

19 **Abstract**

20 Understanding habitat use and distribution of threatened species is a cornerstone of
21 conservation, however many of the techniques available can be resource intensive. One cost-
22 effective method is by collecting information on species presence and absence from people who
23 regularly interact with the area of interest, also known as Local Ecological Knowledge (LEK).
24 However, the reliability of this type of data has been questioned, especially when there is a
25 possibility that the focal species is being misidentified or their presence misreported. This can
26 introduce false negatives, when a species is present but has not been reported, and false positives,
27 when the species has been reported but is not present. These biases are not always accounted for
28 which can result in the under- or overestimation of species presence. To better understand the
29 reliability of LEK data, we compared the outputs of five different analytical techniques to that of a
30 more widely accepted approach, resource selection functions, using GPS collar data from three
31 different carnivore species (African lion *Panthera leo*, cheetah *Acinonyx jubatus* and African wild dog
32 *Lycaon pictus*). Hierarchical models which accounted for the possibilities of both false negatives and
33 false positives most closely matched that of the GPS collar data, especially for the two rarer species;
34 African wild dog and cheetah. Our results show that when both false negatives and false positives
35 are accounted for that LEK can be used as a rapid and cost-efficient tool for assessing threatened
36 species which can be adopted into practical conservation projects.

37 **Keywords:** carnivores, GPS collar data, interview survey, local ecological knowledge (LEK), species
38 distribution

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39 **Introduction**

40 Wildlife populations are increasingly pressured by human-induced habitat loss and
41 degradation (Ceballos et al. 2017). Accurately determining species occurrence, habitat use and
42 distribution are fundamental for conservation, especially for threatened and rare species
43 (MacKenzie et al. 2003, Gu and Swihart 2004, MacKenzie and Nichols 2004). However, obtaining
44 robust data for cryptic species can be challenging, especially across large spatial extents or in areas
45 where they occur at low densities, such as outside protected areas (Karanth et al. 2011, Andresen et
46 al. 2014). Carnivores in particular exhibit wide-ranging behaviour and much of the available habitat
47 for many species lies outside protected areas, where conflict with humans occurs (Jackson et al.
48 2012, Ripple et al. 2014). As a result, many carnivore species have experienced rapid declines as
49 human populations, and their subsequent need for more space, increase (Durant et al. 2017, Wolf
50 and Ripple 2017). Being at the top of the food web, carnivores are sensitive to impacts from human
51 activities and therefore function as an indicator for ecosystem health (Dalerum et al. 2008). As such,
52 methods for determining species distribution that are reliable, repeatable, rapid and resource-light
53 are needed to ensure suitable habitat protection and safeguarding of carnivore populations.

54 Various field methods have been developed to determine habitat use and occurrence of rare
55 species, including camera trapping (Rowcliffe and Carbone 2008), DNA monitoring (López-Bao et al.
56 2018), and sign surveys (Gopaldaswamy et al. 2012). Another commonly used and widely accepted
57 method is the use of GPS collars (Whittington-Jones et al. 2014, Klaassen and Broekhuis 2018). While
58 these methods can provide accurate spatial data, they can be resource intensive. In contrast,
59 harnessing local knowledge, also known as Local Ecological Knowledge (LEK; Zeller et al. 2011, Riggio
60 and Caro 2017, Petracca et al. 2018) represents a relatively quick and cost-efficient method of
61 collecting data on species presence over large areas. A common method of collecting LEK is by
62 interviewing people about a landscape with which they regularly interact, usually through their daily
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63 activities (Poizat and Baran 1997, Huntington 2000, Turvey et al. 2014). In the last decade, the use of
64 LEK has proliferated and been used to determine species distributions at scales that range from local
65 (Farhadinia et al. 2018, Madsen and Broekhuis 2018) to national (Riggio and Caro 2017) or multi-
66 national (Turvey et al. 2014). Furthermore, LEK has been applied to determine species' occurrence
67 (Kotschwar Logan et al. 2015, Cullen-Unsworth et al. 2017, Ghoshal et al. 2017), corridors (Zeller et
68 al. 2011), changes in distributions (Cano and Tellería 2013), habitat use (Madsen and Broekhuis
69 2018), abundance (Anadón et al. 2009) and the effects of habitat fragmentation (Anderson et al.
70 2007, Braulik et al. 2014).

71 Despite LEK being a well-established data source in fisheries and avian studies (e.g. Gilchrist
72 and Mallory 2007, Eddy et al. 2010, Taylor et al. 2011, Cullen-Unsworth et al. 2017), its reliability has
73 been questioned for studies on terrestrial mammals (Caruso et al. 2017). Among the major criticisms
74 of LEK are that there may be an inherent bias in what is reported (Caruso et al. 2017), the reliability
75 of an individual's memory (Pauly 1995) and heterogeneity in biases for species depending on their
76 ecology and the attitude of the interviewees to focal species (Caruso et al. 2017). Although some of
77 these concerns have been addressed through standardising interview methodologies (Huntington
78 2000, Gilchrist et al. 2005) the way that interview data are analysed can vary greatly.

79 To determine species habitat use and occurrence, LEK data can be used such that a reported
80 sighting, or presence, is recorded as a '1' and no sighting, or pseudo-absence, is recorded as a '0'.
81 These data are often analysed using simple linear models, such as binomial logistic regression
82 (Kotschwar Logan et al. 2015, Teixeira et al. 2015). However, simple linear models do not account for
83 detection probability, which is the probability that a species is detected if it is there. This can be
84 influenced by various factors such as time spent in an area (Petracca et al. 2018), habitat type which
85 may affect the surveyor's ability to detect a species when present (Madsen and Broekhuis 2018),
86 socio-cultural factors of the interviewee which may affect the accuracy of their recollection and
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87 reporting (Turvey et al. 2015), and the behaviour of the species in question (MacKenzie and Royle
88 2005). By not explicitly accounting for detection probability, false negatives, where an animal is
89 present but not detected, are not accounted for. This can lead to an underestimation of the species'
90 distribution and potentially inaccurate assumptions about habitat preferences (MacKenzie et al.
91 2002). More complex linear models can, to a certain degree, account for biases associated with the
92 probability of detection by including factors such as observer or habitat as a random effect (e.g.
93 generalised linear mixed models) (Anderson et al. 2007, Nash et al. 2016). A drawback of linear
94 models is that they do not separate the observation process (detection probability) from the state
95 process (e.g. habitat use and occurrence) and therefore may not fully account for the impact of
96 detection probability (MacKenzie et al. 2002). False negatives can be accounted for by using
97 hierarchical models, such as occupancy models, which separate the observation process from the
98 state process (MacKenzie et al. 2002, Royle et al. 2005).

99 In addition to false negatives, false positives can also occur when a species has been
100 reported but is not present. This is especially the case with interview data as interviewees may
101 misidentify or misremember sightings (Royle and Link 2006). Not accounting for false positives can
102 result in an overestimation of occurrence (Petracca et al. 2018). False positives can be minimised
103 during the data collection stage by, for example, using photo cards to ensure the interviewee can
104 correctly identify focal species (Zeller et al. 2011, Madsen and Broekhuis 2018) and carefully
105 selecting the most experienced interviewees (Davis and Wagner 2003). Additionally, false positives
106 can be accounted for by using appropriate analytical methods, such as false-positive occupancy
107 models (Royle and Link 2006, Miller et al. 2011, Louvrier et al. 2018). However, although several
108 studies have shown that using models which account for false positives can improve predictions
109 (Miller et al. 2011, Petracca et al. 2018), they are rarely used.

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110 While LEK is potentially useful for predicting species occurrence, the presence of false
111 negatives and false positives can produce misleading results and therefore the reliability of LEK,
112 especially for mammalian species such as carnivores, needs to be evaluated (Gilchrist et al. 2005,
113 Caruso et al. 2017). As such, there have been a few studies that have compared different
114 hierarchical models to each other (e.g. Petracca et al. 2018), qualitatively assessed results from LEK
115 to direct monitoring (e.g. Gilchrist et al. 2005), compared one analytical method to sign surveys
116 (Farhadinia et al. 2018) or collar data (Shumba et al. 2018a), and evaluated models from simulated
117 data with false positives (e.g. Miller et al. 2011). However, to our knowledge no study has
118 quantitatively compared the outputs from multiple different analytical methods for LEK to outputs
119 from more commonly used methods.

120 Here we test the validity of using LEK to determine species habitat use and occurrence by
121 comparing the outputs to those of resource selection functions (RSF) using data from Global
122 Positioning System (GPS) collars. RSFs use a binary logistic regression design to compare used habitat
123 to available habitat and, whilst they do still have biases (Frair et al. 2010), are a commonly accepted
124 method of assessing the distributions and habitat use of wildlife (Cagnacci et al. 2010). More
125 specifically, we aim to understand the influence of false negatives and false positives on the outputs
126 we analysed LEK data using five different methods (two linear models and three hierarchical models
127 that account for false negatives and false positives). We test this for three African large carnivores
128 (African lion *Panthera leo*, cheetah *Acinonyx jubatus* and African wild dog *Lycaon pictus*) with
129 different life histories, ecological traits and densities that could influence the probability that they
130 are detected and therefore impact the accuracy of the predictions. We hypothesised that the
131 outputs based on LEK data will vary significantly depending on the analytical method used. In
132 general, we predict that the linear models, which do not explicitly account for false negatives and
133 false positives, would lead to inaccurate selection of covariates and therefore poorly predict species

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134 occurrence. However, we predict that including a measure of observer bias as a random factor
135 would improve the predictions. We also predict that the outputs from the hierarchical models would
136 better resemble the outputs based on collar data, especially the models that accounted for both
137 false positives and false negatives. In addition, we hypothesised that there will be variation in the
138 outputs of the interview data per species. We predict that the social, large bodied lions would have
139 higher detectability, reducing the effect of not accounting for false negatives and positives so the
140 linear models will perform relatively better than the less social cheetah. As wild dogs are very rare in
141 this system we predict that, even though they are social, their detectability will be low so the
142 hierarchical models will significantly outperform the linear models.

143 **Methods**

144 ***Study area***

145 The study was conducted in the Maasai Mara (centred at 1°S, 35°E; elevation c. 1,700 m) in
146 southwestern Kenya. The Maasai Mara National Reserve (MMNR) borders the Serengeti National
147 Park in Tanzania to the south and wildlife conservancies to the north. The MMNR and the adjacent
148 wildlife conservancies, which will hereafter be referred to as the wildlife areas (WAs; Fig. 1), are
149 bordered by intensive agricultural land to the west and pastoralist settlement to the east. The
150 communities outside the WAs are predominantly Maasai pastoralists who keep a mixture of cattle,
151 sheep and goats. The human population in the areas surrounding the Serengeti-Mara are estimated
152 to have increased 2.4% per year from 1999 to 2012 (Veldhuis et al. 2019). The MMNR, wildlife
153 conservancies and surrounding unprotected areas are not divided by physical barriers thus allowing
154 for free movement of animals. However, land subdivision has resulted in a proliferation of fences
155 being erected outside the WAs to secure grazing for livestock and there are concerns that these
156 fences might impede the movement of wildlife (Løvschal et al. 2017). The north-western border of

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157 WAs is characterised by an escarpment which rises to roughly 300m above the plains, while to the
158 north-east of the WAs there is a flat region known as the Pardamat Plains which then rises into the
159 Pardamat Hills. The area to the east of the WAs is characterised by dense vegetation eventually
160 rising to the Loita Hills.

161 ***Data collection***

162 *Interview survey*

163 Data on the presence of lion, cheetah and African wild dog outside the wildlife areas were
164 collected through interviews conducted in June and July 2015. For more details on how interviewees
165 were selected see Broekhuis et al. (2017) but briefly, homesteads were selected randomly and at
166 each location the head of the household was interviewed resulting in all interviewees being male. To
167 ensure species were identified correctly, respondents were asked to identify photographs of the
168 focal species (lion, cheetah and African wild dog) along with other predators (leopard *P. pardus*,
169 spotted hyaena *Crocuta crocuta*, striped hyaena *Hyaena hyaena* and tigers *P. tigris*). Only data from
170 respondents who correctly identified the focal species were included in the analyses. The
171 respondents were then asked how frequently they see lion, cheetah or African wild dog in the area
172 around their homestead in the last year: daily, weekly, monthly, yearly, or never. From each
173 interview one data point per species was created and there was no replication of interviewees. This
174 frequency data was turned into presence/absence data by counting daily and weekly sightings as a
175 presence and all other sightings as an absence. Due to African wild dog scarcity in this area we also
176 included monthly sightings to assist model convergence. The study area was then divided into 5 x 5
177 km sites, and the sighting data were then converted into a series of detections and non-detections
178 for each site. Data were also collected on respondent's occupation, which could impact the amount
179 of time they spent outside and their alertness for wild animals, and used this as a variable to account

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180 for detection probability (see Data processing and analysis – Hierarchical models). We expected that
181 pastoralists would have better local ecological knowledge than businessmen due to more frequent
182 interactions with their environment which would increase their detection probability. Data on
183 individuals were kept confidential and collected in line with Zoological Society of
184 London's (ZSL) guidelines and methods were approved by the ZSL Ethical Committee (see Madsen
185 and Broekhuis 2018 for details).

186 GPS data

187 Iridium satellite collars (IR-SAT, African Wildlife Tracking (www.awt.co.za/product/)) were
188 fitted to six sub-adult male lions from 2016 to 2018, six cheetahs from 2015 to 2017 and eight
189 African wild dogs from 2013 to 2017. The lions and cheetahs were immobilised in the Maasai Mara
190 (Kenya) by a Kenya Wildlife Service veterinarian and the African wild dogs were immobilised in
191 Loliondo Game Controlled Area (Tanzania) under a permit from the Tanzania Wildlife Research
192 Institute, whose veterinarians immobilised and collared all animals. All individuals were free-darted
193 from a vehicle using a Dan-Inject CO₂ rifle (DanInject, Denmark). Lions were immobilised using
194 ketamine (1.1–1.2 mg/kg) and medetomidine (0.025-0.04 mg/kg) and reversed with atipamezole
195 (0.125 – 0.20 mg/kg; Kock et al. 2006). Cheetahs were immobilised using a combination of ketamine
196 (2–2.5 mg/kg) and medetomidine (0.07 mg/kg) and reversed with atipamezole (0.35 mg/kg; Kock et
197 al. 2006). Wild dogs were immobilised with Zoletil (4 mg/kg; Van Heerden et al. 1991). In all cases,
198 sedation time was kept to a minimum, typically less than 1 hr. After immobilisation, all individuals
199 recovered fully, showing no signs of distress and no apparent side effects were observed on both the
200 short- and long-term. The lion collars, which weighed 1,200 grams, were fitted with a drop-off
201 mechanism and recorded locations every hour. Collars fitted on cheetahs weighed 400 grams
202 (Broekhuis et al. 2018) and recorded locations every 2-3 hours. The wild dog collars weighed <640

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203 grams, representing ca. 2.6% of collared animal's body weights, and recorded locations every 4-12
204 hours during peak activity periods.

205 ***Environmental variables***

206 For each of the analyses, the following eight environmental variables, grouped into four
207 categories, were used:

208 *Human disturbance* – Per site we calculated four proxies for human disturbance: 1) the
209 proportion of each site that was fenced using data from Løvschal et al. (2017); 2) the average
210 distance to the nearest man-made structure; 3) the mean density of man-made structures and 4) the
211 sum of man-made structures. The latter three proxies were calculated using a human footprint layer
212 which included settlements, livestock enclosures, dams, towns and agricultural land (Klaassen and
213 Broekhuis 2018). To calculate the density of man-made structures, polygons were first drawn around
214 each human development to reflect the size of the structure. The polygons were then converted to
215 points and the density was calculated using the point density function in ArcGIS 10.2.2
216 (Environmental Systems Research Institute Inc., 2014).

217 *Habitat type* – The proportions of open and semi-closed/closed habitat for each site were
218 calculated using the habitat layer from Broekhuis et al. (2017). Open habitat was predominantly
219 characterised by grasslands while semi-closed/closed habitat included Croton thickets (*Croton*
220 *dichogamous*), *Vachellia* woodlands (*Vachellia drepanolobium* and *V. gerrardii*) and riparian
221 vegetation.

222 *Wildlife areas* - The Euclidean distances to the WAs were calculated and averaged per site.

223 *Rivers distance* - The Euclidean distances to rivers were calculated and averaged per site.

224 Each of the variables were calculated per 5 x 5 km site and standardised using a z-score
225 transformation with a mean of 0 and a standard deviation of 1 unless it was a proportion. In
226 addition, the variables were tested for collinearity with a threshold of $|r|>0.6$ indicating correlation
227 (Dormann et al. 2013), but no correlations were found.

228 ***Data processing and analysis***

229 Habitat use and occurrence based on LEK

230 *Linear Models*

231 We used a simple generalised linear model (GLM) with binomial error structure on the
232 presence/absence data generated from the interviews for each of the three species. In addition, to
233 account for potential biases that could be introduced based on a person's occupation, we used a
234 generalised linear mixed model (GLMM) where the interviewee's occupation was added as a random
235 factor. All the analyses using linear models were conducted using the *lme4* package (Bates et al.
236 2014).

237 *Hierarchical Models*

238 The presence/absence data that were collected per site were used to create the detection
239 histories. To aid in model convergence, we randomly reduced the number of interviews per site to a
240 maximum of 10 (Petraçca et al. 2018). To determine which factors influenced the detection
241 probability we used two covariates, the proportion of open habitat in a site and the occupation of
242 the interviewee or a combination of the two. As the 5 x 5 km sites were smaller than the average
243 home ranges of the species being assessed, which violates the assumption of closure, ψ (ψ) was
244 interpreted as the “probability of occurrence” rather than the “probability of occupancy”. We used a
245 basic single-season occupancy model and two different false positive models. The probability of false
246 positives is expected to increase with the number of interviews per site (Royle and Link 2006). This
247 can be accounted for by including a variable in the model associated with the number of interviews
248 that were conducted. We used two different methods to account for these false positives by
249 including 1) a binary variable where “1” was equal to or more than the mean number of surveys (in
250 this case six) and “0” as less than the mean (Royle and Link 2006, Petraçca et al. 2018) and 2) a
251 continuous variable for number of interviews per site, hereafter referred to as the false positive
252 binary (FPbinary) and the false positive count (FPcount) models respectively. All occupancy analyses
253 were performed using the *unmarked* package (Fiske and Chandler 2011).

254 Habitat use and occurrence based on GPS collar data

255 Data from the GPS collars were used to determine habitat use and occurrence for each
256 species using resource selection functions (RSF; Manly et al. 2002) where the environmental
257 variables at actual locations (used) were compared to an equal number of random data points
258 (available) that were generated within the extent of the study area (Fig. 1). We compared the used
259 data (1) to the available data (0) using generalised linear mixed models with a binomial error

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260 structure in the package *lme4* (Bates et al. 2014). We used the Moran's Index to test for spatial
261 autocorrelation. To account for individual variation within the data, we added the individual's ID as a
262 random factor (Gillies et al. 2006).

263 Covariate Selection, Model Building and Selection

264 For all modelling methods we used a two-stage process to determine the probability of
265 occurrence for lion, cheetah and African wild dog. For each species, we first conducted a univariate
266 analysis within covariate categories to identify the covariate with the lowest Akaike Information
267 Criterion (AIC) (Burnham and Anderson 2002). If there was only one covariate in the category then it
268 was compared to the null model. If no covariates in a group performed better than the null model,
269 then they were not included in the multivariate stage. The second stage was a multivariate analysis
270 where the best performing covariates were used and all model variations were compared using AIC
271 with their relative support assessed using the Δ AIC and AIC weights. If the top model AIC weight was
272 <0.9 then the probability of occurrence was averaged using a weighted method for all the models
273 with Δ AIC <2 (Burnham and Anderson 2002, Arnold 2010). Unless stated otherwise, parameter
274 estimates are presented with standard errors and were considered statistically significant if the 95%
275 confidence intervals do not overlap zero. All statistical analyses were performed in R 3.4.3 (R
276 Development Core Team 2018) and AICs were compared using package *AICmodavg* (Mazerolle
277 2019).

278 Method comparison

279 Two different metrics were used to assess which LEK-based model output most closely
280 resembled occurrence based on the outputs from the collar data. Firstly, we used a Kendall's tau-b
281 test with 95% confidence to determine the amount of correlation between the LEK-based and collar-
282 based outputs. A positive Tau value would suggest a positive correlation and values closer to 1

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283 would indicate a greater similarity between the LEK- and collar-based outputs whilst a negative value
284 would indicate a negative correlation. Secondly, we assessed the presence of positive deviations,
285 when the probability of occurrence predicted by the LEK data was high and collar data low ($P_{\text{interview}} \geq$
286 ($P_{\text{collar}} + 0.5$)), and negative deviations when the probability of occurrence predicted by the LEK data
287 was low and collar data high ($P_{\text{interview}} \leq (P_{\text{collar}} - 0.5)$).

288 **Results**

289 A total of 630 people were interviewed in the communities surrounding the wildlife areas
290 and 67 of the 139 sites were sampled (Fig. 1). The total number of interviews used per species varied
291 as they were only included if they correctly identified that species. All 630 interviewees correctly
292 identified lion and of these 158 (25.1%) people reported seeing a lion. Cheetah were correctly
293 identified by 584 people (92.7%) of which 63 (10.8%) reported seeing a cheetah. For African wild
294 dog, 598 people (94.9%) correctly identified the species and 61 (10.2%) reported seeing them. From
295 the collars we obtained 16,602 locations for lions, 10,320 for cheetahs and 1,647 for African wild
296 dogs and the Moran I values indicated that there was no spatial autocorrelation present in the
297 residuals.

298 For lion, the GPS data predicted that they preferred semi-closed habitat, avoided areas with
299 high human disturbance and preferred areas away from rivers but close to the WAs (Table 2). The
300 LEK data predicted similar habitat preferences to the GPS data. In particular, all five models
301 predicted that lion avoided human disturbance, preferring areas further away from man-made
302 structures, and that they were more likely to use areas close to the WAs. In contrast to the collar-
303 based habitat use, the LEK-based outputs predicted that lion preferred areas close to rivers. A
304 difference was also observed amongst the LEK-based outputs with regards to habitat type. Similar to
305 the collar-based outputs, the three hierarchical models predicted that lion preferred semi-closed

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306 habitat by either selecting for semi-closed habitat or avoiding open habitat. The two linear models
307 on the other hand predicted that lion avoided semi-closed habitat. However, the hierarchical models
308 indicate that the detection probability was significantly influenced by open habitat, in other words,
309 lion were more likely to be detected as the proportion of open habitat in a site increased (Fig. 2).
310 When comparing the probability of occurrence between the collar- and LEK-based outputs, the
311 outputs from the FPbinary model were most similar (Tau = 0.71), closely followed by the FPcount
312 model (Tau = 0.69; Table 3). However, both these models showed negative deviations meaning that
313 when the collar data predicted a high probability of occurrence, these two models predicted a low
314 probability of occurrence resulting in an underestimation in occurrence when mapped compared to
315 the collar data, which was less evident in the two linear models (Fig. 3).

316 Data from the GPS collars predicted that cheetah preferred open habitat and areas with low
317 human disturbance (Table 2). Cheetah also preferred areas close to the WAs and close to rivers. For
318 the LEK-based models, the FPcount model only contained the habitat variable and, in contrast to the
319 collar-based outputs, it predicted that cheetah would avoid open habitats. For the remaining LEK-
320 based models the predicted habitat use based on human disturbance and the distance to rivers and
321 WAs was similar to the results from the collars. The only exception was that the top FPbinary models
322 did not include the distance to river variable and the top GLMM models did not include the distance
323 to WAs variable. In terms of habitat type, all the models, apart from the FPcount models, predicted
324 that cheetah were more likely to use areas as the proportion of open habitat increased. The FPcount
325 model predicted that cheetah were most likely to be detected in open habitats (Fig. 2) and by
326 pastoralists. Similarly, the simple occupancy models also predicted the cheetah were more likely to
327 be detected in open habitat whereas the FPbinary model predicted that cheetah were less likely to
328 be detected in open habitats, but this was not significant. The probability of occurrence predicted by
329 the FPbinary model was the most similar to the collar-based results (Tau = 0.63, Table 3) with the
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330 FPcount models being the least similar. Unlike the lion, the occupancy and FPbinary models
331 overpredicted the probability of occurrence, in other words if these models predicted a high
332 probability of occurrence then the collar data predicted a low probability (Fig. 3). When mapped,
333 and this is especially the case for the occupancy models, it looks like cheetah are widespread and
334 that there is a high probability of occurrence outside the WAs.

335 For African wild dog, the collar data predicted that they selected areas with semi-closed
336 habitat, avoided areas with a high proportion of fencing and preferred areas that were further away
337 from rivers and WAs (Table 2). The LEK-based models all predicted that African wild dog avoid
338 human disturbance but only the FPbinary models included the proportion of the site that was fenced
339 as a variable. All the LEK-based models predicted that African wild dog preferred areas further away
340 from rivers. Neither of the linear models had the distance to WAs in their top models and in contrast
341 to the collar-based predictions the FPbinary model predicted that African wild dog preferred areas
342 close to the WAs. In terms of habitat type, all the models predicted that African wild dog preferred
343 semi-closed habitat by either having a positive coefficient for semi-closed habitat or a negative
344 coefficient for open habitat. Unlike lion and cheetah, all three hierarchical models predicted that the
345 detection probability for African wild dog decreased with increased proportion of open habitat (Fig.
346 2). When comparing the probability of occurrence, the outputs from the FPbinary model were the
347 most similar to the outputs from the collar data (Tau = 0.73) whereas all the other models showed
348 very few similarities (Table 3 and Fig. 3). As a result, the mapped probability of occurrence for the
349 collar and FPbinary outputs are very similar (Fig. 4).

350 **Discussion**

351 *Method comparison*

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352 For all three carnivore species, the LEK-based models that accounted for both false negatives
353 and false positives were most like the predictions based on data from GPS-collars. The importance of
354 including detection probability was particularly evident for lion. For lion the collar data predicted
355 that they preferred semi-closed habitat however, the LEK-based models that did not account for the
356 fact that detection probability was influenced by habitat (GLM and GLMM) predicted that lion were
357 more likely to use open habitat. Therefore, the outputs from the linear models reflected habitats
358 where lion are more visible rather than areas that they use. Surprisingly, and in contrast to the lion
359 and cheetah outputs, the detection probability for African wild dog decreased as the proportion of
360 open habitat within a site increased. This indicates that African wild dog are less likely to be seen in
361 open habitats, which is unlikely especially as they tend to occur in groups (Frame et al. 1979). It is
362 therefore more likely that African wild dogs are present but that they are being misidentified. In
363 open habitats, sightings can occur over longer distances than in closed habitats, and at longer
364 distances it is possible that African wild dog are mistaken for spotted hyaena or domestic dogs *Canis*
365 *familiaris* which are common in this study site. This could then lead to the introduction of false
366 negatives in open areas decreasing their detection probability. Similar to cheetah and lion, the
367 results for African wild dog show the importance of including the detection probability as the linear
368 models predicted a low probability of occurrence in areas where the collar data predicted a high
369 probability of occurrence and therefore the distribution of African wild dog is likely to be
370 underestimated if detection probability is not accounted for.

371 The results also highlight the issues that can occur when an animal is reported, but not
372 present (false positives). For example, for African wild dog the collar based output and the FPbinary
373 models indicated that African wild dog avoided areas of human presence, which is corroborated by
374 previous studies (e.g. Woodroffe 2011). However, the models that did not account for false positives
375 (GLM, GLMM and occupancy) predicted that African wild dog selected for human presence. This
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376 could be because the probability of false positives increases with more interviews per site (Royle and
377 Link 2006). The way this study was designed we inherently had more interviews per site in areas
378 with more people. Therefore, if this increased probability of false positives was not accounted for,
379 the results may reflect a selection for higher human presence. One way of minimising this bias is by
380 conducting the same number of interviews per site. However, this is often not realistic and therefore
381 the use of models that account for false positives are likely to give better results. Additionally, the
382 hierarchical models for cheetah and African wild dog that did not account for false positives showed
383 an overestimation of occurrence. An overestimation of the hierarchical model compared to results
384 from a sign survey was also seen by Farhadinia et al. (2018). This supports other studies which show
385 that not accounting for false positives can lead to overestimation especially where occurrence
386 records are sparse (Petracca et al. 2018) or the species is wide-ranging (Berigan et al. 2019) like
387 these two species which were only seen by ~10% of the people that were interviewed and are both
388 known to be wide-ranging (Masenga et al. 2016, Durant et al. 2017). This overestimation for cheetah
389 specifically could be, in part, related to misidentification. Cheetah have a similar coat pattern to
390 leopard and as a result the two species can be frequently misidentified (Dickman et al. 2014). Whilst
391 we only used data from respondents who correctly identified the focal species, it is still possible that
392 an animal is misidentified, especially if it was seen fleetingly.

393 These results show that even if photographs are used to try and minimise misidentification,
394 it is still important to account for possible misidentifications in the analysis as they can affect both
395 false negatives and false positives. Interestingly, we found differences in the outputs from the
396 hierarchical models that include false positives, in particular that the FPbinary model outputs are
397 more similar to the collar data compared to FPcount model. It could be that for small samples it is
398 better to collapse the information on the number of interviews into a binary covariate to minimise
399 overparamaterisation. For example, for lion the Kendall tau-b test indicated that outputs from the
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400 FPbinary and FPcount model were similar whereas for cheetah and African wild dog the FPcount
401 model had a lower value compared to the FPbinary model. This could be because lion were sighted
402 more frequently compared to cheetah and African wild dog. This suggests that for species which are
403 rarely sighted a simple false-positive covariate should be used, but this requires further
404 investigation.

405 *Limitations*

406 Whilst using collar data means it is possible to obtain a precise location of an individual,
407 collars are often only deployed on a few individuals within a population. In this study collars were
408 only deployed on sub-adult male lions which may not be representative of the whole population.
409 However, it is likely that a high proportion of lion seen in the unprotected areas are dispersing males
410 as they are more likely to utilise community land compared to adult males and females (Elliot *et al.*
411 2014). In addition, data from collars are often used to investigate habitat selection at a fine-scale i.e.
412 at the location of the GPS point. Whilst the majority of our GPS-based results for lion, cheetah and
413 African wild dog are similar to other studies, there are some differences. For example, in this study
414 cheetahs were found to prefer open habitat whereas recent research has shown that this is not
415 necessarily the case (Klaassen and Broekhuis 2018). However, it is likely that cheetah select semi-
416 closed habitat on a fine scale but that they prefer open habitat at a coarser scale (Klaassen and
417 Broekhuis 2018). This illustrates the importance of considering scale when interpreting habitat use
418 results, especially those based on LEK data where a grid design is needed to obtain repeats. While
419 there are inherent biases associated with the use of GPS collars and RSFs such as fix-rates and
420 location imprecision as discussed in Boyce *et al.* (2002), and Frair *et al.* (2010), our aim was not to
421 assess the reliability of these approaches but rather to compare LEK-based results to these more
422 commonly used methods. It is also worth noting that in this study we reduced the number of
423 interviews per site to a maximum of ten for the occupancy models to converge, which means that

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424 the GLMMs and GLMs had more interviews potentially affecting the results. When using a GLM or
425 GLMM more data will increase the accuracy of the results but hierarchical models on the other hand
426 can struggle to converge with high variation in the number per site (Pettracca et al. 2018).

427 *Conclusion*

428 In summary, we show that LEK data can be a reliable method to assess species' habitat use
429 and occurrence. These results contradict those by Caruso et al. (2017) who tested the reliability of
430 using interview data by comparing the outputs to those from camera traps. Based on the low
431 congruence between the two methods they suggested that interview data are not a reliable method
432 to determine the presence of elusive species. However, when analysing the interview data they did
433 not account for either detection probability or false positives. Our results however illustrate the
434 importance of accounting for these biases when using LEK data, especially for species that are rare,
435 wide-ranging and easily misidentified in the field and when data collection has resulted in an
436 unbalanced sample design. We also show that for species that are rarely sighted and sample sizes
437 are small the use of a binary, rather than a count, variable for the number of interviews is likely to
438 give more reliable results. Not accounting for these biases in the appropriate manner could lead to
439 misleading results. This can be particularly harmful to the conservation of rare species because it can
440 lead to incorrect diversion of limited conservation resources (Jetz et al. 2008) which could lead to
441 local extinction.

442 In this study we used trained enumerators to collect data but this analytical approach could also
443 be used for citizen scientist projects where volunteers collect data for a specific study (Shumba et al.
444 2018b). The use of citizen scientists could assist in further reducing the required resources and
445 whilst this study was on a local scale, these methods could be used to cover a larger extent which is
446 particularly important when assessing wide-ranging species that require large areas of contiguous
447 habitat for their long-term survival. With ever increasing pressures on wildlife populations around
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448 the globe the need for data on species status is increasing (Mace et al. 2018), however, resources
449 are stretched (Field et al. 2005), even with increasing public attention. The ability to rapidly, reliably
450 and cost-effectively assess occurrence of elusive and threatened species is essential to inform
451 conservation decisions. Engaging the local community may well provide a promising way to both
452 obtain LEK and help bridge the gap between research and action (Sauer and Knutson 2008, Brooks et
453 al. 2012).

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471 **Author contributions**

472 **Emily K. Madsen:** Methodology, Formal analysis, Data Curation, Writing - Original Draft. **Nicholas B.**
473 **Elliot:** Conceptualization, Methodology, Investigation, Writing - Review & Editing, Funding
474 acquisition. **Ernest E. Mjingo:** Investigation, Writing - Review & Editing, Funding acquisition.
475 **Emmanuel H. Masenga:** Investigation, Writing - Review & Editing, Funding acquisition. **Craig R.**
476 **Jackson:** Investigation, Data Curation, Writing - Review & Editing. **Roel F. May:** Investigation, Writing
477 - Review & Editing. **Eivin Røskaft:** Investigation, Writing - Review & Editing. **Femke Broekhuis:**
478 Conceptualization, Methodology, Investigation, Data Curation, Writing - Original Draft, Visualization,
479 Supervision, Funding acquisition, Project administration.

480 **References**

481 Anadón, J. D., A. Giménez, R. Ballestar, and I. Pérez. 2009. Evaluation of Local Ecological Knowledge
482 as a method for collecting extensive data on animal abundance. *Conservation Biology*
483 **23**:617-625.

484 Anderson, J., J. M. Rowcliffe, and G. Cowlshaw. 2007. Does the matrix matter? A forest primate in a
485 complex agricultural landscape. *Biological Conservation* **135**:212-222.

486 Andresen, L., K. T. Everatt, and M. J. Somers. 2014. Use of site occupancy models for targeted
487 monitoring of the cheetah. *Journal of Zoology* **292**:212-220.

488 Arnold, T. W. 2010. Uninformative parameters and model selection using Akaike's Information
489 Criterion. *Journal of Wildlife Management* **74**:1175-1178.

490 Bates, D., M. Mächler, B. Bolker, and S. Walker. 2014. Fitting linear mixed-effects models using lme4.
491 arXiv preprint arXiv:1406.5823.

Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

- 492 Berigan, W. J., G. M. Jones, S. A. Whitmore, R. Gutiérrez, and M. Peery. 2019. Cryptic wide-ranging
493 movements lead to upwardly biased occupancy in a territorial species. *Journal of applied*
494 *Ecology* **56**:470-480.
- 495 Boyce, M. S., P. R. Vernier, S. E. Nielsen, and F. K. A. Schmiegelow. 2002. Evaluating resource
496 selection functions. *Ecological Modelling* **157**:281-300.
- 497 Braulik, G. T., M. Arshad, U. Noureen, and S. P. Northridge. 2014. Habitat fragmentation and species
498 extirpation in freshwater ecosystems; causes of range decline of the Indus River Dolphin
499 (*Platanista gangetica minor*). *PloS one* **9**:e101657.
- 500 Broekhuis, F., C. Bissett, and E. V. Chelysheva. 2018. Chapter 32 - Field Methods for Visual and
501 Remote Monitoring of the Cheetah. Pages 447-455 in P. J. Nyhus, L. Marker, L. K. Boast, and
502 A. Schmidt-Küntzel, editors. *Cheetahs: Biology and Conservation*. Academic Press.
- 503 Broekhuis, F., S. A. Cushman, and N. B. Elliot. 2017. Identification of human–carnivore conflict
504 hotspots to prioritize mitigation efforts. *Ecology and Evolution* **7**:10630-10639.
- 505 Brooks, J. S., K. A. Waylen, and M. B. Mulder. 2012. How national context, project design, and local
506 community characteristics influence success in community-based conservation projects.
507 *Proceedings of the National Academy of Sciences* **109**:21265-21270.
- 508 Burnham, K. P., and D. R. Anderson. 2002. *Model selection and multimodel inference: a practical*
509 *information-theoretic approach*. Springer-Verlag, New York.
- 510 Cagnacci, F., L. Boitani, R. A. Powell, and M. S. Boyce. 2010. Animal ecology meets GPS-based
511 radiotelemetry: a perfect storm of opportunities and challenges. *The Royal Society*.
- 512 Cano, L. S., and J. L. Tellería. 2013. Local ecological knowledge as a tool for assessing the status of
513 threatened vertebrates: a case study in Vietnam. *Oryx* **47**:177-183.
- 514 Caruso, N., E. Luengos Vidal, M. Guerisoli, and M. Lucherini. 2017. Carnivore occurrence: do
515 interview-based surveys produce unreliable results? *Oryx*:1-6.

Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

516 Ceballos, G., P. R. Ehrlich, and R. Dirzo. 2017. Biological annihilation via the ongoing sixth mass
517 extinction signaled by vertebrate population losses and declines. *Proceedings of the National*
518 *Academy of Sciences* **114**:E6089-E6096.

519 Cullen-Unsworth, L. C., B. L. Jones, R. Seary, R. Newman, and R. K. Unsworth. 2017. Reasons for
520 seagrass optimism: Local ecological knowledge confirms presence of dugongs. *Marine*
521 *pollution bulletin* **134**:118-122.

522 Dalerum, F., M. J. Somers, K. E. Kunkel, and E. Z. Cameron. 2008. The potential for large carnivores to
523 act as biodiversity surrogates in southern Africa. *Biodiversity and Conservation* **17**:2939-
524 2949.

525 Davis, A., and J. R. Wagner. 2003. Who Knows? On the Importance of Identifying “Experts” When
526 Researching Local Ecological Knowledge. *Human Ecology* **31**:463-489.

527 Dickman, A. J., L. Hazzah, C. Carbone, and S. M. Durant. 2014. Carnivores, culture and ‘contagious
528 conflict’: Multiple factors influence perceived problems with carnivores in Tanzania’s Ruaha
529 landscape. *Biological Conservation* **178**:19-27.

530 Dormann, C. F., J. Elith, S. Bacher, C. Buchmann, G. Carl, G. Carré, J. R. G. Marquéz, B. Gruber, B.
531 Lafourcade, P. J. Leitão, T. Münkemüller, C. McClean, P. E. Osborne, B. Reineking, B.
532 Schröder, A. K. Skidmore, D. Zurell, and S. Lautenbach. 2013. Collinearity: a review of
533 methods to deal with it and a simulation study evaluating their performance. *Ecography*
534 **36**:27-46.

535 Durant, S. M., N. Mitchell, R. Groom, N. Pettorelli, A. Ipavec, A. P. Jacobson, R. Woodroffe, M. Böhm,
536 L. T. Hunter, and M. S. Becker. 2017. The global decline of cheetah *Acinonyx jubatus* and
537 what it means for conservation. *Proceedings of the National Academy of Sciences* **114**:528-
538 533.

Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

539 Eddy, T. D., J. P. Gardner, and A. Pérez-Matus. 2010. Applying fishers' ecological knowledge to
540 construct past and future lobster stocks in the Juan Fernández Archipelago, Chile. *PloS one*
541 **5**:e13670.

542 Farhadinia, M. S., R. J. Moll, R. A. Montgomery, S. Ashrafi, P. J. Johnson, L. T. B. Hunter, and D. W.
543 Macdonald. 2018. Citizen science data facilitate monitoring of rare large carnivores in
544 remote montane landscapes. *Ecological Indicators* **94**:283-291.

545 Field, S., A. Tyre, K. Thorn, P. O'Connor, and H. Possingham. 2005. Improving the efficiency of wildlife
546 monitoring by estimating detectability: a case study of foxes (*Vulpes vulpes*) on the Eyre
547 Peninsula, South Australia. *Wildlife Research* **32**:253-258.

548 Fiske, I., and R. Chandler. 2011. Unmarked: an R package for fitting hierarchical models of wildlife
549 occurrence and abundance. *Journal of Statistical Software* **43**:1-23.

550 Frair, J. L., J. Fieberg, M. Hebblewhite, F. Cagnacci, N. J. DeCesare, and L. Pedrotti. 2010. Resolving
551 issues of imprecise and habitat-biased locations in ecological analyses using GPS telemetry
552 data. *Philosophical Transactions of the Royal Society B: Biological Sciences* **365**:2187-2200.

553 Frame, L. H., J. R. Malcolm, G. W. Frame, and H. Van Lawick. 1979. Social Organization of African
554 Wild Dogs (*Lycaon pictus*) on the Serengeti Plains, Tanzania 1967–1978 1. *Zeitschrift für*
555 *Tierpsychologie* **50**:225-249.

556 Ghoshal, A., Y. V. Bhatnagar, B. Pandav, K. Sharma, C. Mishra, R. Raghunath, and K. R. Suryawanshi.
557 2017. Assessing changes in distribution of the Endangered snow leopard *Panthera uncia* and
558 its wild prey over 2 decades in the Indian Himalaya through interview-based occupancy
559 surveys. *Oryx*:1-13.

560 Gilchrist, G., M. Mallory, and F. Merkel. 2005. Can local ecological knowledge contribute to wildlife
561 management? Case studies of migratory birds. *Ecology and Society* **10**.

**Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.;
Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.**
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference
and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

562 Gilchrist, G., and M. L. Mallory. 2007. Comparing expert-based science with local ecological
563 knowledge: What are we afraid of? *Ecology and Society* **12**.

564 Gillies, C. S., M. Hebblewhite, S. E. Nielsen, M. A. Krawchuk, C. L. Aldridge, J. L. Frair, D. J. Saher, C. E.
565 Stevens, and C. L. Jerde. 2006. Application of random effects to the study of resource
566 selection by animals. *Journal of Animal Ecology* **75**:887-898.

567 Gopaldaswamy, A., K. Karanth, N. Kumar, and D. Macdonald. 2012. Estimating tropical forest ungulate
568 densities from sign surveys using abundance models of occupancy. *Animal Conservation*
569 **15**:669-679.

570 Gu, W., and R. K. Swihart. 2004. Absent or undetected? Effects of non-detection of species
571 occurrence on wildlife–habitat models. *Biological Conservation* **116**:195-203.

572 Huntington, H. P. 2000. USING TRADITIONAL ECOLOGICAL KNOWLEDGE IN SCIENCE: METHODS AND
573 APPLICATIONS. *Ecological Applications* **10**:1270-1274.

574 Jackson, C. R., J. W. McNutt, and P. J. Apps. 2012. Managing the ranging behaviour of African wild
575 dogs (*Lycaon pictus*) using translocated scent marks. *Wildlife Research* **39**:31-34.

576 Jetz, W., C. H. Sekercioglu, and J. E. Watson. 2008. Ecological correlates and conservation
577 implications of overestimating species geographic ranges. *Conservation Biology* **22**:110-119.

578 Karanth, K. U., A. M. Gopaldaswamy, N. S. Kumar, S. Vaidyanathan, J. D. Nichols, and D. I. MacKenzie.
579 2011. Monitoring carnivore populations at the landscape scale: occupancy modelling of
580 tigers from sign surveys. *Journal of applied Ecology* **48**:1048-1056.

581 Klaassen, B., and F. Broekhuis. 2018. Living on the edge: Multiscale habitat selection by cheetahs in a
582 human-wildlife landscape. *Ecology and Evolution* **8**:7611-7623.

583 Kock, M., D. Meltzer, and R. Burroughs. 2006. Chemical and physical restraint of wild animals: a
584 training and field manual for African species. International Wildlife Veterinary Services,
585 Johannesburg, South Africa.

**Madsen, Emily K.; Elliot, Nicholas B.; Mjinga, Ernest E.; Masenga, Emmanuel H.;
Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.**
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference
and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

586 Kotschwar Logan, M., B. Gerber, S. Karpanty, S. Justin, and F. Rabenahy. 2015. Assessing carnivore
587 distribution from local knowledge across a human-dominated landscape in central-
588 southeastern Madagascar. *Animal Conservation* **18**:82-91.

589 López-Bao, J. V., R. Godinho, C. Pacheco, F. Lema, E. García, L. Llaneza, V. Palacios, and J. Jiménez.
590 2018. Toward reliable population estimates of wolves by combining spatial capture-
591 recapture models and non-invasive DNA monitoring. *Scientific reports* **8**:2177.

592 Louvrier, J., T. Chambert, E. Marboutin, and O. Gimenez. 2018. Accounting for misidentification and
593 heterogeneity in occupancy studies using hidden Markov models. *Ecological Modelling*
594 **387**:61-69.

595 Løvschal, M., P. K. Bøcher, J. Pilgaard, I. Amoke, A. Odingo, A. Thuo, and J.-C. Svenning. 2017. Fencing
596 bodes a rapid collapse of the unique Greater Mara ecosystem. *Scientific Reports* **7**:41450.

597 Mace, G. M., M. Barrett, N. D. Burgess, S. E. Cornell, R. Freeman, M. Grooten, and A. Purvis. 2018.
598 Aiming higher to bend the curve of biodiversity loss. *Nature Sustainability* **1**:448.

599 MacKenzie, D. I., and J. D. Nichols. 2004. Occupancy as a surrogate for abundance estimation. *Animal*
600 *Biodiversity and Conservation* **27**:461-467.

601 MacKenzie, D. I., J. D. Nichols, J. E. Hines, M. G. Knutson, and A. B. Franklin. 2003. Estimating site
602 occupancy, colonization, and local extinction when a species is detected imperfectly. *Ecology*
603 **84**:2200-2207.

604 MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002.
605 Estimating site occupancy rates when detection probabilities are less than one. *Ecology*
606 **83**:2248-2255.

607 MacKenzie, D. I., and J. A. Royle. 2005. Designing occupancy studies: general advice and allocating
608 survey effort. *Journal of applied Ecology* **42**:1105-1114.

Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

609 Madsen, E. K., and F. Broekhuis. 2018. Determining multi-species site use outside the protected
610 areas of the Maasai Mara, Kenya, using false positive site-occupancy modelling. *Oryx*:1-10.

611 Manly, B. F. J., L. L. McDonald, D. L. Thomas, T. L. McDonald, and W. P. Erickson. 2002. Resource
612 selection by animals: Statistical design and analysis for field studies. 2nd edition. Kluwer
613 Academic Publishers, Dordrecht.

614 Masenga, E. H., C. R. Jackson, E. E. Mjingo, A. Jacobson, J. Riggio, R. D. Lyamuya, R. D. Fyumagwa, M.
615 Borner, and E. Røskaft. 2016. Insights into long-distance dispersal by African wild dogs in
616 East Africa. *African Journal of Ecology* **54**:95-98.

617 Mazerolle, M. J. 2019. AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c). R
618 package version 2.2-2., <https://cran.r-project.org/package=AICcmodavg>.

619 Miller, D. A., J. D. Nichols, B. T. McClintock, E. H. C. Grant, L. L. Bailey, and L. A. Weir. 2011. Improving
620 occupancy estimation when two types of observational error occur: non-detection and
621 species misidentification. *Ecology* **92**:1422-1428.

622 Nash, H. C., M. H. Wong, and S. T. Turvey. 2016. Using local ecological knowledge to determine
623 status and threats of the Critically Endangered Chinese pangolin (*Manis pentadactyla*) in
624 Hainan, China. *Biological Conservation* **196**:189-195.

625 Pauly, D. 1995. Anecdotes and the shifting baseline syndrome of fisheries. *Trends in ecology &*
626 *evolution* **10**:430.

627 Petracca, L. S., J. L. Frair, J. B. Cohen, A. P. Calderón, J. Carazo-Salazar, F. Castañeda, D. Corrales-
628 Gutiérrez, R. J. Foster, B. Harmsen, and S. Hernández-Potosme. 2018. Robust inference on
629 large-scale species habitat use with interview data: The status of jaguars outside protected
630 areas in Central America. *Journal of Applied Ecology* **55**:723-734.

Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

631 Poizat, G., and E. Baran. 1997. Fishermen's knowledge as background information in tropical fish
632 ecology: a quantitative comparison with fish sampling results. *Environmental Biology of*
633 *fishes* **50**:435-449.

634 R Development Core Team. 2018. R: A language and environment for statistical computing. R
635 Foundation for Statistical Computing, Vienna, Austria.

636 Riggio, J., and T. Caro. 2017. Structural connectivity at a national scale: Wildlife corridors in Tanzania.
637 *PLoS ONE* **12**:e0187407.

638 Ripple, W. J., J. A. Estes, R. L. Beschta, C. C. Wilmers, E. G. Ritchie, M. Hebblewhite, J. Berger, B.
639 Elmhagen, M. Letnic, and M. P. Nelson. 2014. Status and ecological effects of the world's
640 largest carnivores. *Science* **343**:1241484.

641 Rowcliffe, J. M., and C. Carbone. 2008. Surveys using camera traps: are we looking to a brighter
642 future? *Animal Conservation* **11**:185-186.

643 Royle, J. A., and W. A. Link. 2006. Generalized site occupancy models allowing for false positive and
644 false negative errors. *Ecology* **87**:835-841.

645 Royle, J. A., J. D. Nichols, and M. Kéry. 2005. Modelling occurrence and abundance of species when
646 detection is imperfect. *Oikos* **110**:353-359.

647 Sauer, J. R., and M. G. Knutson. 2008. Objectives and metrics for wildlife monitoring. *The Journal of*
648 *Wildlife Management* **72**:1663-1664.

649 Shumba, T., R. A. Montgomery, G. S. Rasmussen, and D. W. Macdonald. 2018a. African wild dog
650 habitat use modelling using telemetry data and citizen scientist sightings: are the results
651 comparable? *African Journal of Wildlife Research* **48**.

652 Shumba, T., R. A. Montgomery, G. S. Rasmussen, and D. W. Macdonald. 2018b. African wild dog
653 habitat use modelling using telemetry data and citizen scientist sightings: are the results
654 comparable? *African Journal of Wildlife Research* **48**:1-13.

Madsen, Emily K.; Elliot, Nicholas B.; Mjinga, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

655 Taylor, R. B., M. A. Morrison, and N. T. Shears. 2011. Establishing baselines for recovery in a marine
656 reserve (Poor Knights Islands, New Zealand) using local ecological knowledge. *Biological*
657 *Conservation* **144**:3038-3046.

658 Teixeira, B., A. Hirsch, V. D. Goulart, L. Passos, C. P. Teixeira, P. James, and R. Young. 2015. Good
659 neighbours: distribution of black-tufted marmoset (*Callithrix penicillata*) in an urban
660 environment. *Wildlife Research* **42**:579-589.

661 Turvey, S. T., C. Fernández-Secades, J. M. Nuñez-Miño, T. Hart, P. Martinez, J. L. Brocca, and R. P.
662 Young. 2014. Is local ecological knowledge a useful conservation tool for small mammals in a
663 Caribbean multicultural landscape? *Biological Conservation* **169**:189-197.

664 Turvey, S. T., C. T. Trung, V. D. Quyet, H. V. Nhu, D. V. Thoai, V. C. A. Tuan, D. T. Hoa, K. Kacha, T.
665 Sysomphone, and S. Wallate. 2015. Interview-based sighting histories can inform regional
666 conservation prioritization for highly threatened cryptic species. *Journal of applied Ecology*
667 **52**:422-433.

668 Van Heerden, J., R. Burroughs, J. Dauth, and M. Dreyer. 1991. Immobilization of wild dogs (*Lycaon*
669 *pictus*) with a tiletamine hydrochloride/zolazepam hydrochloride combination and
670 subsequent evaluation of selected blood chemistry parameters. *Journal of Wildlife Diseases*
671 **27**:225-229.

672 Veldhuis, M. P., M. E. Ritchie, J. O. Ogutu, T. A. Morrison, C. M. Beale, A. B. Estes, W. Mwakilema, G.
673 O. Ojwang, C. L. Parr, and J. Probert. 2019. Cross-boundary human impacts compromise the
674 Serengeti-Mara ecosystem. *Science* **363**:1424-1428.

675 Whittington-Jones, B. M., D. M. Parker, R. T. Bernard, and H. T. Davies-Mostert. 2014. Habitat
676 selection by transient African wild dogs (*Lycaon pictus*) in northern KwaZulu-Natal, South
677 Africa: implications for range expansion. *South African Journal of Wildlife Research-*
678 *subscription access* **44**:135-147.

Madsen, Emily K.; Elliot, Nicholas B.; Mjinga, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskaft, Eivin; Broekhuis, Femke.
Evaluating the use of local ecological knowledge (LEK) in determining habitat preference and occurrence of multiple large carnivores. *Ecological Indicators* 2020 ;Volum 118.
DOI [10.1016/j.ecolind.2020.106737](https://doi.org/10.1016/j.ecolind.2020.106737) CC-BY-NC-ND

679 Wolf, C., and W. J. Ripple. 2017. Range contractions of the world's large carnivores. Royal Society
680 open science **4**:170052.

681 Woodroffe, R. 2011. Ranging behaviour of African wild dog packs in a human-dominated landscape.
682 Journal of Zoology **283**:88-97.

683 Zeller, K. A., S. Nijhawan, R. Salom-Pérez, S. H. Potosme, and J. E. Hines. 2011. Integrating occupancy
684 modeling and interview data for corridor identification: a case study for jaguars in Nicaragua.
685 Biological Conservation **144**:892-901.

686

687

Madsen, Emily K.; Elliot, Nicholas B.; Mjingo, Ernest E.; Masenga, Emmanuel H.; Jackson, Craig Ryan; May, Roelof Frans; Røskft, Eivin; Broekhuis, Femke.
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688 Tables

689 **Table 1** A summary of the models that were used to analyse the LEK data to map habitat use and
690 occurrence of lion, cheetah and African wild dog.

Model	Abbreviation	State process	Occupational bias	Detection process/False negatives	False positives
Linear model	GLM	X			
Generalized linear mixed effect model	GLMM	X	X		
Occupancy	Occupancy	X	X	X	
False positive binary	FPbinary	X	X	X	X
False positive count	FPcount	X	X	X	X

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692 Table 2 The coefficients and standard errors for the covariates in the top models for the LEK and collar based analyses. **Bold** indicates covariates that were
 693 significant, X indicates the model included this covariate but did not provide coefficients and – indicates that no covariates from this category were in the
 694 top models

Species	Model	Detection probability covariates		Occurrence probability covariates							
		Open habitat	Occupation	Habitat type	Coefficient	Human disturbance	Coefficient	Rivers	Coefficient	Wildlife area	Coefficient
Lion	GLM	-	-	Semi-closed	-0.44 (0.45)	Distance	4.39 (2.33)	Distance	-9.22 (2.25)	Distance	-1.55 (0.31)
	GLMM	-	X	Semi-closed	-0.43 (0.46)	Distance	4.61 (2.32)	Distance	-9.04 (2.28)	Distance	-1.56 (0.31)
	Occupancy	1.46 (0.42)	-	Open	-0.24 (2.42)	Distance	18.46 (18.40)	Distance	-4.01 (7.74)	Distance	-1.22 (1.05)
	FPbinary	2.70 (0.74)	-	Semi-closed	4.48 (3.66)	Distance	19.06 (16.98)	Distance	-10.21 (8.49)	Distance	-5.16 (2.74)
	FPcount	2.84 (0.67)	-	Open	-4.61 (3.46)	Distance	20.14 (16.24)	Distance	-5.84 (8.65)	Distance	-6.43 (2.89)
	RSF	-	-	Semi-closed	2.62 (0.06)	Sum	-0.67 (0.04)	Distance	0.09 (0.17)	Distance	-3.59 (0.06)
Cheetah	GLM	-	-	Open	3.06 (0.68)	Distance	14.34 (2.85)	Distance	-10.46 (2.83)	Distance	-0.61 (0.46)
	GLMM	-	X	Open	3.28 (0.61)	Distance	15.25 (2.52)	Distance	-10.89 (2.74)	-	-
	Occupancy	1.80 (0.73)	-	Open	1.89 (1.61)	Distance	39.21 (16.30)	Distance	-18.82 (8.68)	Distance	-1.15 (1.31)
	FPbinary	-1.78 (3.17)	-	Open	10.97 (7.15)	Distance	30.59 (15.00)	-	-	Distance	-4.32 (3.60)
	FPcount	5.25 (2.03)	Pastoralists	Open	-4.78 (3.01)	-	-	-	-	-	-
	RSF	-	-	Open	0.65 (0.08)	Sum	-12.51 (0.76)	Distance	-3.99 (0.30)	Distance	-5.44 (0.19)
African wild dog	GLM	-	-	Open	-4.44 (0.75)	Sum	0.62 (0.56)	Distance	-7.30 (3.73)	-	-
	GLMM	-	X	Open	-4.44 (0.75)	Sum	0.62 (0.56)	Distance	-7.30 (3.73)	-	-
	Occupancy	-3.81 (1.05)	-	Open	-1.47 (1.75)	Mean	2.82 (4.88)	Distance	-7.62 (6.76)	Distance	0.23 (0.85)
	FPbinary	-1.35 (2.73)	-	Semi-closed	5.17 (2.41)	Fenced proportion	-7.04 (17.18)	Distance	-25.65 (12.89)	Distance	-0.58 (1.23)
	FPcount	-3.93 (1.01)	Pastoralists	Open	-1.45 (1.80)	Mean	3.12 (4.82)	Distance	-7.98 (6.87)	Distance	0.53 (0.88)
	RSF	-	-	Semi-closed	2.33 (0.20)	Fenced proportion	-23.89 (3.01)	Distance	7.74 (0.88)	Distance	0.80 (0.10)

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695 **Table 3** Metrics for comparison of the different methods of analysing LEK-based data to the collar-
 696 based outputs **Bold** indicates the model which performed best using that metric.

Species	Model	Kendall's tau-b		Deviations	
		P Value	tau	Positive	Negative
Lion	GLM	< 0.001	0.60	0	11
	GLMM	< 0.001	0.61	0	6
	Occupancy	< 0.001	0.53	3	16
	FPbinary	< 0.001	0.71	0	19
	FPcount	< 0.001	0.69	0	43
Cheetah	GLM	< 0.001	0.59	3	0
	GLMM	< 0.001	0.53	4	2
	Occupancy	< 0.001	0.51	66	0
	FPbinary	< 0.001	0.63	18	0
	FPcount	< 0.001	0.39	4	7
African wild dog	GLM	< 0.001	0.24	11	40
	GLMM	< 0.001	0.24	11	38
	Occupancy	0.01	0.15	28	0
	FPbinary	< 0.001	0.73	0	3
	FPcount	0.01	0.14	28	0

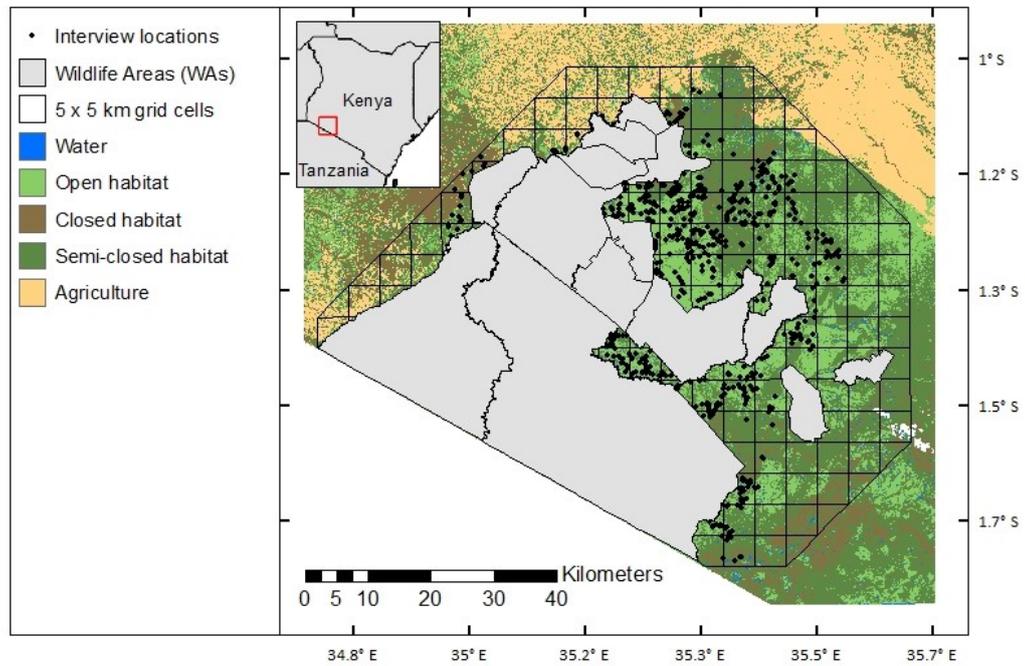
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699 Figures

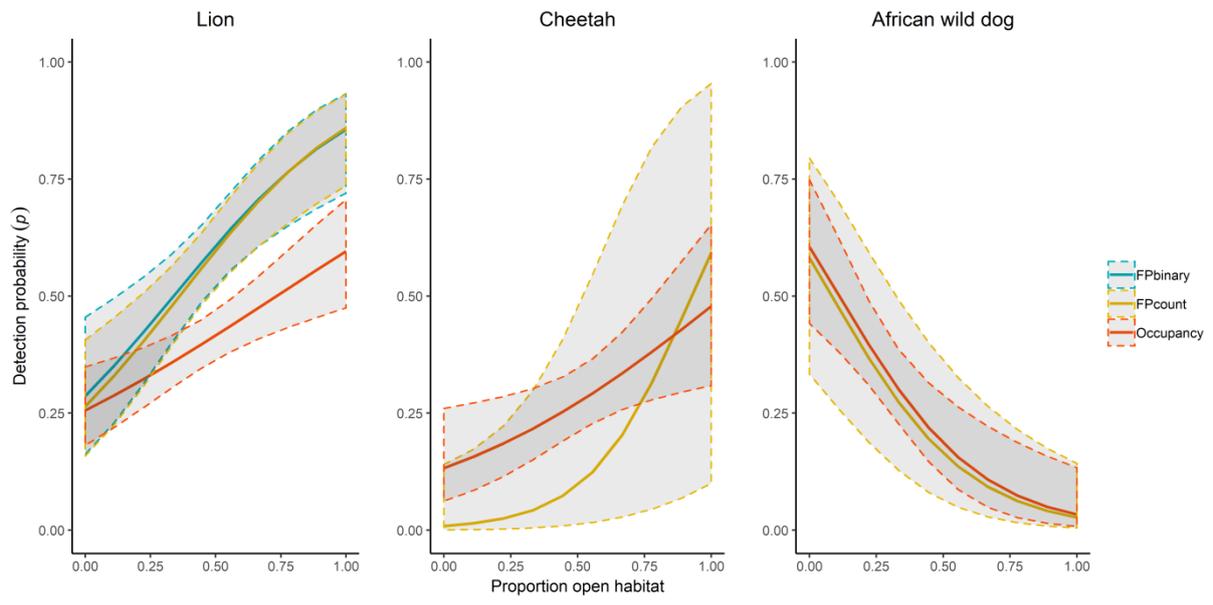
700 **Figure 1** Study site in the Maasai Mara, Kenya, displaying the interview locations and wildlife areas

701 (WAs).



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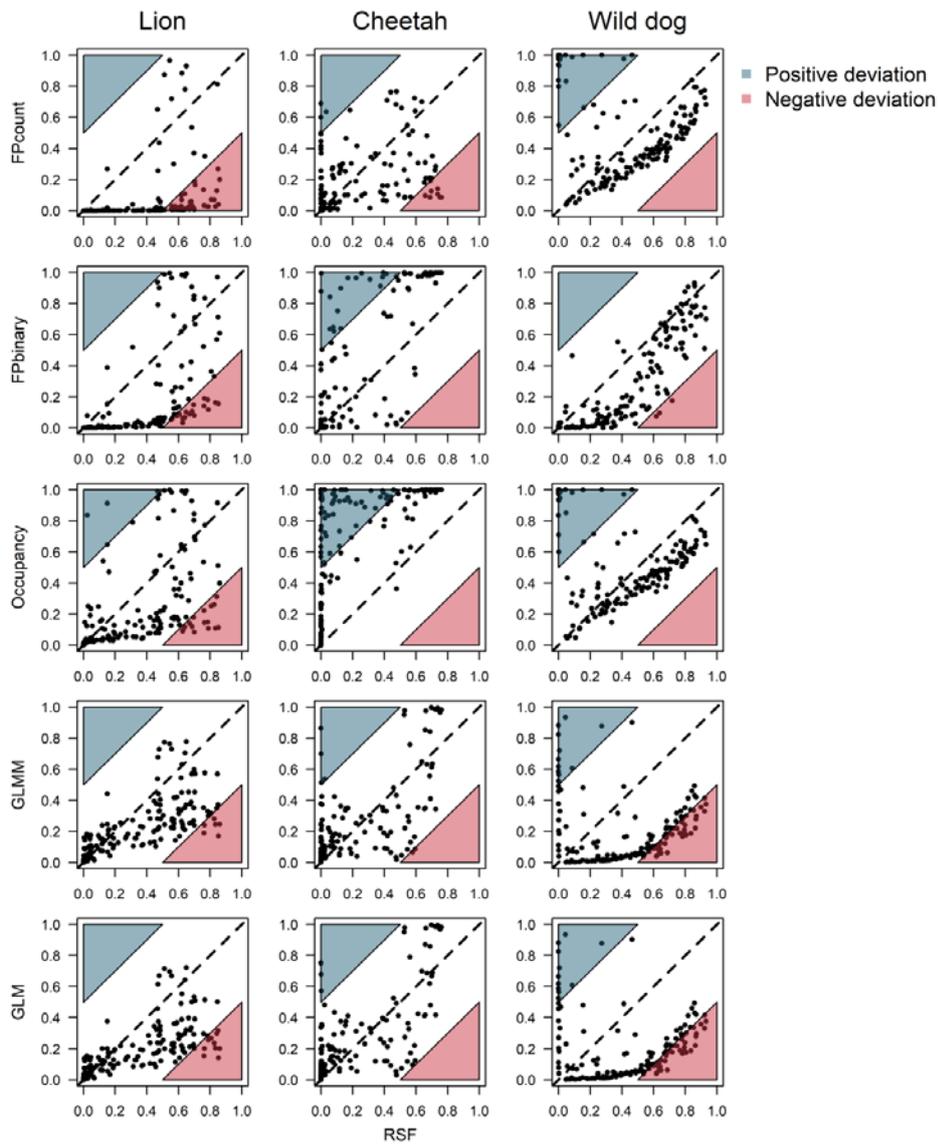
703 **Figure 2** Detection probability and standard errors for the proportion of open habitat for lion,
704 cheetah and African wild dog in the hierarchical models.



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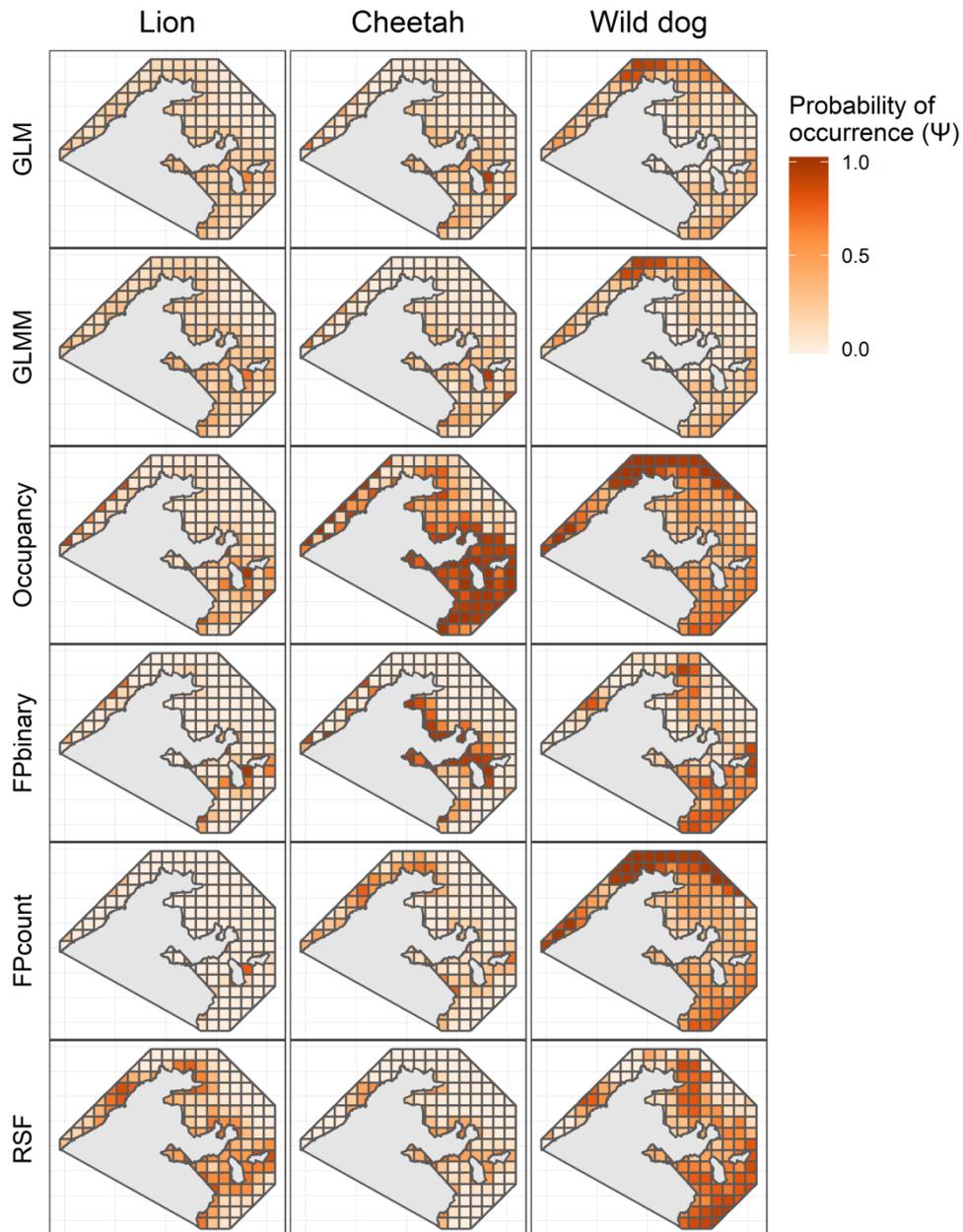
707 **Figure 3** The five different interview analysis method outputs (y-axis) plotted against the collar-
708 based outputs (x-axis) for lion, cheetah and African wild dog for each 5 x 5 km site. The dotted line
709 indicates the LEK-based probability of occurrence predicted is exactly the same as the collar-based
710 probability of occurrence.



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713 **Figure 4** Maps showing the model predictions for occurrence for lion, cheetah and African wild dog
714 for the outputs based on the collar data and LEK data analysed using five different methods; a
715 general linear model (GLM), a generalized linear mixed effect model (GLMM), an occupancy model
716 (occupancy), a false positive binary occupancy model (FPbinary) and a false positive count occupancy
717 model (FPcount).



718