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Author/s:

Geary, WL;Hradsky, BA;Robley, A;Wintle, BA

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Predators, fire or resources: What drives the distribution of herbivores in fragmented mesic forests?

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MR. WILLIAM GEARY (Orcid ID : 0000-0002-6520-689X)

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Corresponding author mail id : billygeary4@gmail.com

Title: Predators, fire or resources: what drives the distribution of herbivores in fragmented mesic forests?

Running title: Drivers of herbivore distributions

Authors: William L. Geary^{1,2,3}, Bronwyn A. Hradsky^{1,4}, Alan Robley⁵, Brendan A. Wintle^{1,4}

¹Quantitative and Applied Ecology group, School of BioSciences, University of Melbourne, Parkville, Melbourne, 3010

²Biodiversity Division, Department of Environment, Land, Water & Planning, East Melbourne, 3002

³Centre for Integrative Ecology, School of Life and Environmental Sciences (Burwood Campus), Deakin University, Geelong, Victoria, Australia

⁴NESP Threatened Species Recovery Hub, School of Biosciences, University of Melbourne, Parkville, Melbourne, 3010

⁵Arthur Rylah Institute for Environmental Research, Department of Environment, Land, Water and Planning, Heidelberg, 3078

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Abstract: Trophic interactions and disturbance events can shape the structure and function of ecosystems. However, the effects of drivers such as predation, fire and climatic variables on species distributions are rarely considered concurrently. We used a replicated landscape-scale predator management experiment to compare the effects of red fox *Vulpes vulpes* control, time-since-fire, vegetation type and other environmental variables on native herbivore distributions. Occurrence data for four native herbivores, and an invasive predator—the red fox—were collected from 240 sites across three baited (for lethal fox control) and three unbaited forest blocks (4659 – 9750 ha) in south-western Victoria, Australia, and used to build species distribution models. The herbivore taxa were: red-necked wallaby *Macropus rufogriseus*, black wallaby *Wallabia bicolor*, grey kangaroo *Macropus fuliginosus* and *Macropus giganteus*. and common brushtail possum *Trichosurus vulpecula*. Fox control and fire had little effect on herbivore occurrence, despite the literature suggesting it can influence abundance, while climate, proximity to farmland and topography were more influential. This may be because the region’s high productivity and agricultural pastures subsidise food resources for both predators and prey within the forest blocks, and so dampen trophic interactions. Alternatively, these drivers may affect herbivore abundance, but not herbivore occurrence. Understanding the drivers of herbivore distributions is an important step in predicting the effects of herbivory on other species, particularly after management interventions such as predator control and prescribed burns.

Key Words: herbivore, fire, predation, trophic relationships, spatial distribution, *Vulpes vulpes*, species distribution model, macropod, predator control, motion-sensing camera

Introduction

Understanding the processes that drive the distributions of herbivores is fundamental to managing ecosystems (Franklin 2010). Herbivores consume and trample organic matter, and so shape ecosystems globally by simplifying vegetation structure, changing the composition of plant communities and altering ecosystem successional trajectories (Bond 1994; Olofsson *et al.* 2004; Raffaele *et al.* 2011). Herbivores are also an important food source for predators, and can be a key driver of predator abundance (Sinclair and Krebs 2002).

62 Management actions that inadvertently affect herbivore populations may therefore have
63 important implications for ecosystem composition and biodiversity conservation.

64

65 Climate, disturbance events and habitat modification by humans can influence food
66 availability for herbivores from the bottom-up (Eby *et al.* 2014; Muhly *et al.* 2013). For
67 example, wildfires promote nutrient-rich vegetative growth and attract herbivores
68 (Fuhlendorf and Engle 2004), with cascading effects on the ecosystem (Raffaele *et al.* 2011).
69 Likewise, management interventions such as prescribed burns can facilitate increased
70 herbivory, with herbivores taking advantage of high-nutrient regrowth and potentially
71 restricting vegetation recovery (Fuhlendorf *et al.* 2010; Meers and Adams 2003). High food
72 availability may enable herbivore abundance to increase beyond the point where predators
73 can suppress the population (Jedrzejewska *et al.* 2005).

74

75 Top-down processes such as predation can also strongly influence patterns of herbivory
76 (Sandom *et al.* 2013). By killing and consuming herbivores, and altering their behaviour,
77 predators can restrict herbivore abundance and cause individuals to graze where they are
78 less vulnerable to predation. For example, small-medium herbivores can hide from
79 predators in dense vegetation cover (Kuijper *et al.* 2013) and large herbivores can
80 selectively graze in open areas with high visibility (Valeix *et al.* 2009). Herbivory then
81 becomes concentrated over small areas, producing changes to vegetation (Ford *et al.* 2014;
82 Ripple *et al.* 2001). Consequently, reductions in apex predator populations, by lethal control
83 or otherwise, are associated with increases in herbivore abundance and occurrence in
84 forests globally (Colman *et al.* 2015; Waser *et al.* 2014). Lethal control of predators can also
85 induce trophic cascades, including herbivore-related changes to vegetation structure
86 (Schmitz *et al.* 2000). Herbivore-release following invasive predator control can sometimes
87 have harmful ecological outcomes (Bergstrom *et al.* 2009), causing uncertainty about the
88 net value of predator control for biodiversity conservation (Doherty and Ritchie 2016). For
89 example, poison baiting of red foxes *Vulpes vulpes* in Booderee National Park, Australia,
90 caused an irruption in black wallabies *Wallabia bicolor* that reduced vegetation cover
91 (Dexter *et al.* 2013).

92

93 Bottom-up and top-down forces can also interact to shape herbivore distributions (Wisz *et*
94 *al.* 2013). For example, white-tailed deer *Odocoileus virginianus* select for unburnt areas
95 post-fire as they offer concealment from predators (Cherry *et al.* 2016). The role of
96 interactions in determining herbivore distributions is an important knowledge gap for
97 ecosystem management, particularly as variations in herbivore numbers may influence
98 vegetation change over multiple decades (Nuttle *et al.* 2011).

99

100 Management interventions such as lethal predator control and prescribed burning are
101 common across Australia, and case-studies indicate that they may promote population
102 growth in native herbivores, with cascading effects for vegetation and other fauna (Dexter
103 *et al.* 2013; Foster *et al.* 2016). Historically, grazing or browsing by invasive herbivores has
104 also contributed to the decline of fauna such as the burrowing bettong *Bettongia lesueur*
105 (McKenzie *et al.* 2007; Newsome 1971). Given that native herbivores can also cause
106 vegetation structural change (Bennett *et al.* 2019), it is conceivable that overabundant
107 native herbivores may also drive fauna declines. Further, loss of vegetation cover due to
108 grazing and prescribed fire may make native mammals more vulnerable to predators
109 (Hradsky 2019; McGregor *et al.* 2014). Understanding the indirect effects of management
110 interventions on both invasive and native herbivore populations is therefore important for
111 biodiversity conservation.

112

113 Species distribution models predict the likelihood of species occurrence based on presence
114 (and sometimes absence) records, and can be useful approach for informing environmental
115 management and planning (Guisan *et al.* 2013). However, they have not been widely used
116 to examine the impacts of management interventions on species' distributions, or to
117 identify areas where unwanted ecological consequences (such as high herbivory pressure)
118 are likely to occur.

119

120 We used a large-scale replicated predator management experiment to examine the relative
121 influence of red fox control, fire, and other environmental and bioclimatic drivers on the
122 landscape-scale distribution of medium and large native herbivores. Our study was
123 conducted in a fragmented mesic forest ecosystem of south-eastern Australia. We predicted
124 that herbivores would be more likely to occur at sites that: (1) were within fox-baited zones;

125 (2) had been recently burnt as these species commonly feed on new post-fire vegetation
126 growth, and (3) were closer to surrounding farmland due to the food resources (e.g.
127 pasture) provided by agricultural areas. We expected that rainfall and temperature
128 gradients would mediate these relationships but that, overall, they would have relatively
129 little influence on herbivore distributions. We also modelled red fox occurrence to confirm
130 that the fox baiting program influenced the distribution of red foxes.

131

132 **Methods**

133 *Field surveys*

134 Data were collected across the Glenelg region in far-south-west Victoria, Australia. This
135 43,500 ha landscape comprises patches of mixed sclerophyll woodland forest and heathy
136 forest within an agricultural matrix (Fig. 1, Robley *et al.* 2014). The climate is temperate,
137 with a mean annual rainfall of 835 - 971 mm, and a mean annual temperature of 11.9 –
138 17.6 °C (BoM 2017).

139

140 There are two main vegetation types in this region: woodland forest and heathy forest. In
141 the woodland forest, tall *Eucalyptus* trees are mixed with a diverse, open midstorey and
142 understorey. Heathy forests are typified by smaller *Eucalyptus* species and a complex, often
143 dense understory dominated by bracken, shrubs and sedges. Natural and prescribed fires
144 are frequent, creating a complex mosaic of fire histories. Fire in sclerophyll forest impacts
145 vegetation structure, removing understorey and midstorey vegetation (Bradstock *et al.*
146 2002). High severity fires can also cause loss of canopy cover (Bradstock *et al.* 2002).

147

148 The study area comprised six 'blocks' of similar size (Fig. 1; Robley *et al.* 2014). Three blocks
149 have undergone an intensive fox baiting program since 2005: southern Lower Glenelg
150 National Park (8954 ha), Mt Clay State Forest (4703 ha) and Cobboboonee National Park
151 (9750 ha). The other three blocks have never been baited: northern Lower Glenelg National
152 Park (4659 ha), Annya State Forest, (8520 ha) and Hotspur State Forest (6940 ha). Blocks
153 were at least 10 km apart except for the southern and northern sections of Lower Glenelg
154 National Park, which are separated by the Glenelg River, forming a barrier to fox movement.

155

156 To quantify the patterns of red fox and native herbivore distribution, camera trap data were
157 collected annually between October and November from 2013 to 2015 across 40 survey
158 sites in each block (240 sites in total – Fig. 1; Robley *et al.* 2014). Camera traps are
159 commonly used to study fauna occurrence, and are triggered by animal movement through
160 the camera's detection range (Rovero *et al.* 2013). During each survey, camera traps were
161 deployed for at least 28 days. Camera traps were baited with a mixture of peanut butter,
162 oats and honey fixed in a small, ventilated container 2 m in front of camera. Full site
163 selection and camera trapping procedures are described in Robley *et al.* (2014).

164

165 *Variables*

166 We collated presence-absence data for four medium-large native herbivores (black wallaby
167 *Wallabia bicolor*, red-necked wallaby *Macropus rufogriseus*, eastern and western grey
168 kangaroo *Macropus giganteus* and *Macropus fuliginosus*, and common brushtail possum
169 *Trichosurus vulpecula*) that were recorded from at least 150 sites across the study period
170 (2013-2015), as well as the red fox. The two species of grey kangaroo were grouped as they
171 were difficult to distinguish from camera trap images. We aimed to model species'
172 occurrence over the whole study period, and so merged occurrence data at each camera
173 site across years.

174

175 We used species' presence/absence to test for associations between environmental
176 variables and the occurrence of grey kangaroos, common brushtail possums and red foxes.
177 An absence was defined as no records of the species over the three-year survey period. We
178 were unable to use this approach for black wallabies or red necked wallabies, as they had
179 few, or no, recorded absences across the study sites. However, black wallaby habitat use
180 varies with time of day (Hradsky 2014), so we separated presences and absences for each
181 wallaby species at each site into day and night datasets. 'Night' presences were recorded
182 between one hour before sunset and one hour after sunrise, and the remainder were
183 considered 'day'.

184

185 We used time-since-fire (categorical: ≤ 2 years post-fire, 2-15 years post-fire, 15-35 years
186 post-fire, or >35 years post-fire), fox control (categorical: baited or unbaited), and the
187 distance of the camera site from farmland to test our primary hypotheses. These time-since-

188 fire groupings were selected because they represent the key post-fire growth stages of the
189 vegetation types in the study area (Cheal 2010). We also included a suite of environmental
190 variables, relating to vegetation type (categorical: woodland forest or heathy forest),
191 terrain, soil type, and climate (precipitation and temperature) variables that were
192 hypothesized to influence distribution (Table S1). Environmental variables that exhibited
193 little or no variation across the study region were not included (e.g. isothermality). Predictor
194 variables were stored and manipulated in the statistical freeware R v3.3.1 (R Core
195 Development Team 2017) using the packages raster (Hijmans and van Etten 2014), rgdal
196 (Keitt *et al.* 2011) and maptools (Bivand and Lewin-Koh 2013), and software ArcMap v10.3
197 (ESRI 2014).

198
199 To control for the spatial arrangement of the study blocks, we grouped the study area into
200 three distinct, ecologically similar regions, each including a baited and unbaited block:
201 *Region 1* encompassed sites in southern and northern Lower Glenelg National Park, *Region*
202 *2* the sites in Cobobboonee National Park and Hotspur State Forest, and *Region 3* the sites in
203 Mt Clay State Forest and Annya State Forest (Figure 1).

204 205 *Model development*

206 We used a two-stage process to develop candidate model sets and identify important
207 drivers of species' distributions. First, we selected a subset of environmental variables to
208 include in the candidate model sets for each species and checked the shape of the
209 univariate relationships. We used generalised additive mixed models (GAMMs) with high
210 degrees of freedom to explore the relationship between each environmental variable and
211 species separately (Wintle *et al.* 2005), using the package gam (Hastie 2013). The purpose of
212 this was to identify the type of environmental variables and their shape that could be used
213 in explaining species occurrence. We fitted the GAMMs with binomial distributions, using
214 'region' as the random effect. We used the shape of the relationship (e.g. linear, quadratic,
215 cubic) between candidate variables and species occupancy to determine the number of
216 degrees of freedom in the full generalised linear mixed model (GLMM) model selection
217 routine (see below). We checked for correlations between candidate variables using
218 Spearman's rank correlation test. Where two variables were strongly correlated ($R > 0.7$) or
219 represented similar environmental factors (e.g. BioClim temperature-related variables), the

220 variable with the highest univariate GAMM R^2_m was retained and the other excluded from
221 further analysis.

222

223 Using the variables identified with the GAMM process, we then developed at least 20
224 candidate GLMMs for each species, based on the hypothesised major drivers of their
225 distributions (predator control, fire, vegetation type, climate, topography and landscape
226 context). The appropriate response shapes for each variable determined in the previous
227 step. We also included a null model in the candidate set. All candidate models were allowed
228 no more than $m/10$ degrees of freedom, where m is the lesser of the number of presences
229 and the number of absences (Wintle *et al.* 2005). GLMMs were fitted with binomial error
230 distributions and logit-link functions, and 'region' was included as a random effect to
231 account for the spatial grouping of sites. For the red-necked wallaby and black wallaby
232 models, 'site' nested within 'region' was used as the random effect to account for repeat
233 sampling of sites between day and night. The full sets of candidate models for each species
234 are listed in Appendix 1. Analyses were conducted using the packages lme4 (Bates *et al.*
235 2014) and MuMin (Barton 2013).

236

237 *Model selection & evaluation*

238 We used an information-theoretic approach to select the best model(s) in the set, by using
239 Akaike's Information Criterion adjusted for small sample size (AICc) and Akaike weights to
240 evaluate the relative support for alternative candidate models (Burnham and Anderson
241 2003). We considered that the model with the lowest AICc was the most highly-ranked, and
242 those within 2 AICc of the top-ranked model as strong candidates (Burnham and Anderson
243 2003).

244

245 The most highly-ranked models were checked for over dispersion ($\phi > 1.5$), which can arise
246 through higher than expected variance in the model (Quinn and Keough 2002). Models were
247 also checked for spatial autocorrelation of the residuals by plotting spline correlograms of
248 Moran's I for the residuals of the most highly-ranked model (Dormann *et al.* 2007). For all
249 models, the 95% confidence intervals overlapped zero at the distances between sites,
250 indicating that residuals were not spatially autocorrelated. This was done in the package ncf
251 (Bjørnstad 2008).

252

253 To check that merging species' occurrence data across years did not mask any effects of
254 between-year variation in fire history on model predictions, we built the same set of
255 candidate models for each species by treating the 13 sites that changed fire history (i.e.
256 were burnt) during the study period as separate sites. Model ranks and coefficients were
257 not substantially different to the merged dataset, and so results are not presented.

258

259 To evaluate how well the most highly-ranked models fitted the data, we calculated the
260 variance explained by the fixed effects (marginal R^2), and fixed and random effects
261 (conditional R^2) (Nakagawa and Schielzeth 2013).

262

263 To evaluate model performance, we calculated the area under the receiver operating curve
264 (AUC) statistic using the k -fold cross-validation technique, using ten folds, following the
265 process outlined in Hijmans and Elith (2013). For each species, we present the mean AUC
266 value and standard error across the ten folds. AUC indicates the ability of a model to rank
267 locations of presences more highly than locations of absences when predicting the
268 probability of occurrence at a location. Models with an AUC between 0.5 and 0.7 have a
269 better than random predictive capacity, and models with an AUC between 0.7 and 0.9 have
270 good predictive capacity (Pearce and Ferrier 2000). Analysis was done using the *dismo*
271 package (Hijmans *et al.* 2015).

272

273 For the best model for each species, we used the *predict* function in *dismo* to generate
274 raster-based model predictions. We then used these maps to predict each species'
275 probability of occurrence across the study area. For these maps, we defined the study area
276 as the broad baited and unbaited blocks in which the camera surveys were undertaken.

277

278 **Results**

279 *Models*

280 The two top-ranked models of grey kangaroo occurrence received similar support (Table 1).
281 Grey kangaroos were less likely to occur at sites in blocks that had been baited for foxes (Fig
282 2a); the 95% confidence intervals of all other predictors overlapped zero.

283

284 The top-ranked model of red-necked wallaby occurrence had strong support (Table 1),
285 indicating a positive association of the species with soil thorium, and a higher likelihood of
286 red-necked wallabies occurring in woodland forest vegetation than heathy forest during the
287 day (Fig 2b) and either vegetation type at night.

288
289 Two candidate models were highly ranked and explained a moderate amount of variation in
290 common brushtail possum occurrence (Table 1). Brushtail possums were more likely to
291 occur in woodland forest. There was also some evidence that brushtail possum occurrence
292 was positively related to precipitation in the coldest quarter and negatively related to
293 distance from farmland, but confidence intervals were wide (Fig 2c).

294
295 The distribution of the black wallaby could not be modelled as it was present at nearly all
296 sites during both day and night.

297
298 Three similar candidate models for the red fox had predictive value, each explaining at least
299 45% of variation in red fox occurrence (Table 1). All top-ranked models indicated that red
300 foxes were half as likely to occur at sites within baited blocks than unbaited blocks, and
301 were more likely to occur in woodland forest vegetation than heathy forest (Table 1, Fig.
302 2d).

303
304 The full set of candidate models for red fox (Table S2), red-necked wallaby (Table S3), grey
305 kangaroo (Table S4) and common brushtail possum (Table S5) are detailed in the
306 Supplementary Information.

307
308 *Model evaluation*

309 The highest ranked GLMM had good predictive capacity for grey kangaroos (AUC = $0.72 \pm$
310 0.05 , Deviance Explained by fixed effects (DE) = 0.12), common brushtail possums (AUC =
311 0.80 ± 0.02 , DE = 0.26) and red foxes (AUC = 0.83 ± 0.03 , DE = 0.26). The predictive capacity
312 of the red-necked wallaby model was good during the day (AUC = 0.70 ± 0.07 , DE = 0.11),
313 but low for night (AUC = 0.65 ± 0.05 , DE = 0.04).

314

315 **Discussion**

316 Our study highlights the importance of climatic and habitat-related factors as drivers of
317 native herbivore occurrence in south-eastern Australia. Although fox baiting substantially
318 reduced fox occurrence, herbivore distributions were generally more strongly associated
319 with climate, soil chemistry, topography and proximity to agricultural land than predator
320 management. Time-since-fire also did not affect the occurrence of any target herbivore
321 species, or foxes. These findings contrast strongly with other Australian studies that have
322 found that variation in predation rates and fire strongly influence the abundance (rather
323 than occurrence) of native herbivores (Dexter *et al.* 2013; Foster *et al.* 2015), although
324 effects on native herbivore occurrence are less well understood. Our findings are, however,
325 consistent with other studies that have found little influence of time-since-fire on fox
326 distribution at a landscape scale (Hradsky *et al.* 2017; Payne *et al.* 2014) and broader trends
327 across other predators species (Geary *et al.* 2019).

328

329 Red foxes were significantly less likely to occur in fox-baited blocks than unbaited blocks
330 across Glenelg. Red foxes prey heavily on small and medium-sized macropods (e.g. black
331 wallaby) and brushtail possums (Davis *et al.* 2015), and so we expected that these
332 herbivores would respond positively to fox control and be more likely to occur at sites
333 within the baited blocks. However, we found no evidence of a positive association with fox
334 baited areas. This contrasts with findings from other mesic forest systems in Australia on
335 changes in herbivore abundance after fox and dingo removal, respectively (Colman *et al.*
336 2014; Dexter *et al.* 2013), and suggests that in the Glenelg region, either: (1) foxes do not
337 exert top-down pressure on herbivore occurrence (as they may not be predated on a
338 significant proportion of the herbivore population, and/or their top-down pressure of fox
339 predation on herbivores is relatively weak compared to dingo predation), (2) fox densities in
340 baited areas have not been reduced enough to release herbivores from top-down control
341 and lead to increases in occurrence, or (3) any effects of fox baiting on herbivore occurrence
342 were masked by the north-south spatial configuration of baited and unbaited blocks (Fig. 1),
343 which may correlate with a relatively dryer climate in the north of the study area compared
344 with the south. Given the widespread occurrence of the herbivore species and the
345 fragmented nature of the ecosystem, we suspect the former: the suppressive effects of
346 predators can be reduced in high productivity systems of agriculture-forest matrices

347 (Pasanen-Mortensen *et al.* 2017). This is despite top-down control typically being stronger
348 in intact, productive landscapes compared with unproductive landscapes (Elmhagen *et al.*
349 2010; Greenville *et al.* 2014). However, the north-south gradient may explain why grey
350 kangaroos were less likely to occur at baited sites, contrary to our expectations – we are not
351 aware of a reasonable mechanism that would cause grey kangaroo occurrence to decrease
352 in response to fox-baiting.

353
354 Although fox baiting had no effect on the occurrence of herbivores, more subtle effects of
355 predator baiting on herbivore populations (e.g. changes in abundance) may not have been
356 apparent from our presence-absence data. For example, differences in predation pressure
357 could influence herbivore abundance and herbivory pressure, without affecting herbivore
358 distributions. Recent studies that have reported positive herbivore responses to dingo or fox
359 control have used abundance, fecundity and activity indices to measure herbivore
360 responses, rather than presence-absence data (e.g. Banks *et al.* 2000; Colman *et al.* 2015;
361 Dexter *et al.* 2013).

362
363 Our second hypothesis—that herbivores would be more likely to occur at recently-burnt
364 sites was also not supported. Other studies have highlighted the importance of fire in
365 determining herbivore distributions (Bowman *et al.* 2016; Eby *et al.* 2014; Meers and Adams
366 2003), yet we found no evidence of this within the Glenelg region. Similarly, Kelly *et al.*
367 (2017) found that temperature and precipitation were more important drivers of vertebrate
368 distributions than fire history in foothill forests. There are several possible explanations.
369 First, relationships between herbivore abundance and fire history may have been reflected
370 by changes in abundance, but not changes in occurrence. Second, herbivores may respond
371 more strongly to fires in ecosystems with grassy understories, rather than those in mesic
372 forests (Kirkpatrick *et al.* 2016). Alternatively, consistently high resource availability from
373 the surrounding farmland might dampen the effect of stochastic changes in resources (such
374 as those caused by fire) on herbivore occurrence: high-nutrient vegetation in recently burnt
375 patches may not provide greater sustenance than surrounding vegetation in highly
376 productive environments (Styger *et al.* 2011).

377

378 Time-since-fire metrics, such as the one used in our study, have limited use in predicting
379 faunal responses to fire (Sitters *et al.* 2014). Fire often indirectly influences fauna through its
380 effects on habitat structure, meaning that habitat complexity is more strongly associated
381 with faunal occurrence than time-since-fire (Monamy and Fox 2000; Swan *et al.* 2015). In
382 addition, environmental variables that influence habitat recovery after fire can cause
383 divergent responses at sites with similar fire histories (Hale *et al.* 2016; Keeley *et al.* 2011;
384 Nimmo *et al.* 2014). The quality of spatial fire history information may also limit our
385 understanding the effects of fire on ecosystems (Avitabile *et al.* 2013; Callister *et al.* 2016).

386

387 Our third hypothesis—that herbivores would be more likely to occur at sites closer to
388 farmland—was partially supported. We found some evidence that common brushtail
389 possums were more likely to occur at sites closer to farmland, but no evidence of a
390 relationship for grey kangaroos or red-necked wallabies. Some herbivores use agricultural-
391 forest matrices (Molloy *et al.* 2016), and can be released from top-down suppression in
392 highly productive anthropogenic landscapes that provide abundant food resources
393 (Pasanen-Mortensen *et al.* 2017). Food is also more readily available to some predators in
394 modified landscapes (Kuijper *et al.* 2016; Newsome *et al.* 2017), further weakening
395 predator-prey interactions (Rodewald *et al.* 2011). Given that the study area is in an
396 agricultural matrix, this might explain why there was no evidence that herbivores were
397 more likely to occur in fox-baited blocks at Glenelg.

398

399 Climate, soil and vegetation-related variables can be important drivers of herbivore
400 distributions as they influence resource availability (Ritchie *et al.* 2008). Contrary to our
401 predictions, these variables were the most important predictors of herbivore occurrence in
402 our study region. Red-necked wallabies, common brushtail possums and foxes were all
403 more likely to occur in woodland forest than heathy forest. Woodland forests are likely to
404 provide more food resources for herbivores, and facilitate easier movement of both
405 herbivores and predators due to the more open understorey (Catling *et al.* 2001).

406 Precipitation was positively associated with the occurrence of common brushtail possums.
407 positive relationship with soil thorium for red-necked wallabies and brushtail possums may
408 also relate to resource availability, as high soil thorium concentrations are associated with
409 nutrient-rich clay soils favourable for the growth of palatable plants (Mernagh and Mieztis

410 2008). Topography was an important predictor of occurrence for grey kangaroos, with this
411 species being more likely to occur at higher elevations. These associations could reflect the
412 influence of environmental gradients on the food plants for each species, and/or direct
413 ecophysiological constraints (Kearney and Porter 2009; Sunday *et al.* 2014).

414
415 The role of predators in ecosystems, hypothesized interactions between ecological
416 processes (e.g. trophic interactions, disturbance) and the potential unintended
417 consequences of lethal predator control are increasingly relevant for ecosystem
418 management (Doherty *et al.* 2015). Evidence is required to inform changes in management
419 regimes. In our study, herbivore distributions appeared to be most influenced by vegetation
420 type and topographic factors, rather than disturbance or red fox control. While predator
421 and fire management actions may influence herbivore occurrence or abundance at a finer
422 spatial or temporal resolution than explored here, our study suggests that habitat features
423 play a more important role at the broad-scale.

424
425 Pairing herbivore distribution models with distribution models of species that are
426 potentially vulnerable to increased herbivory, such as small and medium-sized mammals
427 (Foster *et al.* 2014), could help managers prioritise locations where interventions may be
428 needed. Species distribution models have been applied in similar fashion elsewhere globally
429 to predict, among other things, the impacts of invasive species (Gallien *et al.* 2012). Further
430 developments that incorporate biotic interactions into spatial models and decision tools,
431 such as joint species distribution models (Pollock *et al.* 2014) or spatially explicit population
432 dynamic models (Akçakaya *et al.* 1995) would provide additional insight into the trophic
433 dynamics and optimal management of fragmented forest ecosystems.

434

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440 Science Program through the Threatened Species Recovery Hub.

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442

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690 interactions in shaping distributions and realised assemblages of species: implications for
691 species distribution modelling. *Biological Reviews* **88**, 15-30.

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697 **Figure Captions**

698

699 **Figure 1:** Camera survey sites within the three baited (black dots) and three unbaited (grey
700 circles) blocks within Victoria (inset), south-eastern Australia. The solid black line indicates
701 areas where poison baits are deployed for red fox *Vulpes vulpes* control. Grey shading
702 shows public land.

703

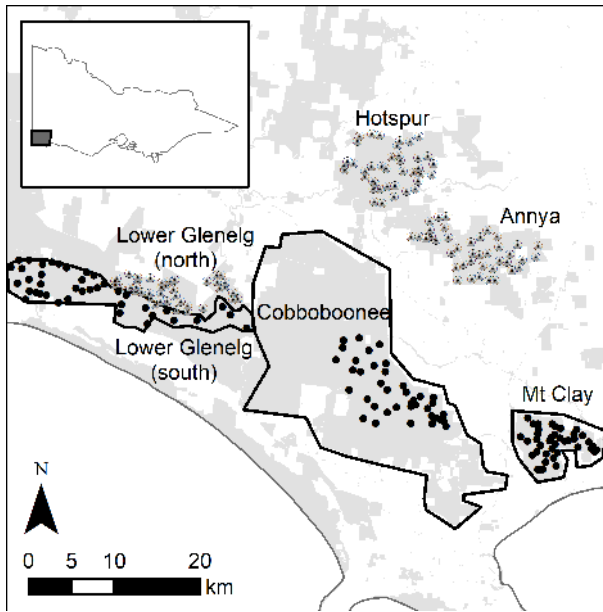
704 **Figure 2:** Mapped predicted probability of occurrence for the most highly-ranked
705 distribution model (fixed effects only) for a) grey kangaroo *Macropus sp.*, b) red-necked
706 wallaby *M. rufogriseus* (day time model), c) common brushtail possum *Trichosurus vulpecula*
707 and d) red fox *Vulpes vulpes*.

708

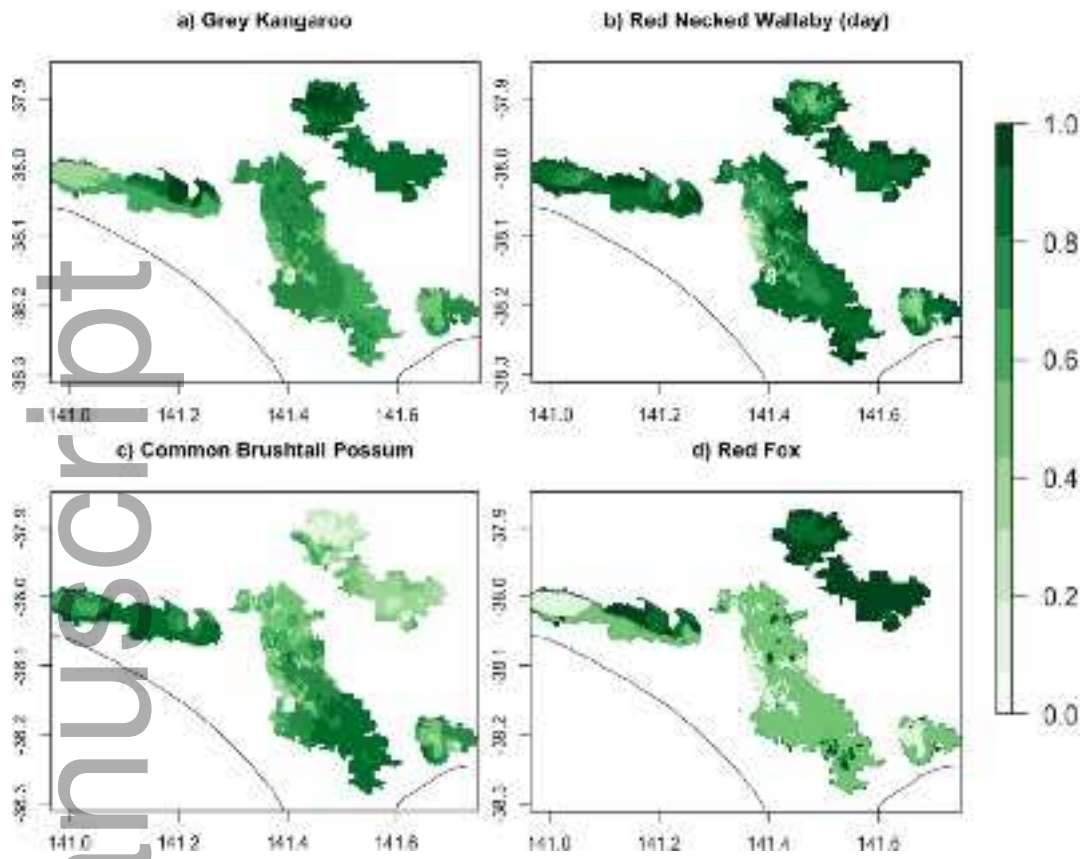
709 **Table 1:** Coefficients, 95% confidence intervals and sum of Akaike weights ($\sum w_i$) for each predictor in the highly ranked species distribution models ($\Delta AICc < 2.0$).
710 Coefficients are relative to the reference level of unbaited heathy forest. Also shown is the difference in Akaike Information Criterion adjusted for small sample size from
711 the top-ranked model ($\Delta AICc$), the Akaike weight (w), and the marginal (R^2m) and conditional (R^2c) R^2 of each model. Bolded coefficients are those whose 95% confidence
712 intervals do not overlap zero.
713

Species	Rank	Coefficients				$\Delta AICc$	w	R^2m	R^2c
Red-necked wallaby		Vegetation type (woodland)	Diel period (night)	Diel : veg	Thorium				
	1	1.59 [0.75, 2.46]	-0.58 [-1.29, 0.09]	-1.10 [-2.01, -0.22]	0.44 [0.21, 0.67]	0.00	0.99	0.15	0.36
	$\sum w_i$	1.00	1.00	1.00	1.00				
Grey kangaroo		Vegetation type (woodland)	Treatment (baited)	Veg : treatment	Thorium	Ruggedness	Elevation	Precipitation during driest Q	
	1	-1.23 [-3.34, 0.88]	-3.14 [-5.26, -1.03]	1.95 [-0.31, 4.21]	-	-	0.38 [-0.02, 0.78]	-	0.00 0.22 0.27 0.27
	2	-	-2.05 [-2.81, -1.29]	-	0.22 [-0.14, 0.59]	-0.19 [-0.53, 0.15]	-	0.28 [-0.04, 0.59]	1.36 0.11 0.24 0.24
$\sum w_i$	0.57	1.0	0.37	0.48	0.46	0.48	0.29		
Common brushtail possum		Vegetation type (woodland)	Treatment (baited)	Paddock Distance	Precipitation in Coldest Q	Mean Temp in Coldest Q	Elevation		
	1	1.77 [0.88, 2.65]	-	-0.33 [-0.72, 0.06]	0.34 [-0.06, 0.75]	0.39 [-0.14, 0.92]	-	0.00 0.28 0.15 0.50	
	2	1.80 [0.92, 2.68]	-0.92 [-2.40, 0.66]	-0.35 [-0.75, 0.05]	0.67 [0.06, 1.29]	-	-0.79 [-1.65, 0.07]	0.95 0.17 0.24 0.45	
$\sum w_i$	1.0	0.5	1.0	0.88	0.55	0.54			
Red fox		Vegetation type (woodland)	Treatment (baited)	Tree Density	Precipitation in Coldest Q				
	1	1.36 [0.59, 2.12]	-2.95 [-3.76, -2.13]	-0.45 [-1.05, 0.14]	-	-	0.00 0.29 0.48 0.48		
	2	1.33 [0.57, 2.09]	-2.98 [-3.78, -2.17]	-	-	-	0.84 0.19 0.45 0.45		
3	1.31 [0.55, 2.08]	-2.54 [-3.65, -1.44]	-	-0.32 [-0.91, 0.27]	-	-	1.75 0.12 0.46 0.46		

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aec_12861_f1.tif



aec_12861_f2.png