

Kent Academic Repository

Full text document (pdf)

Citation for published version

Gálvez, Nicolás and Guillera-Aroita, Gurutzeta and St. John, Freya A.V. and Schuttler, Elke and Macdonald, David W. and Davies, Zoe G. (2017) A spatially integrated framework for assessing socio-ecological drivers of carnivore decline. *Journal of Applied Ecology*, 54 (6). pp. 1919-1929. ISSN 0021-8901.

DOI

<https://doi.org/10.1111/1365-2664.12880>

Link to record in KAR

<http://kar.kent.ac.uk/64233/>

Document Version

Author's Accepted Manuscript

Copyright & reuse

Content in the Kent Academic Repository is made available for research purposes. Unless otherwise stated all content is protected by copyright and in the absence of an open licence (eg Creative Commons), permissions for further reuse of content should be sought from the publisher, author or other copyright holder.

Versions of research

The version in the Kent Academic Repository may differ from the final published version.

Users are advised to check <http://kar.kent.ac.uk> for the status of the paper. **Users should always cite the published version of record.**

Enquiries

For any further enquiries regarding the licence status of this document, please contact:

researchsupport@kent.ac.uk

If you believe this document infringes copyright then please contact the KAR admin team with the take-down information provided at <http://kar.kent.ac.uk/contact.html>

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27

A spatially integrated framework for assessing socio-ecological drivers of carnivore decline

Nicolás Gálvez^{1,2,3*}, Gurutzeta Guillera-Arroita⁴, Freya A.V. St. John^{1,5}, Elke Schüttler^{3,6}, David W. Macdonald⁷ and Zoe G. Davies¹

¹Durrell Institute of Conservation and Ecology (DICE), School of Anthropology and Conservation, University of Kent, Canterbury, Kent, CT2 7NR, UK

²*Department of Natural Sciences, Centre for Local Development, Villarrica Campus, Pontificia Universidad Católica de Chile, O'Higgins 501, Villarrica, Chile*

³Fauna Australis Wildlife Laboratory, School of Agriculture and Forestry Sciences, Pontificia Universidad Católica de Chile, Avenida del Libertador Bernardo O'Higgins 340, Santiago de Chile, Chile

⁴School of BioSciences, University of Melbourne, Parkville, Victoria, Australia

⁵School of Environment, Natural Resources & Geography, Bangor University, Bangor, Gwynedd, LL57 2UW, Wales, UK

⁶Department of Conservation Biology, UFZ - Helmholtz Centre for Environmental Research GmbH, Permoserstraße 15, 04318 Leipzig, Germany

⁷Wildlife Conservation Research Unit, Department of Zoology, University of Oxford, The Recanati-Kaplan Centre, Tubney House, Tubney, Oxon OX13 5QL UK

*Corresponding author: ng253@kent.ac.uk; +562 -23547307

Running title: Socio-ecological drivers of carnivore decline

Article type: Standard

Word count: 8,600

Number of tables: 4

Number of references: 67

28 **Abstract**

- 29 1. Habitat loss, fragmentation and degradation are key threats to the long-term persistence of
30 carnivores, which are also susceptible to direct persecution by people. Integrating natural and
31 social science methods to examine how habitat configuration/quality and human-predator
32 relations may interact in space and time to effect carnivore populations within human-
33 dominated landscapes will help prioritise conservation investment and action effectively.
- 34 2. We propose a socio-ecological modelling framework to evaluate drivers of carnivore decline
35 in landscapes where predators and people coexist. By collecting social and ecological data at
36 the same spatial scale, candidate models can be used to quantify and tease apart the relative
37 importance of different threats.
- 38 3. We apply our methodological framework to an empirical case study, the threatened guiña
39 (*Leopardus guigna*) in the temperate forest ecoregion of southern Chile, to illustrate its use.
40 Existing literature suggests that the species is declining due to habitat loss, fragmentation and
41 persecution in response to livestock predation. Data used in modelling were derived from four
42 seasons of camera-trap surveys, remote-sensed images and household questionnaires.
- 43 4. Occupancy dynamics were explained by habitat configuration/quality covariates rather than by
44 human-predator relations. Guiñas can tolerate a high degree of habitat loss (>80% within a
45 home range). They are primarily impacted by fragmentation and land subdivision (larger farms
46 being divided into smaller ones). Ten percent of surveyed farmers (N=233) reported illegally
47 killing the species over the past decade.
- 48 5. Synthesis and applications. By integrating ecological and social data into a single modelling
49 framework, our study demonstrates the value of an interdisciplinary approach to assessing the
50 potential threats to a carnivore. It has allowed us to tease apart effectively the relative
51 importance of different potential extinction pressures, make informed conservation
52 recommendations and prioritise where future interventions should be targeted. Specifically for
53 the guiña, we have identified that human-dominated landscapes with large intensive farms can
54 be of conservation value, as long as an appropriate network of habitat patches are maintained

55 within the matrix. Conservation efforts to secure the long-term persistence of the species should
56 focus on reducing habitat fragmentation, rather than human persecution in our study system.

57 **Keywords:** camera trapping, conservation, randomised response technique, habitat fragmentation,
58 habitat loss, human-wildlife co-existence, illegal killing, güiña, kodkod, multi-season occupancy
59 modelling

60

61 **Introduction**

62 Land-use change is one of the greatest threats facing terrestrial biodiversity globally (Sala et al. 2000),
63 as species persistence is negatively influenced by habitat loss, fragmentation, degradation and isolation
64 (Henle et al. 2004a). In general, species characterised by a low reproductive rate, low population
65 density, large individual area requirements or a narrow niche are more sensitive to habitat loss and
66 fragmentation (Fahrig 2002; Henle et al. 2004b) and, therefore, have a higher risk of extinction (Purvis
67 et al. 2000). Consequently, many territorial carnivores are particularly vulnerable to land-use change.
68 Furthermore, the disappearance of such apex predators from ecosystems can have substantial cascading
69 impacts on other species (Estes et al. 2011; Ripple et al. 2014).

70

71 Additionally, in human-dominated landscapes, mammal populations are threatened directly by the
72 behaviour of people (Ceballos et al. 2005). For instance, larger species (body mass >1 kg) are often
73 persecuted because they are considered a pest, food source or marketable commodity (Woodroffe,
74 Thirgood & Rabinowitz 2005). Carnivores are especially vulnerable to persecution after livestock
75 predation, attacks on humans, or as a result of deep rooted social norms or cultural practices (Treves &
76 Karanth 2003; Inskip & Zimmermann 2009; Marchini & Macdonald 2012). Indirectly, many mammals
77 are also threatened by factors such as the introduction of invasive plant species, which reduce habitat
78 complexity (Rojas et al. 2011), and domestic pets, which can transmit diseases or compete for resources
79 (Hughes & Macdonald 2013).

80

81 To ensure the long-term future of carnivore populations within human-dominated landscapes outside
82 protected areas, it is imperative that we identify potential ecological and social drivers of species decline
83 and assess their relative importance (Redpath et al. 2013). For example, it is essential to disentangle the
84 impacts of habitat loss and fragmentation on a species, as the interventions required to alleviate the
85 pressures associated with the two processes are likely to be different (Fahrig 2003; Fischer &
86 Lindenmayer 2007). If habitat loss is the dominant issue causing population reduction, then large
87 patches may need to be protected to ensure long-term survival, whereas a certain configuration of
88 remnant vegetation may be required if fragmentation is the main threat. At the same time, it is important
89 to understand if, how and why people persecute species, if conservationists are to facilitate human-
90 wildlife coexistence (St John, Keane & Milner-Gulland 2013). However, there is a paucity of
91 interdisciplinary research that evaluates explicitly both ecological and social drivers of species decline
92 in a single coherent framework, across geographic scales pertinent to informing conservation decision-
93 making (Dickman 2010).

94

95 From an ecological perspective, data derived from camera-traps and analysed via occupancy models
96 are widely used to study carnivores over large geographic areas (Burton et al. 2015; Steenweg et al.
97 2016). Occupancy modelling offers a flexible framework that can account for imperfect detection and
98 missing observations, making it highly applicable to elusive mammals of conservation concern
99 (MacKenzie et al. 2003; MacKenzie & Reardon 2013). Monitoring population dynamics temporally,
100 and identifying the factors linked to any decline, is critical for management (Di Fonzo et al. 2016). For
101 this reason, dynamic (i.e. multi-season) occupancy models are particularly useful because they examine
102 trends through time and can be used to ascertain the drivers underlying observed changes in occupancy
103 (MacKenzie et al. 2003, 2006). Similarly, there are a range of specialised social science methods for
104 asking sensitive questions that can be used to yield valuable information on human behaviour, including
105 the illegal killing of species (Nuno & St. John 2015). One such example is the unmatched count
106 technique, which has recently been used to examine the spatial distribution of hunting and its proximity
107 to Serengeti National Park, Tanzania (Nuno et al. 2013), and bird hunting in Portugal (Fairbrass et al.
108 2016). Another method is the randomised response technique (RRT), previously used to estimate the

109 prevalence of predator persecution in South Africa (St John et al. 2012) and vulture poisoning in
110 Namibia (Santangeli et al. 2016).

111

112 In this paper, we propose an integrated socio-ecological modelling framework that draws together these
113 natural and social science methods to examine how habitat configuration/quality and “human-predator
114 relations” (Pooley et al. 2016) may interact in space and time to effect carnivore populations across a
115 human-dominated landscape. An important aspect of the approach is that the social and ecological data
116 are collected at a matched spatial scale, allowing different potential drivers of decline to be contrasted
117 and evaluated. We showcase the approach using the guña (*Leopardus guigna*), a felid listed as
118 Vulnerable on the International Union for Conservation of Nature (IUCN) Red List, as a case study
119 species. Specifically, we use data derived from multi-season camera-trap surveys, remote-sensed
120 images and a household questionnaire which uses RRT to estimate prevalence and predictors of illegal
121 killing. The outputs from our framework provide a robust evidence-base to direct future conservation
122 investment and efforts.

123

124 **Materials and methods**

125 **Integrated socio-ecological framework**

126 Our proposed framework comprises four stages (Fig. 1). The first step is to gather information on the
127 ecology of the species and likely drivers of decline, including habitat configuration/quality issues (e.g.
128 habitat loss, habitat fragmentation, presence/absence of habitat requirements) and human-predator
129 relations (e.g. species encounter frequency, livestock predation experiences), that require evaluation.
130 The best available information can be acquired from sources such as peer-reviewed and grey literature,
131 experts and IUCN Red List assessments. The next task, step two, is to define a suite of candidate models
132 a priori to assess and quantify the potential social and ecological predictors on species occupancy
133 dynamics. Dynamic occupancy models estimate parameters of change across a landscape, including the
134 probability of a sample unit (SU) becoming occupied (local colonisation) or unoccupied (local
135 extinction) over time (MacKenzie et al. 2006).

136

137 The third step involves the collection of ecological and social data in SUs distributed across the
138 landscape, to parametrise the models. Camera-trap survey effort allocation (i.e. the number of SUs that
139 need to be surveyed) for occupancy estimation can be determined a priori using freely-available tools
140 (Gálvez et al. 2016). The final stage is the evaluation of evidence, using standard model selection
141 methods (Burnham & Anderson 2002) to establish which of the social and ecological variables within
142 the candidate models are indeed important predictors of occupancy, and to contrast their relative
143 importance. Results from the models can be contextualised with additional supporting evidence not
144 embedded in the models to inform where conservation action should be directed. For instance, during
145 questionnaire delivery, valuable qualitative data may be recorded that provides in-depth insights related
146 to the human-predator system (e.g. Inskip et al. 2014).

147

148 **Study species and system**

149 The guiña is the smallest neotropical felid (<2 kg) (Napolitano et al. 2015). It is thought to require forest
150 habitat with dense understory and the presence of bamboo (*Chusquea* spp.) (Nowell & Jackson 1996;
151 Dunstone et al. 2002), but is also known to occupy remnant forest patches within agricultural areas
152 (Sanderson, Sunquist & Iriarte 2002; Acosta-Jamett & Simonetti 2004; Gálvez et al. 2013; Fleschutz et
153 al. 2016; Schüttler et al. 2017). Guiñas are considered pests by some people as they can predate chickens
154 and, while the extent of persecution has not been formally assessed, killings have been reported
155 (Sanderson, Sunquist & Iriarte 2002; Gálvez et al. 2013). Killing predominately occurs when the felid
156 enters a chicken coop (Gálvez & Bonacic 2008). Due to these attributes, the species makes an ideal case
157 study to explore how habitat configuration/quality and human-predator relations may interact in space
158 and time to influence the population dynamics of a threatened carnivore existing in a human-dominated
159 landscape.

160

161 The study was conducted in the Araucanía region in southern Chile (Fig. 2), at the northern limit of the
162 South American temperate forest eco-region (39°15'S, 71°48'W) (Armesto et al. 1998). The system
163 comprises two distinct geographical sections common throughout Southern Chile: the Andes mountain
164 range and central valley. Land-use in the latter is primarily intensive agriculture (e.g. cereals, livestock,

165 fruit trees) and urban settlements, whereas farmland in the Andes (occurring <600 m.a.s.l) is less
166 intensively used and surrounded by tracks of continuous forest on steep slopes and protected areas
167 (>800 m.a.s.l). The natural vegetation across the study landscape consists of deciduous and evergreen
168 Nothofagus forest (Luebert & Pliscoff 2006), which remains as a patchy mosaic in agricultural valleys
169 and as continuous tracts at higher elevations within the mountains (Miranda et al. 2015).

170

171 **Data collection**

172 Predator detection/non-detection data

173 We obtained predator detection/non-detection data via a camera-trap survey. Potential SUs were
174 defined by laying a grid of 4 km² across the study region, representing a gradient of forest habitat
175 fragmentation due to agricultural use and human settlement below 600 m.a.s.l. The size of the SUs was
176 informed by mean observed guinea home range size estimates of collared individuals in the study area
177 (MCP 95% mean=270 ±137 ha; Schüttler et al. 2017).

178

179 In this study system, detectability was modelled based on the assumption that a two-day survey block
180 is a separate independent sampling occasion. This time threshold was chosen because initial
181 observations of collared individuals indicated that they did not stay longer than this time in any single
182 location (Schüttler et al. unpublished data). Minimum survey effort requirements (i.e. number of SUs
183 and sampling occasions) were determined following Guillera-Arroita, Ridout & Morgan (2010), using
184 species specific parameter values from Gálvez et al. (2013) and a target statistical precision in
185 occupancy estimation of SE<0.075. A total of 145 SUs were selected at random from the grid of 230
186 cells, with 73 and 72 located in the central valley and Andes mountain valley respectively (Fig. 2). The
187 Andean valleys were surveyed for four seasons (summer 2012, summer 2013, spring 2013, summer
188 2014), while the central valley was surveyed for the latter three seasons. A total of four rotations (i.e.
189 blocks of camera-traps) were used to survey all SUs within a 100-day period each season.
190 Detection/non-detection data were thus collected for 20-24 days per SU, resulting in 10-12 sampling
191 occasions per SU. Two camera-traps (Bushnell TMtrophy cam 2012) were used per SU, positioned 100-
192 700 m apart, with a minimum distance of >2 km between camera-traps in adjacent SUs. The detection

193 histories of both camera-traps in a SU were pooled, and camera-trap malfunctions or thefts (five in total)
194 were treated as missing observations.

195

196 Habitat configuration/quality data

197 The extent of habitat loss and fragmentation were evaluated using ecologically meaningful metrics
198 which have been reported in the literature as being relevant to guiñas, using either field or remote-
199 sensed landcover data (Table 1, Appendix S1 & Table S1). The metrics were measured within a 300 ha
200 circular buffer, centred on the midpoint between both cameras in each SU using FRAGSTATS 4.1
201 (McGarigal et al. 2002). Habitat quality surrounding a camera-trap might influence species activity
202 (Acosta-Jamett, Simonetti, 2004). We collected data on a number of variables within a 25-m radius
203 around each camera-trap (Table S1), as this is deemed to be the area over which localised conditions
204 may influence species detectability. The habitat quality data from both camera-traps in each SU were
205 pooled and the median was used if values differed.

206

207 Human-predator relations data

208 Between May and September 2013 the questionnaire (Appendix S2) was administered face-to-face by
209 NG who is Chilean and had no previous interaction with respondents. All SUs contained residential
210 properties and one or two households closest to the camera-trap locations were surveyed (mean number
211 of households per km² across the study landscape: 3.4; range: 1.4 to 5.1 from INE 2002). For each
212 household, the family member deemed to be most knowledgeable with respect to farm management
213 and decision-making was surveyed. The questionnaire gathered data on socio-demographic/economic
214 background, guiña encounters, livestock ownership, frequency of livestock predation by guiñas and
215 ownership of dogs on the land parcel. To measure tolerance to livestock predation, participants were
216 asked how they would respond to different scenarios of livestock loss (mortality of 2, 10, 25, 50, >50
217 animals), with one possible option explicitly stating that they would kill guiña. These data were also
218 used as predictors of killing behaviour in the RRT analysis (see below). The questionnaire was piloted
219 with 10 local householders living outside the SUs; their feedback was used to improve the wording,
220 order and time scale of predation and encounter questions.

221

222 The potential occupancy model predictors (Tables 1 & S1, Appendix S2) were calculated per SU. Where
223 questionnaire responses differed within a SU (e.g. one household report predation and the other did
224 not), presence of the event (e.g. predation) was used as a covariate for that particular SU. For all
225 quantitative measures, and when both respondents report the event (e.g. frequency of predation) median
226 values were used.

227

228 **Illegal killing prevalence across the landscape (other evidence)**

229 As it is illegal to kill guiñas in Chile (Law 19.473 Ministry of Agriculture), RRT (Nuno & St. John
230 2015) was used to ask this sensitive question as part of the questionnaire (Appendix S2). Since RRT,
231 like other methods for asking sensitive questions, require a large sample size for precise estimation of
232 behaviour prevalence (Nuno & St. John 2015), we pooled RRT data from all participants to estimate
233 the prevalence of illegal guiña killing across the landscape over the past decade. We explored predictors
234 that might explain this human behaviour (St John et al. 2012).

235

236 RRT data were bootstrapped 1000 times to obtain a 95% confidence interval. We tested seven non-
237 correlated predictors of illegal guiña killing: age, income, frequency of guiña encounters, number of
238 chickens owned (all continuous variables standardized to z-scores), economic dependency on their land
239 parcel (1=no dependency; 2=partially dependency; 3=complete dependency), knowledge of the guiña's
240 legal protection status (0=hunting prohibited; 1=do not know; 2=hunting permitted), and intention to
241 kill a guiña under a hypothetical predation scenario (0=do nothing; 1=manage guiña; 2=kill guiña)
242 (Appendix S2). We used R (version 3.2.3; R Core Team, 2014) to run the RRlog function of the package
243 RRreg (version 0.5.0; Heck & Moshagen 2016) to conduct a multivariate logistic regression using the
244 model for 'forced response' RRT data. We fitted a logistic regression model with the potential
245 predictors of killing behaviour and evaluated their significance with likelihood ratio tests (LRT ΔG^2).
246 Odds ratios and their confidence values are presented for model covariates.

247

248 **Integrated socio-ecological modelling**

249 First, we evaluated the existence of spatial autocorrelation with detection/non-detection data for each
250 SU, using Moran's I index based on similarity between points (Dormann et al. 2007). We used a fixed
251 band distance of 3 km from the midpoint of camera-traps, equating to an area three times larger than a
252 guña home range.

253

254 We fitted models of occupancy dynamics (MacKenzie et al. 2003) using PRESENCE, which obtains
255 maximum-likelihood estimates via numerical optimisation (Hines 2006). The probabilities of initial
256 occupancy (ψ), colonisation (γ), local extinction (ϵ) and detection sites (p) were used as model
257 parameters. We conducted a preliminary investigation to assess whether a base model structure with
258 Markovian dependence was more appropriate for describing seasonal dynamics, rather than assuming
259 no occupancy changes occur or that changes happen at random (MacKenzie et al. 2006). Once the best
260 model structure had been determined, we then fitted models with habitat configuration/quality and
261 human-predator predictors.

262

263 A total of 15 potential model predictors were tested for collinearity and, in instances where variables
264 were correlated (Pearson's/Spearman's $|r| > 0.7$), we retained the covariate that conferred greater
265 ecological/social meaning and ease of interpretation (Tables 1 & S1). All continuous variables, except
266 percentages, were standardized to z-scores. We approached model selection by increasing model
267 complexity gradually, fitting predictors for each model parameter separately and assessing model
268 performance using Akaike's Information Criterion (AIC). Models that were within $< 2 \Delta AIC$ were
269 considered to have substantial support (Burnham & Anderson 2002), and thus these predictors were
270 selected and used in the next step in a forward manner (e.g. Kéry, Guillera-Aroita & Lahoz-Monfort
271 2013). To prevent over fitting (Burnham & Anderson 2002), we kept models with only one predictor
272 per parameter, with the exception of one model which evaluated the additive effect of shrub and forest
273 cover (shrubs are a marginal habitat for the study species; Dunstone et al. 2002).

274

275 A set of detection models were fitted using the best base structure. Subsequently, we evaluated models
276 that included habitat configuration/quality and human-predator relations data to test its effect on initial

277 occupancy (ψ_1), while keeping colonisation and extinction specific. The best initial occupancy and
278 detection models were then used to add further complexity to the colonisation and extinction
279 components. We fitted all predictors for extinction. However, we assume that colonisation between
280 seasons is primarily influenced by habitat configuration/quality variables, rather than human-predator
281 relations. To explore the candidate model space, we worked on the structure for extinction probability
282 followed by colonisation, and then repeated the process vice versa (Kéry, Guillera- Arroita & Lahoz-
283 Monfort 2013). A constant or null model was included in all candidate model sets. Models with
284 convergence problems or implausible parameter estimates (i.e. very large estimates and standard errors)
285 were eliminated from each set.

286

287 Goodness of fit was evaluated by bootstrapping 5000 iterations (MacKenzie and Bailey 2004) in the R
288 package AICcmodavg. This test provides a model fit statistic based on consideration of the data from
289 all seasons at once (P-Global), as well as separate statistics for each season. We used the predict function
290 in R package unmarked (Fiske & Chandler 2011) to produce plots of estimated relationships with the
291 predictors and derive estimates of occupancy for each of the seasons.

292

293 All aspects of this project were approved by the School of Anthropology and Conservation Research
294 and Research Ethics Committee, University of Kent, as well as the Villarrica Campus Committee of the
295 Pontificia Universidad Católica de Chile.

296

297 **Results**

298 **Habitat configuration/quality data**

299 Across the landscape, variation in the degree of habitat loss and fragmentation was substantial. Forest
300 cover in SU's ranged from 1.8-76% (mean=27.5%; SD=18.9), and shrub cover followed a similar
301 pattern (range: 9.1-53.1%; mean=26%; SD=8.3). The number of habitat patches per SU varied between
302 14 and 163 (mean=52.9; SD=25.7), and patch shape was diverse (index range: 1.3 (highly irregular
303 forms) to 7.8 (regular forms); mean=3.13; SD=1.3). Some SUs included a relatively high length of edge
304 (~48,000 m), whereas others had as little as 4,755 m.

305

306 **Human-predator relations data and illegal killing prevalence across the landscape**

307 A total of 233 respondents completed the questionnaire, of which 20% were women and 80% men. The
308 median age of respondents was 55 years (interquartile range: 46-67). Participants had lived in their
309 properties for 25-50 years (median=35), which varied from 1-1,200 ha in size (median=29). Land
310 subdivision within SUs also varied widely (range: 1-314 properties; mean=41.3; SD=37.2).
311 Respondents, on average, received a monthly income equivalent to US\$558 (SD=2.81) and had
312 completed 10 years of formal schooling.

313

314 Encounters with guiñas were rare. Nearly half of the respondents (49%, n=116) reported seeing a guiña
315 during their lifetime. However, on average, the sighting occurred 17 years ago (SD=15). This
316 percentage dropped to 10% and 21% during the last four (within the timeframe of the camera-trap
317 survey) and 10 years (time period for the RRT question) respectively. Predation events were also
318 uncommon. Only 16% of respondents (n=37) attributed a livestock predation event in their lifetime to
319 a guiña, with just 7% (n=16) stating that this had occurred in the past decade. Of the guiña predation
320 events over the past decade (n=16), 81% were recorded in Andean SUs.

321

322 When presented with scenario-style questions concerning hypothetical livestock predation by a guiña,
323 38% (n=89) of respondents stated that they would kill the felid if two chickens were lost, rising to 60%
324 (n=140) if 25 chickens were attacked. Using RRT, we found that 10% of respondents admitted to having
325 killed a guiña in the last 10 years (SE=0.09; 95% CI=0.02-0.18). The likelihood of a respondent
326 admitting to killing guiña increased significantly with encounter frequency ($\beta=0.85$, SE=0.50; LRT ΔG^2
327 =4.18, p=0.04); those reporting the highest level of encounter rate were 2.3 times more likely to have
328 killed the species compared to those not encountering guiña (Table 2). Data from the scenario-based
329 question on predation were excluded from the model due to a high β and associated standard error.

330

331 **Detection/non-detection data**

332 A total of 23,373 camera-trap days returned 713 sampling occasions with a guiña detection (season
333 1=96; season 2=185; season 3=240; season 4=192). The naïve occupancy (i.e. proportion of sites with
334 detection) was similar across all four seasons (0.54; 0.52; 0.58; 0.59) and between the central valley
335 and Andean SUs (both areas >0.5). There was no evidence of spatial autocorrelation among SUs during
336 any survey season (season 1 Moran's $I=-0.03$ ($\alpha=0.74$); season 2 $I=0.05$ ($\alpha=0.31$); season 3 $I=0.05$
337 ($\alpha=0.36$); season 4 $I=0.07$ ($\alpha=0.17$)).

338

339 **Integrated socio-ecological multi-season occupancy modelling**

340 Our preliminary evaluation indicated that a Markovian dependence model structure was an appropriate
341 description of the data. This dependence implies that guiña presence at a given site in a particular season
342 is dependent on whether that site was occupied in the previous season (Table 3). Model 1.1 was chosen
343 as the base structure for the modelling procedure because: (i) it is supported by AIC; and, (ii) its
344 parameterisation using extinction and colonisation (i.e. not derived parameters) allowed the role of
345 different potential predictors to be tested on these population processes. Also, letting extinction and
346 colonisation be season-specific accommodated for unequal time intervals between sampling seasons.

347

348 Model selection for detection (models 2.1-2.7; Table 4) revealed a positive relationship with understory
349 vegetation cover ($\beta_1=0.343$; $SE=0.055$; Fig. 3b). There was no evidence of an effect associated with the
350 rotational camera-trap survey design, and none of the other predictors were substantiated. Forest cover
351 best explained initial occupancy (models 3.0-3.6; Table 4), with initial occupancy being higher in sites
352 with less forest cover, although the estimated relationship was weak ($\beta_1=-0.0363$; $SE=0.0138$; Fig. 3a).
353 Adding shrub cover only improved model fit marginally. Fragmentation metrics and land subdivision
354 were not supported as good predictors.

355

356 Model selection for extinction and colonisation (models 4.0-4.18 and 5.0-5.12; Table 4) reflected the
357 same trends, irrespective of the order in which parameters were considered. Extinction, rather than
358 colonisation, yielded predictors that improved model fit compared to the null model. Where predictors
359 were fitted first on colonisation (models 5.0-5.5), none of the models tested improved fit substantially

360 compared to the null model. This indicated that, of the available predictors, colonisation was only
361 explained by seasonal differences. The human-predator predictors were not supported as drivers of
362 either initial occupancy or extinction probability (Table 4).

363

364 We fitted a final model (model 5.6; Table 4) with number of patches and land subdivision, which were
365 identified as important predictors in the two top competing extinction models (models 5.7 and 5.8). This
366 model was well supported. A goodness-of-fit test suggested lack of fit based on the global metric (P -
367 $global < 0.05$), but inspection of survey-specific results show no such evidence ($p > 0.05$) apart from
368 season 2 ($p = 0.032$). Inspecting the season 2 data, we found that the relatively large statistic value
369 appeared to be driven by just a few sites with unlikely capture histories (i.e. < 12 detections). Given this,
370 and the fact that data from the other seasons do not show lack of fit, we deem that the final model
371 explains the data appropriately. The model predicts that SU extinction probability becomes high (> 0.6)
372 when there are less than 27 habitat patches, and more than 116 land subdivisions ($\beta_1 = -0.900$; $SE = 0.451$
373 and $\beta_1 = 0.944$; $SE = 0.373$ respectively; Figs. 3cd). Occupancy estimates were high across seasons with
374 derived seasonal estimates of 0.78 ($SE = 0.09$), 0.64 ($SE = 0.06$), 0.80 ($SE = 0.06$) and 0.83 ($SE = 0.06$).

375

376 **Discussion**

377 The integrated socio-ecological modelling framework we present here provides important insights into
378 how habitat configuration/quality and human-predator relations may interact in space and time to effect
379 carnivore populations existing across a human-dominated landscape. We were able to disentangle the
380 relative impact of a range of threats that have been highlighted previously in the literature as potential
381 drivers of decline for our case study species the guiña.

382

383 The guiña is an elusive forest specialist. As such, one might predict that the species would be highly
384 susceptible to both habitat loss and fragmentation (Henle et al. 2004b; Ewers & Didham 2006). While
385 the relationship between occupancy and higher levels of forest cover (Fig. 3a) does suggest guiñas are
386 likely to occupy areas with a large spatial extent of available habitat, our results also indicate that the
387 species can tolerate extensive habitat loss. The effects of habitat loss could be confounded by time, and

388 it is possible that we are not yet observing the impacts of this ecological process (Ewers & Didham
389 2006). However, this is unlikely to be the case in this landscape as over 67% of the original forest cover
390 was lost by 1970 and, since then, deforestation rates have been low (Miranda et al. 2015). Indeed, the
391 findings highlight that intensive agricultural landscapes are very relevant for guiña conservation and
392 should not be dismissed as unsuitable.

393

394 Spatially, the occupancy dynamics of this carnivore appear to be affected by fragmentation and human
395 pressure through land subdivision. Ensuring that remnant habitat patches are retained in the landscape,
396 and land subdivision is reduced so that existing bigger farms are preserved, could ultimately safeguard
397 the long-term survival of this threatened species. This should be the focus of conservation efforts, rather
398 than just increasing the extent of habitat. Our findings further suggest that these remnant patches may
399 play a key role in supporting the guiña in areas where there has been substantial habitat loss and,
400 perhaps, might even offset local extinctions associated with habitat cover (Fahrig 2002). A land sharing
401 scheme within agricultural areas of the landscape could prove to be a highly effective conservation
402 strategy (Phalan et al. 2011) considering that these farms are currently not setting aside land, but are of
403 high value to the species. The results also highlight that farmers with large properties are key
404 stakeholders in the conservation of this species and must be at the centre of any conservation
405 interventions that aim to protect existing native forest vegetation within farmland.

406

407 Following farming trends globally, larger properties in the agricultural areas of southern Chile are
408 generally associated with high intensity production, whereas smaller farms are mainly subsistence-
409 based systems (Carmona et al. 2010). It is therefore interesting, but perhaps counterintuitive, that we
410 found occupancy to be higher (lower local extinction) where there is less land subdivision. However, a
411 greater number of small farms is associated with higher human density which may result in increased
412 persecution by humans (Woodroffe 2000). Also, higher subdivision imposes pressure on natural
413 resources, due to more households being present in the landscape (e.g. Liu et al. 2003), which has been
414 shown to reduce the quality of remaining habitat patches as a result of frequent timber extraction,
415 livestock grazing (Carmona et al. 2010) and competition/interference by domestic animals and pets

416 (Sepúlveda et al. 2014). Native vegetation in non-productive areas, including ravines or undrainable
417 soils with a high water table, is normally spared within agricultural areas (Miranda et al. 2015), and
418 these patches of remnant forest could provide adequate refuge, food resources and suitable conditions
419 for carnivore reproduction (e.g. Schadt et al. 2002). However, it is possible that areas with high land
420 subdivision and a large number of patches could be acting as ecological traps if source-sink dynamics
421 are operating in the landscape (Robertson & Hutto 2006). Additionally, another factor driving the
422 subdivision of land and degradation of remnant forest patches across agricultural areas is the growing
423 demand for residential properties (Petitpas et al. 2017). This is facilitated by Chilean law, which permits
424 agricultural land to be subdivided to a minimum plot size of 0.5 ha. Furthermore, it is common practice
425 for sellers and buyers to completely eliminate all understory vegetation from such plots (C. Rios,
426 personal communication) which, as demonstrated by detection being higher in dense understory, is a
427 key component of habitat quality. The fact that farmers subdivide their land for economic profit, driven
428 by demand for residential properties, is a very complex and difficult issue for future landscape-level
429 conservation.

430

431 Although previous studies have suggested that human persecution may be a factor contributing to the
432 decline of the guiña (Nowell & Jackson 1996; Sanderson, Sunquist & W. Iriarte 2002), illegal killing
433 in the study region appears low and much less of a threat to the species than the habitat configuration
434 in the landscape. Despite the fact that the species occupies a large proportion of the landscape across
435 seasons, people report that they rarely encounter the carnivore or suffer poultry predation. The guiña's
436 elusive behaviour is reinforced by our low camera-trap detection probability ($p < 0.2$ over 2 nights). One
437 in ten respondents (10%) admitted to killing a guiña over the last decade. One potential drawback of
438 RRT is that it is impossible to know if people are following the instructions (Lensvelt-Mulders & Boeije
439 2007). However, we deployed a symmetrical RRT design (both 'yes' and 'no' were assigned as
440 prescribed answers), which increases the extent to which people follow the instructions (Ostapczuk &
441 Musch 2011). Moreover, the proportion of 'yes' answers in the data exceeded the probability of being
442 forced to say 'yes' (which in this study was 0.167), indicating that respondents were reporting illegal
443 behaviour. From our data, it would be difficult to determine whether this prevalence of illegal killing is

444 having a detrimental impact on the population size of the species. However, with our framework we
445 could, in the future, evaluate spatial layers of information such as the probability of illegal killing based
446 on the distribution of encounters with the guiña and landscape attributes that increase extinction
447 probability (e.g. land subdivision and reduced habitat patches) in order to be spatially explicit about
448 where to focus conservation and research efforts (e.g. Santangeli et al. 2016).

449

450 Our results demonstrate the benefits of integrating socio-ecological data into a single modelling
451 framework to gain a more systematic understanding of the drivers of carnivore decline. The framework
452 teased apart the relative importance of different threats, providing a valuable evidence-base for making
453 informed conservation recommendations and prioritising where future interventions should be targeted
454 for the case study species. Prior to applying our framework, conservationists believed that human
455 persecution was instrumental in determining guiña occupancy patterns in human-dominated landscapes.
456 However, our combined socio-ecological approach highlighted that habitat configuration/quality
457 characteristics are the primary determinants, mainly due to the widespread presence of the species
458 across the landscape and lack of interaction with rural homes. The relative importance of, and balance
459 between, social and ecological factors may differ according to the species of conservation concern.
460 While our framework might not be to resolve conflict, it can help to guide potential stakeholder
461 controversies (Redpath et al. 2013; Redpath et al., 2017) by improving our understanding of how
462 carnivores interact with humans in space and time (Pooley et al. 2016). A number of small to medium
463 carnivores in need of research and conservation guidance (Brooke et al. 2014) could benefit from our
464 framework.

465

466 **Acknowledgements**

467 We are grateful to the landowners for their permission to work on their properties and for completing
468 the questionnaire. We wish to thank L. Petracca from Panthera for provideding satellite imagery and
469 landcover classification, as well as K. Henle, M. Fleschutz, B.J. Smith, A. Dittborn, J. Laker, C.
470 Bonacic, G. Valdivieso, N. Follador, D. Bormpoudakis, T. Gálvez and C. Ríos for their valuable
471 support. The Chilean Ministry of the Environment (FPA 9-I-009-12) gave financial support, along with

472 funding provided to D.W.M. from the Robertson Foundation and Recanati-Kaplan Foundation, E.S.
473 from the Marie Curie Fellowship Program (POIF-GA-2009-252682), and G.G.A. from the Australian
474 Research Council Discovery Early Career Research Award program (DE160100904). NG was
475 supported by a postgraduate scholarship from the Chilean National Commission for Scientific and
476 Technological Research (CONICYT-Becas Chile).

477

478 **Authors' contributions**

479 All authors conceived ideas and designed methodology. NG collected and processed data. NG and ZGD
480 led the writing of the manuscript. All authors contributed critically to drafts and have given their
481 approval for publication.

482

483 **References**

- 484 Acosta-Jamett, G. & Simonetti, J.A. (2004) Habitat use by *Oncifelis guigna* and *Pseudalopex*
485 *culpaeus* in a fragmented forest landscape in central Chile. *Biodiversity & Conservation*, **13**,
486 1135–1151.
- 487 Armesto, J.J., Rozzi, R., Smith-Ramírez, C. & Arroyo, M.T.K. (1998) Conservation targets in South
488 American temperate forests. *Science*, **282**, 1271–1272.
- 489 Brooke, Z.M., Bielby, J., Nambiar, K. & Carbone, C. (2014) Correlates of research effort in
490 carnivores: body size, range size and diet matter. *PloS one*, **9**, e93195.
- 491 Burnham, K.P. & Anderson, D.R. (2002) *Model Selection and Multimodel Inference: A Practical*
492 *Information-Theoretic Approach*. Springer Science & Business Media, Verlag New York.
- 493 Burton, A.C., Neilson, E., Moreira, D., Ladle, A., Steenweg, R., Fisher,Boutin, S. (2015) Wildlife
494 camera trapping: a review and recommendations for linking surveys to ecological processes.
495 *Journal of Applied Ecology*.
- 496 Carmona, A., Nahuelhual, L., Echeverría, C. & Báez, A. (2010) Linking farming systems to landscape
497 change: an empirical and spatially explicit study in southern Chile. *Agriculture, Ecosystems &*
498 *Environment*, **139**, 40–50.
- 499 Ceballos, G., Ehrlich, P.R., Soberon, J., Salazar, I. & Fay, J.P. (2005) Global mammal conservation:

500 what must we manage? *Science*, **309**, 603–607.

501 Dickman, A.J. (2010) Complexities of conflict: the importance of considering social factors for
502 effectively resolving human–wildlife conflict. *Animal conservation*, **13**, 458–466.

503 Di Fonzo, M.M.I., Collen, B., Chauvenet, A.L.M. & Mace, G.M. (2016). Patterns of mammalian
504 population decline inform conservation action. *Journal of Applied Ecology*, **53**, 1046–1054.

505 Dormann, C.F., M McPherson, J., B Araújo, M., Bivand, R., Bolliger, J., Carl, G.,Kissling,
506 D.W. (2007) Methods to account for spatial autocorrelation in the analysis of species
507 distributional data: a review. *Ecography*, **30**, 609–628.

508 Dunstone, N., Durbin, L., Wyllie, I., Freer, R., Jamett, G.A., Mazzolli, M. & Rose, S. (2002) Spatial
509 organization, ranging behaviour and habitat use of the kodkod (*Oncifelis guigna*) in southern
510 Chile. *Journal of zoology*, **257**, 1–11.

511 Estes, J.A., Terborgh, J., Brashares, J.S., Power, M.E., Berger, J., Bond, W.J.,Jackson, J.B.C.
512 (2011) Trophic downgrading of planet Earth. *science*, **333**, 301–306.

513 Ewers, R.M. & Didham, R.K. (2006) Confounding factors in the detection of species responses to
514 habitat fragmentation. *Biological Reviews*, **81**, 117–142.

515 Fahrig, L. (2002) Effect of habitat fragmentation on the extinction threshold: A synthesis. *Ecological
516 Applications*, **12**, 346–353.

517 Fahrig, L. (2003) Effects of habitat fragmentation on biodiversity. *Annual review of ecology,
518 evolution, and systematics*, **34**, 487–515.

519 Fairbrass, A., Nuno, A., Bunnefeld, N. & Milner-Gulland, E.J. (2016) Investigating determinants of
520 compliance with wildlife protection laws: bird persecution in Portugal. *European journal of
521 wildlife research*, **62**, 93–101.

522 Fischer, J. & Lindenmayer, D.B. (2007) Landscape modification and habitat fragmentation: a
523 synthesis. *Global Ecology & Biogeography*, **16**, 265–280.

524 Fiske, I. & Chandler, R. (2011) unmarked: An R Package for Fitting Hierarchical Models of Wildlife
525 Occurrence and Abundance. *Journal of Statistical Software.* , **43**, 1–23.

526 Fleschutz, M.M., Gálvez, N., Pe’er, G., Davies, Z.G., Henle, K. & Schüttler, E. (2016) Response of a
527 small felid of conservation concern to habitat fragmentation. *Biodiversity and Conservation*, **25**,

528 1447–1463.

529 Gálvez, N. & Bonacic, C. (2008) Filling gaps for Güiña cat (*Kodkod*) conservation in Southern Chile.

530 *Wild Felid Monitor*, **2**, 13–13.

531 Gálvez, N., Guillera-Arroita, G., Morgan, B.J.T. & Davies, Z.G. (2016) Cost-efficient effort

532 allocation for camera-trap occupancy surveys of mammals. *Biological Conservation*, **204**, 350–

533 359.

534 Gálvez, N., Hernández, F., Laker, J., Gilabert, H., Petitpas, R., Bonacic, C.,Macdonald, D.W.

535 (2013) Forest cover outside protected areas plays an important role in the conservation of the

536 Vulnerable güiña *Leopardus guigna*. *Oryx*, **47**, 251–258.

537 Guillera-Arroita, G., Ridout, M.S. & Morgan, B.J.T. (2010) Design of occupancy studies with

538 imperfect detection. *Methods in Ecology and Evolution*, **1**, 131–139.

539 Henle, K., Lindenmayer, D.B., Margules, C.R., Saunders, D.A. & Wissel, C. (2004a) Species Survival

540 in Fragmented Landscapes: Where are We Now? *Biodiversity and Conservation*, **13**, 1–8.

541 Henle, K., Davies, K.F., Kleyer, M., Margules, C. & Settele, J. (2004b) Predictors of Species

542 Sensitivity to Fragmentation. *Biodiversity and Conservation*, **13**, 207–251.

543 Hines, J.E. (2006) PRESENCE v.6.4 -Software to Estimate Patch Occupancy and Related Parameters.

544 Hughes, J. & Macdonald, D.W. (2013) A review of the interactions between free-roaming domestic

545 dogs and wildlife. *Biological Conservation*, **157**, 341–351.

546 INE. (2002) National population census -Chile, <http://www.ine.cl/estadisticas/demograficas-y-vitales>

547 Inskip, C., Fahad, Z., Tully, R., Roberts, T. & MacMillan, D. (2014) Understanding carnivore killing

548 behaviour: Exploring the motivations for tiger killing in the Sundarbans, Bangladesh. *Biological*

549 *Conservation*, **180**, 42–50.

550 Inskip, C. & Zimmermann, A. (2009) Human-felid conflict: a review of patterns and priorities

551 worldwide. *Oryx*, **43**, 18–34.

552 Kéry, M., Guillera-Arroita, G. & Lahoz-Monfort, J.J. (2013) Analysing and mapping species range

553 dynamics using occupancy models. *Journal of Biogeography*, **40**, 1463–1474.

554 Lensvelt-Mulders, G.J.L.M. & Boeijs, H.R. (2007) Evaluating compliance with a computer assisted

555 randomized response technique: a qualitative study into the origins of lying and cheating.

556 Computers in Human Behavior, **23**, 591–608.

557 Liu, J., Daily, G.C., Ehrlich, P.R. & Luck, G.W. (2003) Effects of household dynamics on resource
558 consumption and biodiversity. *Nature*, **421**, 530–533.

559 Luebert, F. & Plischoff, P. (2006) *Sinopsis Bioclimática Y Vegetacional de Chile*. Editorial
560 Universitaria, Santiago, Chile.

561 MacKenzie, D.I. & Bailey, L.L. (2004) Assessing the fit of site-occupancy models. *Journal of*
562 *Agricultural, Biological, and Environmental Statistics*, **9**, 300–318.

563 MacKenzie, D.I., Nichols, J.D., Hines, J.E., Knutson, M.G. & Franklin, A.B. (2003) Estimating site
564 occupancy, colonization, and local extinction when a species is detected imperfectly. *Ecology*,
565 **84**, 2200–2207.

566 MacKenzie, D.I., Nichols, J.D., Royle, J.A., Pollock, K.H., Bailey, L.L. & Hines, J.E. (2006)
567 *Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence*.
568 Academic Press, London.

569 MacKenzie, D.I. & Reardon, J.T. (2013) Occupancy methods for conservation management.
570 *Biodiversity Monitoring and Conservation: Bridging the Gap Between Global Commitment and*
571 *Local Action* (eds B. Collen, N. Pettorelli, J.E.M. Baillie, & S.M. Durant), pp. 248–264.

572 Marchini, S. & Macdonald, D.W. (2012) Predicting ranchers' intention to kill jaguars: case studies in
573 Amazonia and Pantanal. *Biological Conservation*, **147**, 213–221.

574 McGarigal, K., Cushman, S.A., Neel, M.C. & Ene, E. (2002) FRAGSTATS: spatial pattern analysis
575 program for categorical maps.

576 Miranda, A., Altamirano, A., Cayuela, L., Pincheira, F. & Lara, A. (2015) Different times, same story:
577 Native forest loss and landscape homogenization in three physiographical areas of south-central
578 of Chile. *Applied Geography*, **60**, 20–28.

579 Napolitano, C., Gálvez, N., Bennett, M., Acosta-Jamett, G. & Sanderson, J. (2015) *Leopardus guigna*.
580 The IUCN Red List of Threatened Species 2015.: e.T15311A50657245. . Downloaded on 11
581 September 2015., <http://www.iucnredlist.org/details/15311/0>

582 Nowell, K. & Jackson, P. (1996) *Wild Cats: Status Survey and Conservation Action Plan*. IUCN
583 Gland.

584 Nuno, A., Bunnefeld, N., Naiman, L.C. & Milner- Gulland, E.J. (2013) A novel approach to
585 assessing the prevalence and drivers of illegal bushmeat hunting in the Serengeti. *Conservation*
586 *Biology*, **27**, 1355–1365.

587 Nuno, A. & St. John, F.A. V. (2015) How to ask sensitive questions in conservation: A review of
588 specialized questioning techniques. *Biological Conservation*, **189**, 5–15.

589 Ostapczuk, M. & Musch, J. (2011) Estimating the prevalence of negative attitudes towards people
590 with disability: A comparison of direct questioning, projective questioning and randomised
591 response. *Disability and Rehabilitation*, **33**, 399–411.

592 Petitpas, R., Ibarra, J.T., Miranda, M. & Bonacic, C. (2017) Spatial patterns over a 24-year period
593 show an increase in native vegetation cover and decreased fragmentation in Andean temperate
594 landscapes, Chile. *Ciencia e Investigación Agraria*, **43**, 384–395.

595 Phalan, B., Onial, M., Balmford, A. & Green, R.E. (2011) Reconciling food production and
596 biodiversity conservation: land sharing and land sparing compared. *Science (New York, N.Y.)*,
597 **333**, 1289–1291.

598 Pooley, S., Barua, M., Beinart, W., Dickman, A., Holmes, G., Lorimer, J.,Redpath, S. (2016) An
599 interdisciplinary review of current and future approaches to improving human- predator
600 relations. *Conservation Biology*.

601 Purvis, A., Gittleman, J.L., Cowlshaw, G. & Mace, G.M. (2000) Predicting extinction risk in
602 declining species. *Proceedings Biological sciences / The Royal Society*, **267**, 1947–1952.

603 Redpath, S.M., Young, J., Evely, A., Adams, W.M., Sutherland, W.J., Whitehouse, A.,Watt, A.
604 (2013) Understanding and managing conservation conflicts. *Trends in Ecology & Evolution*, **28**,
605 100–109.

606 Redpath, S.M., Linnell, J.D.C., Festa-Bianchet, M., Boitani, L., Bunnefeld, N., Dickman, A.
607 ...Milner-Gulland, E.J. (2017). Don't forget to look down - collaborative approaches to predator
608 conservation. *Biological Reviews*, **In press**. doi: 10.1111/brv.12326.

609 Ripple, W.J., Estes, J.A., Beschta, R.L., Wilmers, C.C., Ritchie, E.G., Hebblewhite, M.,Wirsing,
610 A.J. (2014) Status and ecological effects of the world's largest carnivores. *Science (New York,*
611 *N.Y.)*, **343**, 1241484.

- 612 Robertson, B.A. & Hutto, R.L. (2006) A framework for understanding ecological traps and an
613 evaluation of existing evidence. *Ecology*, **87**, 1075–1085.
- 614 Rojas, I., Becerra, P., Gálvez, N., Laker, J., Bonacic, C. & Hester, A. (2011) Relationship between
615 fragmentation, degradation and native and exotic species richness in an Andean temperate forest
616 of Chile. *Gayana. Botánica*, **68**, 163–175.
- 617 Sala, O.E., Stuart, C., Armesto, J.J., Berlow, E., Bloomfield, J., Dirzo, R.,..... Wall, D.H. (2000)
618 Global Biodiversity Scenarios for the Year 2100. *Science*, **287**, 1770–1774.
- 619 Sanderson, J., Sunquist, M.E. & W. Iriarte, A. (2002) Natural history and landscape-use of guignas
620 (*Oncifelis guigna*) on Isla Grande de Chiloé, Chile. *Journal of mammalogy*, **83**, 608–613.
- 621 Santangeli, A., Arkumarev, V., Rust, N. & Girardello, M. (2016) Understanding, quantifying and
622 mapping the use of poison by commercial farmers in Namibia—Implications for scavengers’
623 conservation and ecosystem health. *Biological Conservation*, **204**, 205–211.
- 624 Schadt, S., Knauer, F., Kaczensky, P., Revilla, E., Wiegand, T. & Trepl, L. (2002) Rule-based
625 assessment of suitable habitat and patch connectivity for the Eurasian lynx. *Ecological*
626 *Applications*, **12**, 1469–1483.
- 627 Schüttler, E., Klenke, R., Galuppo, S., Castro, R.A., Bonacic, C., Laker, J. & Henle, K. (2017) Habitat
628 use and sensitivity to fragmentation in America’s smallest wildcat. *Mammalian Biology*, **86**, 1–
629 8.
- 630 Sepúlveda, M.A., Singer, R.S., Silva-Rodríguez, E., Stowhas, P. & Pelican, K. (2014) Domestic Dogs
631 in Rural Communities around Protected Areas: Conservation Problem or Conflict Solution?
632 *PLoS ONE*, **9**, e86152.
- 633 St John, F.A. V, Keane, A.M., Edwards-Jones, G., Jones, L., Yarenell, R.W. & Jones, J.P.G. (2012)
634 Identifying indicators of illegal behaviour: carnivore killing in human-managed landscapes.
635 *Proceedings of the Royal Society : series B biological sciences*, **279**, 804–812.
- 636 St John, F.A. V, Keane, A.M. & Milner-Gulland, E.J. (2013) Effective conservation depends upon
637 understanding human behaviour. *Key Topics in Conservation Biology 2*, 2nd ed (ed D.W.
638 Macdonald & K.J. Willis), pp. 344–361. Blackwell, Oxford, Oxford.
- 639 Steenweg, R., Hebblewhite, M., Kays, R., Ahumada, J., Fisher, J.T., Burton, C.,Rich, L.N. (2016)

640 Scaling-up camera traps: monitoring the planet's biodiversity with networks of remote sensors.
641 *Frontiers in Ecology and the Environment*, **15**, 26–34.

642 Treves, A. & Karanth, K.U. (2003) Human- carnivore conflict and perspectives on carnivore
643 management worldwide. *Conservation Biology*, **17**, 1491–1499.

644 Woodroffe, R. (2000) Predators and people: using human densities to interpret declines of large
645 carnivores. *Animal Conservation*, **3**, 165–173.

646 Woodroffe, R., Thirgood, S. & Rabinowitz, A. (2005) *People and Wildlife, Conflict or Co-Existence?*
647 Cambridge University Press, Cambridge.

648

649

650

651

652

653 **Figure Legends**

654

655 **Figure 1:** Integrated socio-ecological modelling framework to assess drivers of carnivore decline in a
656 human-dominated landscape.

657

658 **Figure 2:** Distribution of landcover classes and protected areas across the study landscape in southern
659 Chile, including the forest habitat of our case study species, the guiña (*Leopardus guigna*). The two
660 zones within which the 145 sample units (SU: 4 km²) were located are indicated, with 73 SUs in the
661 central valley (left polygon) and 72 within the Andes (right polygon). Illustrative examples of the
662 variation in habitat configuration within SUs across the human-domination gradient are provided
663 (bottom of image).

664

665 **Figure 3:** Predicted effects of forest cover, understory density, number of habitat patches and land
666 subdivision on multi-season occupancy model parameters for the guiña (*Leopardus guigna*). These
667 results correspond to the final selected model [$\psi_1(\text{Forest})$, $p(\text{season}+\text{Understory})$,
668 $\epsilon(\text{season}+\text{PatchNo}+\text{Subdivision})$, $\gamma(\text{season})$]. Grey lines delimit 95% confidence intervals.

669

670 **Table 1:** Habitat configuration/quality and human relation predictors evaluated when modelling initial
671 occupancy (ψ_1), colonisation (γ), extinction (ϵ) and detection (p) probability parameters of multi-season
672 camera-trap guinea (Leopardus guigna) surveys. Further details can be found in Appendix S1, S2 &
673 Table S1.

674

Parameter	Predictor	Abbreviation in models
Habitat configuration		
ψ_1, ϵ, γ	Percent of forest cover/habitat [†]	Forest
ψ_1, ϵ, γ	Percent shrub cover/marginal habitat	Shrub
ψ_1, ϵ, γ	Number of forest patches	PatchNo
ψ_1, ϵ, γ	Shape index forest patches	PatchShape
ψ_1, ϵ, γ	Forest patch size area [‡]	PatchAreaW
ψ_1, ϵ, γ	Forest patch continuity [‡]	Gyration
ψ_1, ϵ, γ	Edge length of forest land cover class	Edge
ψ_1, ϵ, γ	Landscape shape index of forest [§]	LSI
ψ_1, ϵ, γ	Patch cohesion [‡]	COH
Human predator relations		
ψ_1, ϵ	Land subdivision	Subdivision
ψ_1, ϵ	Intent to kill (hypothetical scenario questions)	Intent
ψ_1, ϵ	Predation	Predation
ψ_1, ϵ	Frequency of predation	FQPredation
ψ_1, ϵ, p	Frequency of encounter ^{††}	FQEncounter
ψ_1, ϵ	Number of dogs	Dogs
Habitat quality		
p	Bamboo density (Chusquea spp.)	Bamboo
p	Density of understory	Understory
p	Sample Unit rotation block	Rotation
p	Intensity of livestock activity	Livestock
p	Intensity of logging activity	Logging
p	Water availability	Water

675 [†]Pools together all forest types: old-growth, secondary growth, and wetland forest

676 [‡]Predictor excluded due to collinearity with percent of forest cover (Pearson's $|r| > 0.7$)

677 [§]Predictor excluded due to collinearity with number of forest patches (Pearson's $|r| > 0.7$)

678 ^{††}Predictor also fitted with detection probability

679

680

681

682 **Table 2:** The relationship between illegal killing of guiña (*Leopardus guigna*) and potential predictors
 683 of the behaviour. Reported coefficients, standard errors, odds ratios and their 95% confidence intervals
 684 were derived from a multivariate logistic regression which incorporates the known probabilities of the
 685 forced RRT responses. Significance was accepted at the 0.05 level.

686

	Coefficient	SE	P	Odds ratio	Odds ratio	
					Lower CI	Upper CI
(Intercept)	-2.43	1.99	0.25	0.09	0.00	4.36
Age	-0.41	0.43	0.38	0.66	0.29	1.54
Income	0.00	0.55	0.99	0.99	0.34	2.96
Land parcel dependency	0.02	0.83	0.98	12.02	0.20	5.19
Number of chicken holdings	-0.18	0.71	0.78	0.83	0.21	3.38
Knowledge of legal protection	0.48	0.77	0.57	1.62	0.36	7.37
Frequency of encounter	0.85	0.50	0.04	2.34	0.87	6.28

687

688

689 **Table 3:** Seasonal occupancy dynamics models following MacKenzie et. al. (2006), applied to the guiña
690 (Leopardus guigna), to define the base model structure for the subsequent model selection procedure
691 to evaluate potential habitat configuration/quality and human-predator predictors. Fitted probability
692 parameters are occupancy (ψ), colonisation (γ), extinction (ϵ) and detection (p). Models assess whether
693 changes in occupancy do not occur (model 1.6), occur at random (models 1.5, 1.4) or follow a Markov
694 Chain process (i.e. site occupancy status in a season is dependent on the previous season) (models 1.0,
695 1.1, 1.2, 1.3). Initial occupancy (ψ_1) refers to occupancy in the first of four seasons over which the guiña
696 was surveyed. Model selection procedure is based on Akaike's Information Criterion (AIC). Δ AIC is
697 the difference in AIC benchmarked against the best model, w_i is the model weight, K the number of
698 parameters, and $-2*\loglike$ is the value of the log likelihood at its maximum. The selected model is
699 highlighted in bold.

700

Model	Seasonal dynamic models	Δ AIC	w_i	K	$-2*\loglike$
1.0	$\psi(\cdot), \gamma(\cdot), \{\epsilon = \gamma(1 - \psi)/\psi\}, p(\text{season})$	0.00	0.443	6	3982.93
1.1	$\psi_1(\cdot), \epsilon(\text{season}), \gamma(\text{season}), p(\text{season})$	0.36	0.370	11	3973.29
1.2	$\psi_1(\cdot), \epsilon(\cdot), \gamma(\cdot), p(\text{season})$	1.88	0.173	7	3982.81
1.3	$\psi_1(\cdot), \epsilon(\cdot), \gamma(\cdot), p(\cdot)$	6.83	0.015	4	3993.76
1.4	$\psi_1(\cdot), \gamma(\cdot), \{\epsilon = 1 - \gamma\}, p(\text{season})$	41.78	0.000	6	4024.71
1.5	$\psi_1(\cdot), \gamma(\text{season}), \{\epsilon = 1 - \gamma\}, p(\text{season})$	42.78	0.000	8	4021.71
1.6	$\psi(\cdot), \{\gamma = \epsilon = 0\}, p(\text{season})$	104.11	0.000	6	4087.04

701

702

703 **Table 4:** Multi-season models of initial occupancy (ψ_1), extinction (ϵ), colonisation (γ) and detection
704 (p) probability with potential habitat configuration/quality and human-predator predictors for the guiña
705 (*Leopardus guigna*). Predictors were evaluated with a base model of seasonal dynamics [$\psi_1(\cdot)$,
706 $\epsilon(\text{season})$, $\gamma(\text{season})$, $p(\text{season})$] using a step-forward model selection procedure and Akaike's
707 Information Criterion (AIC). Initial occupancy (ψ_1) refers to occupancy in the first of four seasons over
708 which the guiña was surveyed, with occupancy dynamics following a Markov Chain process. ΔAIC is
709 the difference in AIC benchmarked against the best model, w_i is the model weight, K the number of
710 parameters, and $-2*\log\text{like}$ is the value of the log likelihood at its maximum. The selected models for
711 each parameter are highlighted in bold and used in the next step. ϵ was fitted first followed by γ , then
712 vice versa.

Model	Fitted parameter	ΔAIC	w_i	K	$-2*\log\text{like}$
Detection/fitted with $\psi_1(\cdot)$, $\epsilon(\text{season})$, $\gamma(\text{season})$					
2.0	p(season+Understory)	0.00	0.9999	12	3934.47
2.1	p(season+Bamboo)	18.48	0.0001	12	3952.95
Initial occupancy/fitted with $\epsilon(\text{season})$, $\gamma(\text{season})$, p(season+ Understory)					
3.0	$\psi_1(\text{Forest})$	0.00	0.5425	13	3927.46
3.1	$\psi_1(\text{Forest+Shrub})$	1.24	0.2918	14	3926.7
3.4	$\psi_1(\text{PatchNo})$	4.00	0.0734	13	3931.46
3.5	$\psi_1(\cdot)$	5.01	0.0443	12	3934.47
3.6	$\psi_1(\text{Subdivision})$	5.69	0.0315	13	3933.15
3.7	$\psi_1(\text{Dogs})$	7.00	0.0164	13	3934.46
Extinction first/fitted with $\psi_1(\text{Forest})$, p(season+ Understory)					
4.0	$\epsilon(\text{season+PatchNo})$, $\gamma(\text{season})$	0.00	0.4692	14	3920.10
4.1	$\epsilon(\text{season+Subdivision})$, $\gamma(\text{season})$	0.36	0.3919	14	3920.46
4.2	$\epsilon(\text{season+PatchShape})$, $\gamma(\text{season})$	5.15	0.0357	14	3925.25
4.3	$\epsilon(\text{season+Predation})$, $\gamma(\text{season})$	5.24	0.0342	14	3925.34
4.4	$\epsilon(\text{season})$, $\gamma(\text{season})$	5.36	0.0322	13	3927.46
4.5	$\epsilon(\text{season+FQencounter})$, $\gamma(\text{season})$	5.92	0.0243	14	3926.02
4.6	$\epsilon(\text{season+FQPredation})$, $\gamma(\text{season})$	7.24	0.0126	14	3927.34

Colonisation second/fitted with $\psi_1(\text{Forest})$, $p(\text{season}+\text{Understory})$ and 4.0/4.1 for ε					
4.7	$\varepsilon(\text{season}+\text{PatchNo}), \gamma(\text{season})$	0.00	0.1877	14	3920.10
4.8	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season})$	0.36	0.1568	14	3920.46
4.9	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season}+\text{PatchShape})$	0.79	0.1265	15	3918.89
4.10	$\varepsilon(\text{season}+\text{PatchNo}), \gamma(\text{season}+\text{PatchShape})$	1.29	0.0985	15	3919.39
4.11	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season}+\text{PatchNo})$	1.63	0.0831	15	3919.73
4.12	$\varepsilon(\text{season}+\text{PatchNo}), \gamma(\text{season}+\text{Edge})$	1.84	0.0748	15	3919.94
4.13	$\varepsilon(\text{season}+\text{PatchNo}), \gamma(\text{season}+\text{Forest})$	1.98	0.0698	15	3920.08
4.14	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season}+\text{Edge})$	2.16	0.0638	15	3920.26
4.15	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season}+\text{Forest})$	2.20	0.0625	15	3920.30
4.16	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season}+\text{Forest}+\text{Shrub})$	3.50	0.0326	16	3919.60
4.17	$\varepsilon(\text{season}+\text{PatchNo}), \gamma(\text{season}+\text{Forest}+\text{Shrub})$	3.60	0.0310	16	3919.70
4.18	$\varepsilon(\text{season}), \gamma(\text{season})$	5.36	0.0129	13	3927.46
Colonisation first/fitted with $\psi_1(\text{Forest})$, $p(\text{season}+\text{Understory})$					
5.0	$\varepsilon(\text{season}), \gamma(\text{season})$	0.00	0.3303	13	3927.46
5.1	$\varepsilon(\text{season}), \gamma(\text{season}+\text{PatchShape})$	0.96	0.2044	14	3926.42
5.2	$\varepsilon(\text{season}), \gamma(\text{season}+\text{PatchNo})$	1.55	0.1522	14	3927.01
5.3	$\varepsilon(\text{season}), \gamma(\text{season}+\text{Edge})$	1.89	0.1284	14	3927.35
5.4	$\varepsilon(\text{season}), \gamma(\text{season}+\text{Forest})$	1.95	0.1246	14	3927.41
5.5	$\varepsilon(\text{season}), \gamma(\text{season}+\text{Forest}+\text{Shrub})$	3.41	0.06	15	3926.87
Extinction second/fitted with $\psi_1(\text{Forest})$, $p(\text{season}+\text{Understory})$ $\gamma(\text{season})$					
5.6	$\varepsilon(\text{season}+\text{PatchNo}+\text{Subdivision}), \gamma(\text{season})$	0.00	0.8275	15	3913.45
5.7	$\varepsilon(\text{season}+\text{PatchNo}), \gamma(\text{season})$	4.65	0.0809	14	3920.10
5.8	$\varepsilon(\text{season}+\text{Subdivision}), \gamma(\text{season})$	5.01	0.0676	14	3920.46
5.9	$\varepsilon(\text{season}+\text{PatchShape}), \gamma(\text{season})$	9.80	0.0062	14	3925.25
5.10	$\varepsilon(\text{season}+\text{Predation}), \gamma(\text{season})$	9.89	0.0059	14	3925.34
5.11	$\varepsilon(\text{season}), \gamma(\text{season})$	10.01	0.0055	13	3927.46
5.12	$\varepsilon(\text{season}+\text{FQEncounters}), \gamma(\text{season})$	10.57	0.0042	14	3926.02
5.13	$\varepsilon(\text{season}+\text{FQPredation}), \gamma(\text{season})$	11.89	0.0022	14	3927.34