Social Psychology 58:1015-1026

393 Clayton R, Cowan P (2010) Management of animal and plant pests in New Zealand - patterns
394 of control and monitoring by regional agencies. Wildlife Research 37:360-371

395 Corbett JB (2002) Motivations to participate in riparian improvement programs: applying the
396 theory of planned behavior. Science Communication 23:243-263

397 Cumming GS, Olsson P, Chapin F, Holling C (2013) Resilience, experimentation, and scale
398 mismatches in social-ecological landscapes. Landscape Ecology 28:1139-1150

399 Dickman CR (1996) Impact of exotic generalist predators on the native fauna of Australia.
400 Wildlife Biology 2:185-195

401 Efford M (2004) Density estimation in live-trapping studies. Oikos 106:598-610

402 Epanchin-Niell RS, Hufford MB, Aslan CE, Sexton JP, Port JD, Waring TM (2010)
403 Controlling invasive species in complex social landscapes. Frontiers in Ecology and
404 the Environment 8:210-216

405 Fowler JH, Christakis NA (2010) Cooperative behavior cascades in human social networks.
406 Proceedings of the National Academy of Sciences USA 107:5334-5338

407 Gentle MN, Saunders GR, Dickman CR (2007) Poisoning for production: how effective is
408 fox baiting in south-eastern Australia? Mammal Review 37:177-190

409

410 Glen AS, Byrom AE (2014) Implications of landholder buy-in for the success of regional-
411 scale predator control: Part 1: Review of predator movements. Contract Report
412 LC1956 for Hawke's Bay Regional Council. Landcare Research, Lincoln

413 Glen AS, Pech RP, Byrom AE (2013) Connectivity and invasive species management:
414 towards an integrated landscape approach. *Biol Invasions* 15:2127–2138

415 Herrerias PR, Garcia PJ, Cruz RS (2003) A note on the reasonableness of PERT hypotheses.
416 *Operations Research Letters* 31:60-62

417 Innes J, Burns B, Sanders A, Hayward MW (2015) The impact of private sanctuary networks
418 on reintroduction programs. *Advances in Reintroduction Biology of Australian and*
419 *New Zealand Fauna*. CSIRO Publishing, Collingwood, pp. 185-200

420 Innes J, Kelly D, Overton JM, Gillies C (2010) Predation and other factors currently limiting
421 New Zealand forest birds. *New Zealand Journal of Ecology* 34:86-114

422 Karali E, Brunner B, Doherty R, Hersperger A, Rounsevell M (2014) Identifying the factors
423 that influence farmer participation in environmental management practices in
424 Switzerland. *Human Ecology* 42:951-963

425 Kendal JR, Laland KN (2000) Mathematical models for memetics. *Journal of Memetics*
426 4:http://cfpm.org/jom-emit/2000/vol4/kendal_jr&laland_kn.html

427 King CM (2005) (Ed) *The Handbook of New Zealand Mammals*. 2nd Edition. Oxford
428 University Press, Melbourne

429 Kinnear JE, Onus ML, Bromilow RN (1988) Fox control and rock-wallaby population
430 dynamics. *Australian Wildlife Research* 15:435-450

431 Lade SJ, Tavoni A, Levin SA, Schlüter M (2013) Regime shifts in a social-ecological system.
432 *Theoretical ecology* 6:359-372

433 McLeod LJ, Hine DW, Please PM, Driver AB (2015) Applying behavioral theories to
434 invasive animal management: towards an integrated framework. *Journal of*
435 *Environmental Management* 161:63-71

436 Montanari A, Saberi A (2010) The spread of innovations in social networks. *Proceedings of*
437 *the National Academy of Sciences USA* 107:20196-20201

438 Norbury G, Byrom AE, Pech R, Smith J, Clarke D, Anderson DP, Forrester G (2013)
439 Invasive mammals and habitat modification interact to generate unforeseen outcomes
440 for indigenous fauna. *Ecological Applications* 23:1707-1721

441 Prinbeck G, Lach D, Chan S (2011) Exploring stakeholders' attitudes and beliefs regarding
442 behaviors that prevent the spread of invasive species. *Environmental Education*
443 *Research* 17(3): 341–352. <http://doi.org/10.1080/13504622.2010.542451>

444 R Development Core Team (2015) *R: A Language and Environment for Statistical*
445 *Computing*. R Foundation for Statistical Computing, Vienna

446 Rebaudo F, Dangles O (2013) An agent-based modeling framework for integrated pest
447 management dissemination programs. *Environmental Modelling & Software* 45:141-
448 149

449 Russell JC, Innes JG, Brown PH, Byrom AE (2015) Predator-free New Zealand: conservation
450 country. *BioScience* 65:520-525

451 Salo P, Korpimäki E, Banks PB, Nordström M, Dickman CR (2007) Alien predators are more
452 dangerous than native predators to prey populations. *Proceedings of the Royal Society*
453 *of London - Series B: Biological Sciences* 274:1237-1243

454 Sanson R, Cook A, Fairweather J (2004) *A study of smallholdings and their owners*. MAF
455 *Information Paper No. 53*. Ministry of Agriculture & Forestry, Wellington

- 456 Simberloff D (2010) Invasive species in New Zealand. In: Sodhi NS and Ehrlich PR (eds)
457 Conservation Biology for All. Oxford University Press, Oxford, pp. 132-133
458 Ward-Smith T (2011) Translocations to Cape Sanctuary: what has been learnt? *Notornis*
459 58:180
460
461

462 **Figure captions:**

463 **Figure 1:** Map of the *Cape to City* area (shaded) and the Cape Sanctuary reserve (hatched) in
464 Hawke's Bay, New Zealand showing property boundaries (—) and the planned locations of
465 traps (•) for on-going predator control.

466

467 **Figure 2:** Predicted numbers (\pm 95% Bayesian credible interval (CI)) of (a) ferrets (*Mustela*
468 *furo*), (b) feral cats (*Felis catus*) and (c) stoats (*Mustela erminea*) remaining after six years of
469 simulated predator control under each of four scenarios with mean initial knockdown levels
470 (Table 1): (1) Status quo (SQ): participation by all but two properties adjacent to Cape
471 Sanctuary; (2) non-participation by landholders with large properties; (3) non-participation by
472 landholders with small 'lifestyle' properties; (4) relocation of traps from non-participating
473 large properties to neighbouring properties. For each scenario, a range of levels of landholder
474 participation is presented. For comparison, the left-most point shows predicted predator
475 numbers when there is 100% landholder participation.

476

477

478 **Table 1:** Parameters used in a simulation model of the effects of landholder participation on
 479 predator control within the *Cape to City* program, Hawkes Bay, North Island, New Zealand.

480 All distances are in metres.

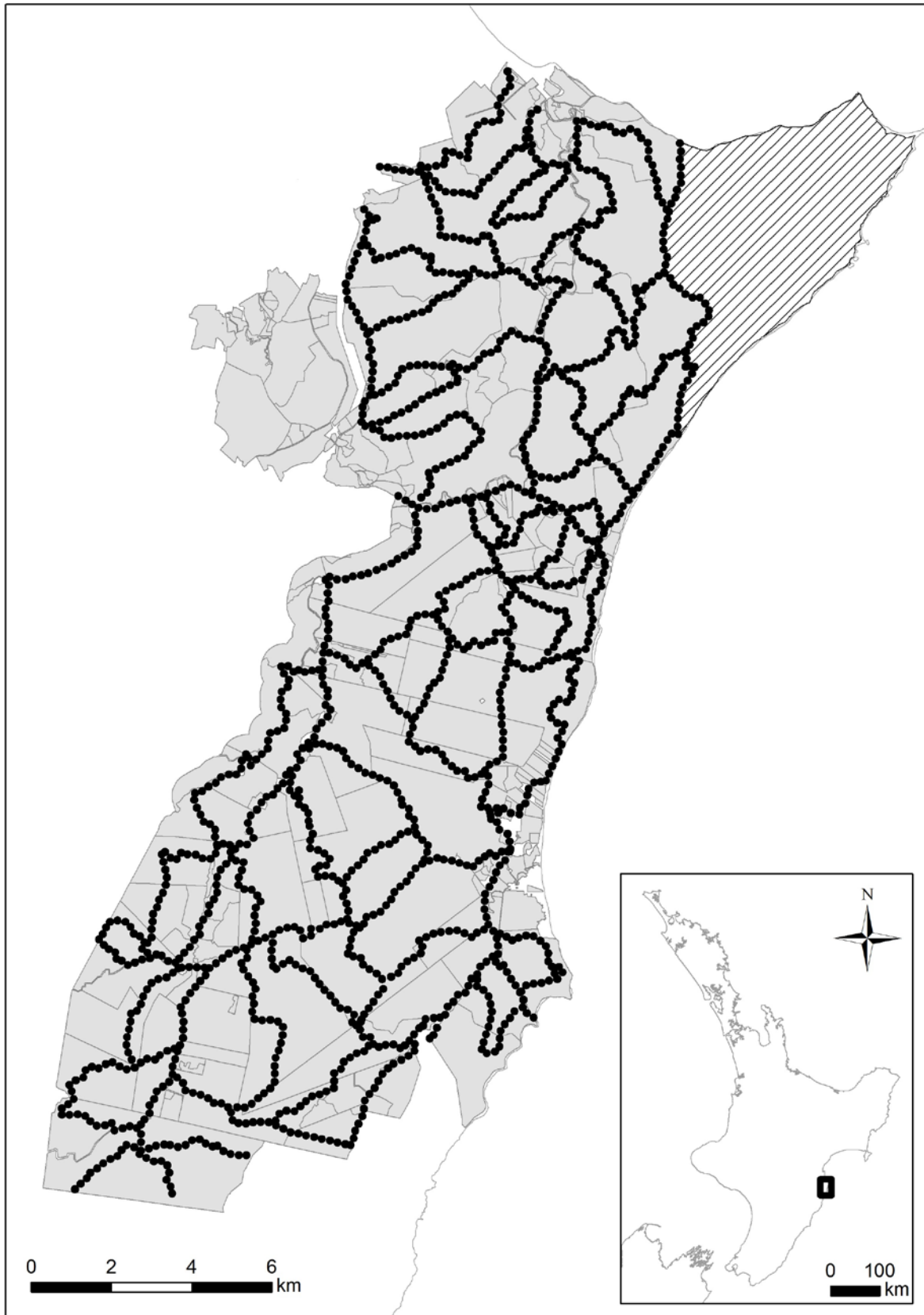
481

	Feral cats			Ferrets			Stoats		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Initial population size	–	500	–	–	200	–	–	200	–
Carrying capacity	–	900	–	–	300	–	–	250	–
Knock-down % kill	54	90	98	61	86	95	No Data ^a		
g_0	0.01	0.04	0.08	0.05	0.079	0.1	0.017	0.04	0.77
Sigma (σ)	259	351	436	430	466	500	492	600	891
Lambda (λ)	–	31	–	–	18	–	–	31	–
Population growth rate (r)	0.98	1	1.09	1	1.1	1.65	0.1	0.23	2.3
Dispersal (m)	–	–	30000	–	–	22000	–	–	65000
Dispersal (μ, ϵ)	2000, 1.5			1500, 2.2			2000, 2.5		

^a Assumed to be similar to that recorded for ferrets

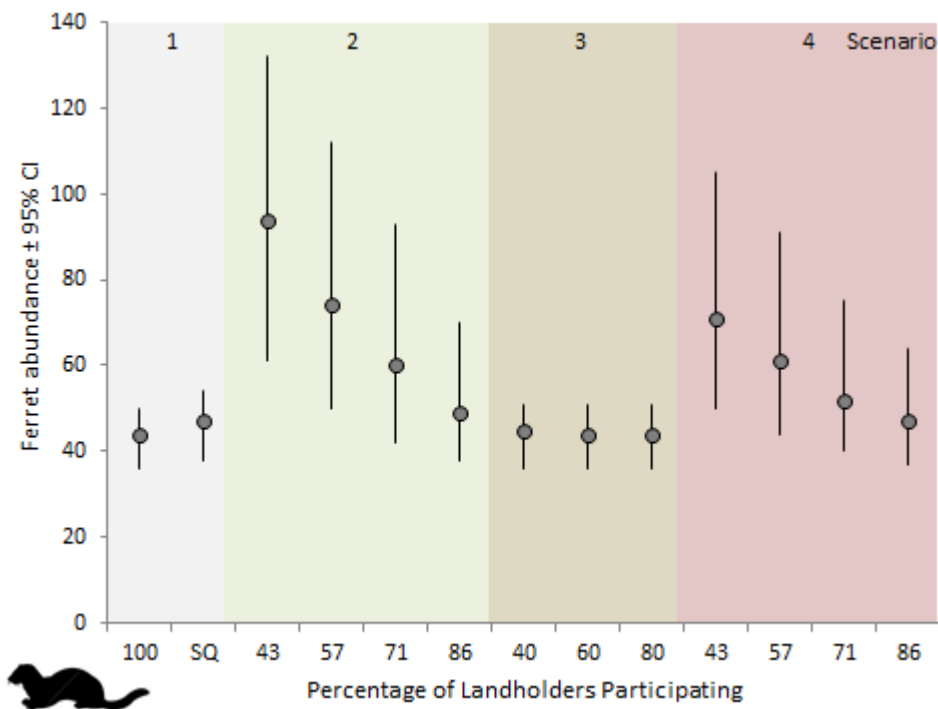
482

483



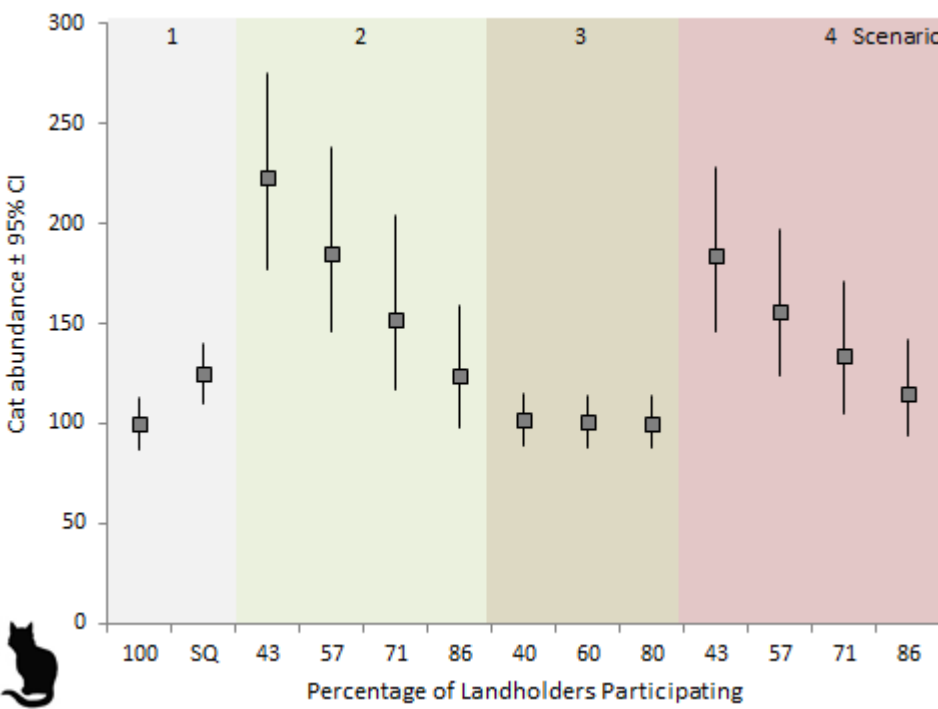
486 [Figure 2]

487 (a)



488

489 (b)

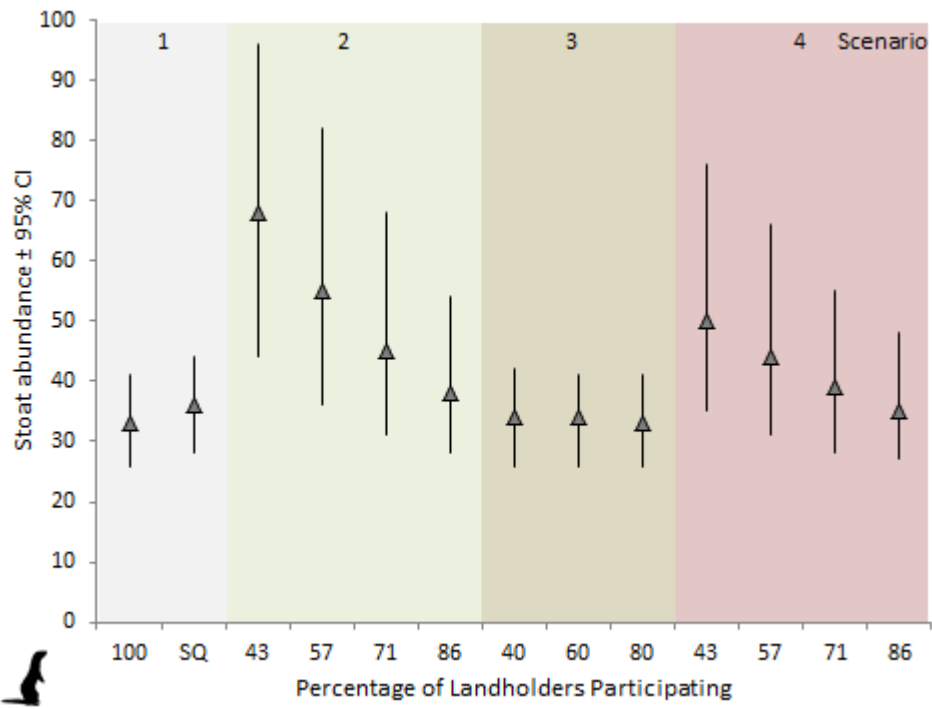


490

491

492

493 (c)



494

495 **Appendix S1.** Code for the spatial model (R version 3.1.3; R Development Core Team 2015).

```
496 Script named "HBPredatorFunctionsAllsims.R", containing the main functions
497
498 ##### START OF SCRIPT #####
499
500 library(mc2d)
501
502 #~~~~~
503 #Supporting functions
504
505 # Function to calculate distances between points, it can be a matrix of points
506 distmat <- function(x1,y1,x2,y2){
507   xd <- outer(x1,x2,function(x1,x2) (x1 - x2)^2)
508   yd <- outer(y1,y2,function(y1,y2) (y1 - y2)^2)
509   d <- t(sqrt(xd + yd))
510   return(d)
511 }
512
513 # Function to combine the probability of detection over x nights
514 combineFX <- function(x, nights) { 1 - prod((1-x)^nights) }
515 #~~~~~
516
517 # Main function POFx
518 # Parameters:
519 #   scenario = 1 to 5 (scenario 4 was not run)
520 #   popkd = %population removed by the initial knock-down (not simulated, just run 3 times for each species)
521 #   trapCent = the location of the traps
522 #   tmpshape = the study area shapefile
523 #   properties = the cadastral shapefile with all the properties
524 #   participation = the level of participation
525 #   cellsize = the size of the grid of home range centers
526 #   parameters = the population parameters for the species that is being simulated
527 #   sessiondat = the details of the trapping sessions
528 #   trapping = does trapping occur or not? (0 = no trapping, 1 = trapping)
529
530 POFx <- function(scenario, popkd, trapCent, tmpshape, properties, participation, cellsize,
531                 parameters, sessiondat, trapping, nIters)
```

```

532 {
533 # Start the clock
534 ptm <- proc.time()
535 nSession <- dim(sessiondat)[2]
536 nIters <- nIters
537
538 # Calculate the initial population after knock-down
539 initPop <- ((100 - popkd)/100) * parameters["initPop", 2]
540 print(paste("Initial population size = ", initPop, sep = ""))
541
542 # The population size at each session of each iteration
543 PopSize <- matrix(0, nIters, nSession)
544
545 # create a matrix to record the included area at each iteration
546 inclareaXiter <- matrix(0, nIters, 1)
547 print(paste("Scenario ", scenario, sep = ""))
548
549 if(scenario == 1)
550 {
551 # scenario 1 = most likely status quo
552 # this scenario has to be run at 0% participation in order for the 2 properties to be removed
553 propIDs <- c(398, 1425)
554 }
555
556 if(scenario == 2)
557 {
558 # create a list of the large properties IDs
559 # This scenario is run at 50%, 60%, 70%, 90% participation
560 propIDs <- as.vector(properties[properties$AreaHA > 800,]$SHU_ID)
561 }
562
563 if(scenario == 3)
564 {
565 # Create a list of the lifestyle block clusters
566 # This scenario is run at 40%, 60%, 80% participation
567 clusters <- seq(1, 5, 1)
568 }
569
570 if(scenario == 5)

```

```

571 {
572 # create a list of the large properties IDs
573 # This scenario is run at 50%, 60%, 70%, 90% participation
574 propIDs <- as.vector(properties[properties$AreaHA > 800,]$SHU_ID)
575 }
576
577 if(scenario > 5)
578 {
579   print(paste("Scenario ", scenario, " is not a correct option", sep = ""))
580 }
581
582 # loop through the iterations
583 for(j in 1:nIters)
584 {
585   print("")
586   print(paste("Iteration = ", as.character(j)))
587
588   # first step is to randomly select a number of non-participating properties
589   # based on %participation, to take out the traps
590   # For scenario 3, need to sample the clusters of properties
591   if(scenario == 3)
592   {
593     ssize <- round(length(clusters) * (100 - participation) / 100)
594     #print(paste("Excluded clusters = ", as.character(ssize)))
595     ranexclclusters <- sample(clusters, ssize)
596     ranexclprop <- as.vector(properties[properties$LBCluster %in% ranexclclusters,]$SHU_ID)
597   }
598   else
599   {
600     ssize <- round(length(propIDs) * (100 - participation) / 100)
601     ranexclprop <- sample(propIDs, ssize)
602   }
603
604   # remove the non-participating properties from the properties shapefile,
605   # the total area of all properties is 24161.548 HA
606   participproperties <- properties[!properties$SHU_ID %in% ranexclprop, ]
607   inclareaXiter[j, 1] <- sum(as.vector(participproperties$AreaHA))
608
609   trapCent.inside <- !is.na(over(trapCent, as(participproperties, "SpatialPolygons")))

```

```

610 # the actual traps that fell inside the participating properties
611 trapCent2 <- trapCent[trapCent.inside == "TRUE",]
612 # the actual traps that fell outside of the participating properties
613 trapCentNO <- trapCent[trapCent.inside == "FALSE",]
614
615 trapline.inside <- !is.na(over(traplineP, as(participproperties, "SpatialPolygons")))
616 # the proposed traps that fell inside the participating properties
617 trapline2 <- traplineP[trapline.inside == "TRUE",]
618
619 trapCent2 <- as.data.frame(trapCent2)
620 trapCentNO <- as.data.frame(trapCentNO)
621 trapline2 <- as.data.frame(trapline2)
622
623 # For scenario 5, need to add additional traps to substitute the traps that were removed
624 if(scenario = 5)
625 {
626 # Now I need to calculate which trap from the trapline2 is
627 # closest to each trap that was excluded (trapCentNO)
628 # if there were some traps excluded, then replace each removed trap by the closest proposed trap
629 if(dim(trapCentNO)[1] != 0)
630 {
631 #print(paste("Scenario ", scenario, ", choosing new traps", sep = ""))
632 #print(paste("Need to replace ", dim(trapCentNO)[1], " new traps", sep = ""))
633 # create a matrix that will hold the new traps (X, Y)
634 newtraps <- matrix(0, dim(trapCentNO)[1], 3)
635 # make a copy of the proposed traps
636 trapline3 <- trapline2
637
638 # loop through each trap that was taken out
639 for (tn in 1:dim(trapCentNO)[1])
640 {
641 xtrapNO <- trapCentNO[tn, 1]
642 ytrapNO <- trapCentNO[tn, 2]
643
644 xtrapline3 <- trapline3[, 1]
645 ytrapline3 <- trapline3[, 2]
646
647 # Calculate distance between removed trap and all proposed traps
648 distntnl <- distmat(xtrapNO, ytrapNO, xtrapline3, ytrapline3)

```

```

649
650     # the new trap is going be the closest one to the excluded one
651     newt <- which(distntnl == min(distntnl))
652     newtraplocX <- trapline3[newt, 1]
653     newtraplocY <- trapline3[newt, 2]
654     newtrapID <- trapline3[newt, 3]
655     newtraps[tn, 1] <- newtraplocX
656     newtraps[tn, 2] <- newtraplocY
657     newtraps[tn, 3] <- newtrapID
658
659     # Finally, need to take out the trap that was chosen to replace
660     # the excluded trap from the proposed traps dataset
661     trapline3 <- trapline3[trapline3$ID != newtrapID, ]
662   }
663
664   newtraps <- as.data.frame(newtraps)
665   names(newtraps) <- c("X", "Y", "ID")
666   trapCent2 <- rbind(trapCent2, newtraps)
667   }
668   else
669   {
670     print(paste("Scenario ", scenario, ", but no traps removed", sep = ""))
671   }
672 }
673
674 else
675 {
676   print(paste("Scenario ", scenario, ", no need to replace traps", sep = ""))
677 }
678
679 # loop through 40 sessions (8 session/yr, 5 yrs)
680 for(i in 1:nSession)
681 {
682   # If trap grid is provided, use that information
683   xtrap <- trapCent2[, 1]
684   ytrap <- trapCent2[, 2]
685
686   # if it is the first session, generate population of animals,
687   # no reproduction or immigrants in this session, just captures

```

```

688 if(i == 1)
689 {
690 # Create a grid of points that cover the whole of the study area
691 # These points act as home range centers for each animal (1 animal per point)
692 # The grid will change in every iteration of the model
693 HRcenters <- spsample(tmpshape, n = 1000, "regular", cellsize = cellsize, iter = 20)
694 HRcentersDF <- as.data.frame(HRcenters)
695 HRcentersDF$cellID <- seq(1, dim(HRcentersDF)[1], 1)
696 adultLoc <- sample(HRcentersDF$cellID, size = initPop, replace = FALSE)
697 adultLocDF <- HRcentersDF[HRcentersDF$cellID %in% adultLoc, ]
698 HRcentersMask <- ifelse(HRcentersDF$cellID %in% adultLoc, 1, 0)
699
700 nAdults <- dim(adultLocDF)[1]
701 animX <- adultLocDF[, 1]
702 animY <- adultLocDF[, 2]
703
704 # a matrix with rows = animal and columns = trap, the value is the distance between them
705 trapAnimDist <- distmat(xtrap, ytrap, animX, animY)
706 # draw the random values for g0, one per individual in the population, add it to the population DF
707 adultLocDF$g0 <- rpert(nAdults, parameters["g0", 1], parameters["g0", 2], parameters["g0", 3])
708 # draw the random values for sigma, one per individual in the population, add it to the population DF
709 adultLocDF$sig <- rpert(nAdults, parameters["sigma", 1], parameters["sigma", 2], parameters["sigma", 3])
710 # The probability of detection for each Animal by each Trap, over 1 single night
711 PdetAT <- adultLocDF$g0 * exp(-(trapAnimDist^2)/(adultLocDF$sig^2))
712 # The probability of detection for each animal by ALL traps over All nights
713 Pdetk <- apply(PdetAT, 1, combineFX, nights = sessiondat["nights", i])
714 adultLocDF$PCK <- Pdetk
715 adultLocDF$Capt <- 0
716
717 for (a in 1:dim(adultLocDF)[1])
718 {
719 # Was there trapping? Was each animal captured or not?
720 adultLocDF$Capt[a] <- ifelse(trapping == 1, rbinom(1, 1, adultLocDF$PCK[a]), 0)
721 }
722 # retain in the population only the animals that were not captured
723 adultLocDF <- adultLocDF[adultLocDF$Capt == 0, ]
724 HRcentersMask <- ifelse(HRcentersDF$cellID %in% adultLocDF$cellID, 1, 0)
725 PopSize[j, i] <- dim(adultLocDF)[1]
726 }

```

```

727
728 # Sessions greater than first session, need to consider ALL of the animals that are now present
729 if(i > 1)
730 {
731 # No reproduction during this session, add new immigrants and then capture the adults that are there
732 if(sessiondat["reproduce", i] == 0)
733 {
734 # Draw the number of invaders from a Poisson distribution
735 nImmig <- rpois(1, lambda = parameters["rateInv", 2])
736
737 #If the population size is under K and there are immigrants
738 if(dim(adultLocDF)[1] < parameters["K", 2] & nImmig > 0)
739 {
740 # adjust the number of immigrants based on k
741 nImmig <- ifelse((nImmig + dim(adultLocDF)[1]) <= parameters["K", 2],
742 nImmig,
743 (parameters["K", 2] - dim(adultLocDF)[1]))
744 # randomly place the invaders within the study area, but only in cells that are not already occupied
745 immigLoc <- sample(HRcentersDF[HRcentersMask == 0, ]$cellID, size = nImmig, replace = FALSE)
746 immigLocDF <- HRcentersDF[HRcentersDF$cellID %in% immigLoc, ]
747 # Draw the random values for g0 for the immigrants
748 immigLocDF$g0 <- rpert(nImmig, parameters["g0", 1], parameters["g0", 2], parameters["g0", 3])
749 # Draw the random values for sigma for the immigrants
750 immigLocDF$sig <- rpert(nImmig, parameters["sigma", 1], parameters["sigma", 2], parameters["sigma", 3])
751 immigLocDF$Pck <- 0.0
752 immigLocDF$Capt <- 0
753 # add the invaders to the resident population
754 adultLocDF <- rbind(adultLocDF, immigLocDF)
755 }
756 else
757 {
758 print("No immigrants")
759 }
760
761 nAdults <- dim(adultLocDF)[1]
762 animX <- adultLocDF[, 1]
763 animY <- adultLocDF[, 2]
764
765 # a matrix with rows = animal and columns = trap, the value is the distance between them

```



```

766 trapAnimDist <- distmat(xtrap, ytrap, animX, animY)
767 # The probability of detection for each Animal by each Trap, over 1 single night
768 PdetAT <- adultLocDF$g0 * exp(-(trapAnimDist^2)/2/(adultLocDF$sig^2))
769 # The probability of detection for each animal by ALL traps over All nights
770 Pdetk <- apply(PdetAT, 1, combineFX, nights = sessiondat["nights", i])
771 adultLocDF$PCk <- Pdetk
772 for (a in 1:dim(adultLocDF)[1])
773 {
774   # Was there trapping? If so, Was each animal captured or not?
775   adultLocDF$Capt[a] <- ifelse(trapping == 1, rbinom(1, 1, adultLocDF$PCk[a]), 0)
776 }
777 # retain in the population only the animals that were not captured
778 adultLocDF <- adultLocDF[adultLocDF$Capt == 0, ]
779 HRcentersMask <- ifelse(HRcentersDF$cellID %in% adultLocDF$cellID, 1, 0)
780 PopSize[j, i] <- dim(adultLocDF)[1]
781 }
782
783 # Reproduction during this session, add and disperse babies
784 if(sessiondat["reproduce", i] == 1)
785 {
786   nAdults <- dim(adultLocDF)[1]
787   # We are assuming that all baby animals are females?
788   # This is already considered in the estimate of fecundity
789   # Draw the number of babies per adult present
790   babyanimals <- round(rpert(nAdults, parameters["rMax", 1], parameters["rMax", 2], parameters["rMax", 3]))
791
792   # If the number of babies plus adults is less than K, the proceed without changing anything
793   if((sum(babyanimals) + nAdults) < parameters["K", 2])
794   {
795     babyanimals <- babyanimals
796   }
797   # else, need to remove some of the prospective babies
798   # first remove babies from adults that will have 2 or more babies,
799   # then start to remove babies from the adults with 1 baby (i.e, they won't have any baby)
800   else
801   {
802     maxbabies2add <- parameters["K", 2] - nAdults
803     babies2remove <- sum(babyanimals) - maxbabies2add
804     t <- babies2remove

```

```

805 while (t > 0)
806   {
807   if(any(babyanimals > 1))
808     {
809     n <- length(which(babyanimals > 1))
810     babyanimals[which(babyanimals > 1)] <- 1
811     t <- t - n
812     }
813   else
814     {
815     index <- sample(which(babyanimals >= 1), t, replace = FALSE)
816     babyanimals[index] <- 0
817     t <- t - length(index)
818     }
819   }
820 }
821
822 babiesLoc <- data.frame("x1" = 0, "x2" = 0, 'cellID' = 0)
823
824 # If the number of adults is less than k, then disperse the babies in the vector babyanimals
825 if(nAdults > 1 & nAdults < parameters["K", 2])
826   {
827   # loop through each adult, for each of the adults present, disperse the offspring
828   for(k in 1:nAdults)
829     {
830     #if the adult doesnt have a baby, then do nothing
831     if(babyanimals[k] == 0)
832       {
833       print('no babies for this adult')
834       }
835     # else, chose where each baby will go
836     else
837       {
838       for(b in 1:babyanimals[k])
839         {
840         # Create a list of the possible cells where the baby can go (i.e. those that are not already occupied)
841         poscells4babies <- HRcentersDF[HRcentersMask == 0, ]$cellID
842         # Calculate the distance between all possible grid cells and the parent location
843         cellAnimDist <- distmat(HRcentersDF[HRcentersDF$cellID %in% poscells4babies, "x1"],

```

```

844         HRcentersDF[HRcentersDF$cellID %in% poscells4babies, "x2"],
845         adultLocDF[k, "x1"], adultLocDF[k, "x2"])
846     cellAnimDistDF <- data.frame(CAdist = cellAnimDist[1, ], cellID = poscells4babies)
847     # remove from the possible cells those that are too far away from this adult
848     # (i.e. the babies would die if they dispersed there)
849     cellAnimDistDF <- cellAnimDistDF[cellAnimDistDF$CAdist <= parameters["DispersalMax", 2], ]
850     # if there are possible neighbouring cells, then choose one where the baby will go
851     if(dim(cellAnimDistDF)[1] > 0)
852     {
853         # Now calculate the probability density of the dispersal distance
854         PdispCA <- dlnorm(cellAnimDistDF$CAdis, mean = log(parameters["DispersalMean", 2]), sd = log(parameters["DispersalSD", 2]))
855         # Transform the probabilities above into multinomial probabilities (i.e. they will all sum to one)
856         multPdistCA <- PdispCA/sum(PdispCA)
857         destination <- rmultinom(1, 1, multPdistCA)
858         cellAnimDistDF$dest <- destination
859         babyLoc <- HRcentersDF[HRcentersDF$cellID == cellAnimDistDF[cellAnimDistDF$dest == 1, 'cellID'], ]
860         babiesLoc <- rbind(babiesLoc, babyLoc)
861         # Now I need to recalculate the mask, to take out the cell where the baby went
862         HRcentersMask <- ifelse(HRcentersDF$cellID %in% c(adultLocDF$cellID, babiesLoc$cellID), 1, 0)
863     }
864     # else we are left with no potential neighbouring cells, then discard the baby
865     else
866     {
867         print("No locations for babies to disperse")
868     }
869 }
870 }
871 }
872 # Draw the random values for g0 for the babies
873 babiesLoc$g0 <- rpert(dim(babiesLoc)[1], parameters["g0", 1], parameters["g0", 2], parameters["g0", 3])
874 # Draw the random values for sigma for the babies
875 babiesLoc$sig <- rpert(dim(babiesLoc)[1], parameters["sigma", 1], parameters["sigma", 2], parameters["sigma", 3])
876 babiesLoc$PCK <- 0.0
877 babiesLoc$Capt <- 0
878 # Add the babies to the adult population
879 adultLocDF <- rbind(adultLocDF, babiesLoc)
880 adultLocDF <- adultLocDF[adultLocDF$x1 != 0, ]
881 }
882

```

```

883 if(nAdults == 1)
884 {
885 #if the adult doesn't have a baby, then do nothing
886 if(babyanimals == 0)
887 {
888 print('no babies for this adult')
889 }
890 # else, chose where those babies go
891 else
892 {
893 for(b in 1:babyanimals)
894 {
895 # Create a list of the possible cells where the baby can go (i.e. those that are not already occupied)
896 poscells4babies <- HRcentersDF[HRcentersMask == 0, ]$cellID
897 # Calculate the distance between of all possible grid cells and the parent location
898 cellAnimDist <- distmat(HRcentersDF[HRcentersDF$cellID %in% poscells4babies, "x1"],
899 HRcentersDF[HRcentersDF$cellID %in% poscells4babies, "x2"],
900 adultLocDF[1, "x1"], adultLocDF[1, "x2"])
901 cellAnimDistDF <- data.frame(CAdist = cellAnimDist[1,], cellID = poscells4babies)
902 # remove from the possible cells those that are too far away from this adult
903 # (i.e. the babies would die if they dispersed there)
904 cellAnimDistDF <- cellAnimDistDF[cellAnimDistDF$CAdist <= parameters["DispersalMax", 2], ]
905 # if there are possible neighbouring cells, then choose one where the baby will go
906 if(dim(cellAnimDistDF)[1] > 0)
907 {
908 # Now calculate the the probability density of the dispersal distance
909 PdispCA <- dlnorm(cellAnimDistDF$CAdist, mean = log(parameters["DispersalMean", 2]), sd = log(parameters["DispersalSD", 2]))
910 # Tranform the probabilities above into multinomial probabilities (i.e. they will all sum to one)
911 multPdistCA <- PdispCA/sum(PdispCA)
912 # Now do a multinomial draw with nbabies draws to get the destination/s for the juvenile/s
913 destination <- rmultinom(1, 1, multPdistCA)
914 cellAnimDistDF$dest <- destination
915 babyLoc <- HRcentersDF[HRcentersDF$cellID == cellAnimDistDF[cellAnimDistDF$dest == 1, 'cellID'], ]
916 babiesLoc <- rbind(babiesLoc, babyLoc)
917 # now I need to recalculate the mask, to take out the cell where the baby went
918 HRcentersMask <- ifelse(HRcentersDF$cellID %in% c(adultLocDF$cellID, babiesLoc$cellID), 1, 0)
919 }
920 # else, we are left with no potential neighbouring cells, then discard the baby
921 else

```

```

922     {
923     print("No locations for babies to disperse")
924     }
925   }
926   # Draw the random values for g0 for the babies
927   babiesLoc$g0 <- rpert(dim(babiesLoc)[1], parameters["g0", 1], parameters["g0", 2], parameters["g0", 3])
928   # Draw the random values for sigma for the babies
929   babiesLoc$sig <- rpert(dim(babiesLoc)[1], parameters["sigma", 1], parameters["sigma", 2], parameters["sigma", 3])
930   babiesLoc$PCK <- 0.0
931   babiesLoc$Capt <- 0
932   # Add the babies to the adult population
933   adultLocDF <- rbind(adultLocDF, babiesLoc)
934   adultLocDF <- adultLocDF[adultLocDF$x1 != 0, ]
935   }
936 }
937
938 if(nAdults == 0)
939 {
940   print("no adults, no babies")
941 }
942
943 if(nAdults == parameters["K", 2])
944 {
945   print("Population at carrying capacity, no babies")
946 }
947
948 # Draw the number of invaders from a Poisson distribution
949 nImmig <- rpois(1, lambda = parameters["rateInv", 2])
950 #If the population size is under K and there are immigrants
951 if(dim(adultLocDF)[1] < parameters["K", 2] & nImmig > 0)
952 {
953   # adjust the number of immigrants based on k
954   nImmig <- ifelse((nImmig + dim(adultLocDF)[1]) <= parameters["K", 2],
955     nImmig,
956     (parameters["K", 2] - dim(adultLocDF)[1]))
957   # randomly place the invaders within the study area, but only in cells that are not already occupied
958   immigLoc <- sample(HRcentersDF[HRcentersMask == 0, ]$cellID, size = nImmig, replace = FALSE)
959   immigLocDF <- HRcentersDF[HRcentersDF$cellID %in% immigLoc, ]
960   # Draw the random values for g0 for the immigrants

```

```

961     immigLocDF$g0 <- rpert(nImmig, parameters["g0", 1], parameters["g0", 2], parameters["g0", 3])
962     # Draw the random values for sigma for the immigrants
963     immigLocDF$sig <- rpert(nImmig, parameters["sigma", 1], parameters["sigma", 2], parameters["sigma", 3])
964     immigLocDF$PCK <- 0.0
965     immigLocDF$Capt <- 0
966     # add the invaders to the resident population
967     adultLocDF <- rbind(adultLocDF, immigLocDF)
968     }
969   else
970     {
971     print("No immigrants")
972     }
973
974     nAdults <- dim(adultLocDF)[1]
975     animX <- c(adultLocDF[, 1])
976     animY <- c(adultLocDF[, 2])
977     # a matrix with rows = animal and columns = trap, the value is the distance between them
978     trapAnimDist <- distmat(xtrap, ytrap, animX, animY)
979     # The probability of detection for each Animal by each Trap, over 1 single night
980     PdetAT <- adultLocDF$g0 * exp(-(trapAnimDist^2)/2/(adultLocDF$sig^2))
981     # The probability of detection for each animal by ALL traps over All nights
982     Pdetk <- apply(PdetAT, 1, combineFX, nights = sessiondat["nights", i])
983     #adultLocDF$PCK <- Pdetk
984     for (a in 1:dim(adultLocDF)[1])
985     {
986     # Was there trapping? If so, was each animal captured or not?
987     adultLocDF$Capt[a] <- ifelse(trapping == 1, rbinom(1, 1, adultLocDF$PCK[a]), 0)
988     }
989     # retain in the population only the animals that were not captured
990     adultLocDF <- adultLocDF[adultLocDF$Capt == 0, ]
991     HRcentersMask <- ifelse(HRcentersDF$cellID %in% adultLocDF$cellID, 1, 0)
992     PopSize[j, i] <- dim(adultLocDF)[1]
993   }
994 }
995 }
996 }
997 # Stop the clock
998 runningtime <- proc.time() - ptm
999 print(runningtime)

```

```

1000     return(list("PopulationSize" = PopSize, "IncludedArea" = inclareaXiter, 'Population' = adultLocDF))
1001 }
1002
1003 ##### END OF SCRIPT #####
1004
1005 ##### TO RUN THE MODEL in R #####
1006
1007 library(mc2d)
1008 library(maptools)
1009 library(spatstat)
1010 library(rgdal)
1011 library(sp)
1012 library(maps)
1013
1014 source("HBPredatorFunctionsAllsims.R")
1015
1016 #read in shapefile of study area
1017 tmpshape <- readShapeSpatial("StudyArea.shp")
1018
1019 #read in properties shapefile
1020 properties <- readOGR(dsn = ".", layer = "Properties")
1021
1022 #read in trap locations
1023 trapCent <- read.table("ActualTraps.csv", sep=",", header=T)
1024 coordinates(trapCent) <- c("X", "Y")
1025 proj4string(trapCent) <- proj4string(properties)
1026
1027 # The shapefile with the proposed trapline (i.e. traps that can be added, as points of traps every 50m)
1028 traplineP <- read.table("PropTraps50m.csv", sep=",", header=T)
1029 coordinates(traplineP) <- c("X", "Y")
1030 proj4string(traplineP) <- proj4string(properties)
1031
1032 #read in model parameters for feral cats, stoats and ferrets
1033 parameters.cat <- read.table("parametersHBcats.csv", sep = ",", header = T, row.names = 1)
1034 parameters.ferret <- read.table("parametersHBferrets.csv", sep = ",", header = T, row.names = 1)
1035 parameters.stoat <- read.table("parametersHBstoats.csv", sep = ",", header = T, row.names = 1)
1036
1037 #read in session data
1038 sessiondat <- read.table("sessionDatHB.csv", sep = ",", header = T, row.names = 1)

```

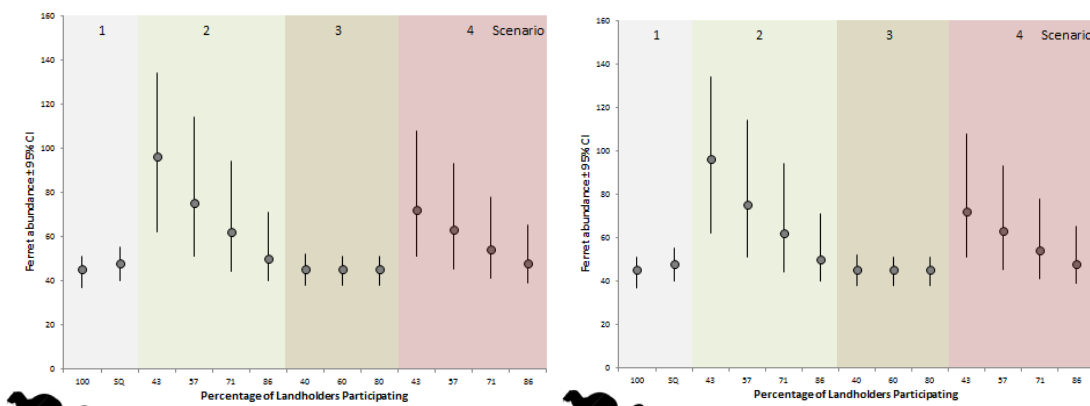
```
1039
1040 dispshape2 <- as(dispshape, "owin")
1041 SAshape <- as(tmpshape, "owin")
1042
1043 #Example call to the main function
1044 POFx(scenario = 2, popkd = 90, trapCent, tmpshape, properties, participation = 50, cellsize = 500, parameters = parameters.cat, sessiondat, trapping = 1, nIters = 100)
```


1045 **Appendix S2.**

1046 Predicted numbers (\pm 95% Bayesian credible interval (CI)) of (a) ferrets (*Mustela furo*), (b)
1047 feral cats (*Felis catus*) and (c) stoats (*Mustela erminea*) remaining after six years of simulated
1048 predator control under each of four scenarios with minimum (left) and maximum (right)
1049 initial knockdown levels (Table 1): (1) Status quo (SQ): participation by all but two
1050 properties adjacent to Cape Sanctuary; (2) non-participation by landholders with large
1051 properties; (3) non-participation by landholders with small 'lifestyle' properties; (4)
1052 relocation of traps from non-participating large properties to neighbouring properties. For
1053 each scenario, a range of levels of landholder participation is presented. For comparison, the
1054 left-most point shows predicted predator numbers when there is 100% landholder
1055 participation.
1056

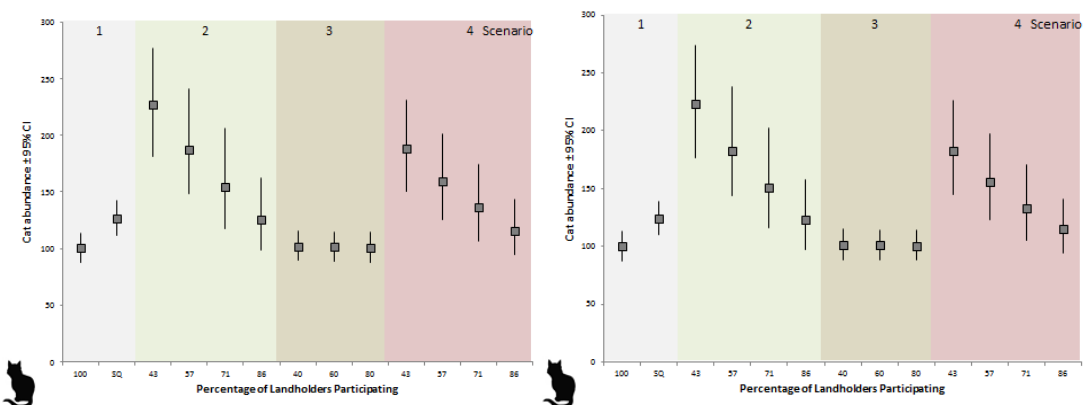
1057 (a) Minimum knock-down


Maximum knock-down



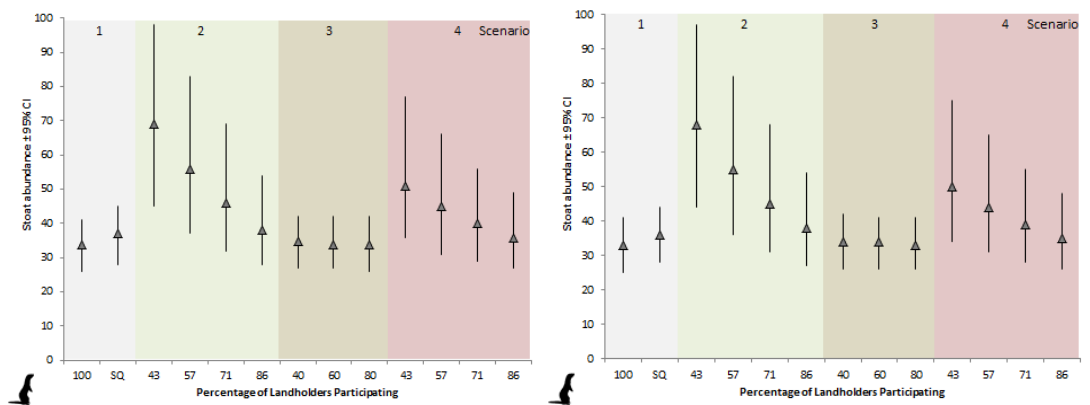
1058 

1059 (b)



1060 

1061 (c)



1062 