Conservation Biology



Numbers count: Reliable estimates of lion density

Manuscript ID Wiley - Manuscript type: Conservation Methods Paper Keywords: Abundance, density, spatial capture-recapture, precision, SECR Reliable estimates of animal density are fundamental to our understanding of ecological processes and population dynamics. Furthermore, their accuracy is vital to conservation biology since wildlife authorities rely on these figures to make decisions. However, it is notoriously difficult to accurately estimate density for wide-ranging species such as carnivores that occur at low densities. In recent years, significant progress has been made in density estimation of Asian carnivores, but the methods have not been widely adapted to African carnivores. African lions (Panthera leo) provide an excellent example as even though index calibration experiments have been shown to produce poor inferences, they continue to be used to estimate lion density and inform management and policy. In this study we adapt a Bayesian spatially explicit capture-recapture model to estimate lior density in the Maasai Mara National Reserve and surrounding conservancies in Kenya. We utilize sightings data from a three-month survey period to produce statistically rigorous spatial density estimates.
Reliable estimates of animal density are fundamental to our understanding of ecological processes and population dynamics. Furthermore, their accuracy is vital to conservation biology since wildlife authorities rely on these figures to make decisions. However, it is notoriously difficult to accurately estimate density for wide-ranging species such as carnivores that occur at low densities. In recent years, significant progress has been made in density estimation of Asian carnivores, but the methods have not been widely adapted to African carnivores. African lions (Panthera leo) provide an excellent example as even though index calibration experiments have been shown to produce poor inferences, they continue to be used to estimate lion density and inform management and policy. In this study we adapt a Bayesian spatially explicit capture-recapture model to estimate lior density in the Maasai Mara National Reserve and surrounding conservancies in Kenya. We utilize sightings data from a three-month
Reliable estimates of animal density are fundamental to our understanding of ecological processes and population dynamics. Furthermore, their accuracy is vital to conservation biology since wildlife authorities rely on these figures to make decisions. However, it is notoriously difficult to accurately estimate density for wide-ranging species such as carnivores that occur at low densities. In recent years, significant progress has been made in density estimation of Asian carnivores, but the methods have not been widely adapted to African carnivores. African lions (Panthera leo) provide an excellent example as even though index calibration experiments have been shown to produce poor inferences, they continue to be used to estimate lion density and inform management and policy. In this study we adapt a Bayesian spatially explicit capture-recapture model to estimate lior density in the Maasai Mara National Reserve and surrounding conservancies in Kenya. We utilize sightings data from a three-month
of ecological processes and population dynamics. Furthermore, their accuracy is vital to conservation biology since wildlife authorities rely on these figures to make decisions. However, it is notoriously difficult to accurately estimate density for wide-ranging species such as carnivores that occur at low densities. In recent years, significant progress has been made in density estimation of Asian carnivores, but the methods have not been widely adapted to African carnivores. African lions (Panthera leo) provide an excellent example as even though index calibration experiments have been shown to produce poor inferences, they continue to be used to estimate lion density and inform management and policy. In this study we adapt a Bayesian spatially explicit capture-recapture model to estimate lior density in the Maasai Mara National Reserve and surrounding conservancies in Kenya. We utilize sightings data from a three-month
Overall posterior mean lion density was estimated to be 16.85 (posterior standard deviation = 1.30) lions over one year of age per 100km2 with a sex ratio of 2.2\(\sigma\):1\(\frac{1}{3}\). We argue that such methods should be developed, improved and favored over less reliable methods such as track and call-up surveys. We call for a unified framework to assess lion numbers across their range in order for better informed management and policy decisions to be made.

SCHOLARONE™ Manuscripts

2

3

4

5

6

7

8

9

10

11

12

13

14

15

16

17

18

19

20

Numbers count: Reliable estimates of lion density

Abstract

Reliable estimates of animal density are fundamental to our understanding of ecological processes and population dynamics. Furthermore, their accuracy is vital to conservation biology since wildlife authorities rely on these figures to make decisions. However, it is notoriously difficult to accurately estimate density for wide-ranging species such as carnivores that occur at low densities. In recent years, significant progress has been made in density estimation of Asian carnivores, but the methods have not been widely adapted to African carnivores. African lions (Panthera leo) provide an excellent example as even though index calibration experiments have been shown to produce poor inferences, they continue to be used to estimate lion density and inform management and policy. In this study we adapt a Bayesian spatially explicit capture-recapture model to estimate lion density in the Maasai Mara National Reserve and surrounding conservancies in Kenya. We utilize sightings data from a three-month survey period to produce statistically rigorous spatial density estimates. Overall posterior mean lion density was estimated to be 16.85 (posterior standard deviation = 1.30) lions over one year of age per 100km^2 with a sex ratio of 2.2 ? : 1 ?. We argue that such methods should be developed, improved and favored over less reliable methods such as track and call-up surveys. We call for a unified framework to assess lion numbers across their range in order for better informed management and policy decisions to be made.

Introduction

21

22

23

24

25

26

27

28

29

30

31

32

33

34

35

36

37

38

39

40

41

42

43

44

45

Population density estimates are indispensable to our understanding of ecological processes, population dynamics and conservation biology (May 1999). That density estimates are accurate is vital to wildlife managers since they inform regional strategies (e.g. Kenya Large Carnivore Taskforce 2009), IUCN, ESA and CITES classifications (e.g. Bauer et al. 2015a), trophy hunting quotas (e.g. Croes et al. 2011) and help to define 'conservation units' and 'strongholds' (e.g. Riggio et al. 2013). Density estimates are also used to advocate for controversial management practices such as fencing (e.g. Packer et al. 2013) and culling (Miller & Funston 2014) or to highlight conservation needs (e.g. Bauer et al. 2015b) and successes (e.g. Blackburn et al. 2016). However, obtaining robust and repeatable density estimates of animals in natural settings is often practically and technically difficult (Gopalaswamy et al. 2012a). This is particularly the case for large carnivores, since they naturally occur at low densities, are wide-ranging and often cryptic. In the last two decades, significant progress has been made in density estimation of Asian and American carnivores, particularly within the, now well-established, mark-recapture framework (e.g. Karanth & Nichols 1998; Gopalaswamy et al. 2012a; Russell et al. 2012). Peculiarly, such methods have not been widely adapted to African species. The African lion (Panthera leo) epitomizes this paradigm: they are one of the most extensively studied large mammals on earth and study sites dotted throughout their range have provided census figures that have informed three continent-level population assessments (Chardonnet 2002; Bauer & van der Merwe 2004; Riggio et al. 2013) and numerous meta-analyses (e.g. Bauer et al. 2015b; Bauer et al. 2015a; Packer et al. 2013; Périquet et al. 2014). However, despite their implications, these studies frequently drew on expert opinion or surveys of debatable reliability. For example, a recent highly publicized study that advocated fencing as the best mechanism to conserve lion populations, cited peer reviewed publications for only three of 42

47

48

49

50

51

52

53

54

55

56

57

58

59

60

61

62

63

64

65

66

67

68

69

70

site specific density estimates and none for the presented trends (Packer et al. 2013). These data, supplemented by additional unpublished data were later used to justify the lions continued classification as 'vulnerable' by the IUCN (Bauer et al. 2015a). The same data were then used in a population viability analysis in a study that garnered much media attention, due to alarming conclusions of widespread population declines (Bauer et al. 2015b). In the most recent continent-wide assessment of lion numbers, where population sizes were mapped and 'strongholds' delineated (Riggio et al. 2013), the authors supplemented previous continent-level assessments (Bauer & van der Merwe 2004; Chardonnet 2002) with conservation strategies, action plans, expert opinion and a few published surveys. An array of methods have been used to estimate lion density, including long-term studies combined with telemetry data (e.g. Mosser et al. 2009), camera trapping (e.g. Cusack et al. 2015), distance sampling (e.g. Durant et al. 2011) and genetic surveys (e.g. Creel & Rosenblatt 2013). Since these techniques are costly and impractical in many sites, track surveys (e.g. Funston et al. 2010) and call-up surveys (e.g. Ogutu & Dublin 1998) are the most commonly used techniques to assess lion density (Midlane et al. 2015), and hence it is worth examining them in more detail. In experiments such as track surveys, it is assumed that animal abundance is estimated reliably at a small scale. Simultaneously, an index of abundance (derived from track surveys) is gathered under the presumption that the estimated abundance and the putative index can be fit by linear regression-based approaches using ordinary least square (OLS) solutions. When index data are accumulated over larger scales, it should be possible to predict density at those scales (Eberhardt & Simmons 1987). The utility of such abundance indices has been widely criticized over the past two decades (see Anderson 2001 and references therein), culminating in a statistical examination of the approach that concluded that index-calibration experiments

72

73

74

75

76

77

78

79

80

81

82

83

84

85

86

87

88

89

90

91

92

93

94

produce faulty inferences (Gopalaswamy et al. 2015; Gopalaswamy 2015). The study statistically demonstrated that principally due to the presence of detection probability (especially when low and variable), there is an overdispersion in the associated relationship between true density and the putative index, and found that the R² parameter drops drastically when there is overdispersion. This implies that there is a much larger variance of the parameters than was previously expected. To obtain a precise estimate of these overdispersion parameters, a massive sample size must be acquired, and expending substantial resources to obtain vague assessments based on track surveys is not justified or meaningful for management. Call-up surveys present similar concerns. In this method loud noises are used to attract lions to a station in order to count them. Prior to the survey a calibration experiment is (not always) conducted in order to assess response likelihood and time and area sampled per station. This approach generally abides by the principles of the 'canonical estimator' (Williams et al. 2002) where we have the relation $\hat{N} = C / \hat{p}\hat{\alpha}$, where \hat{p} is the estimate of detection probability, $\hat{\alpha}$ is the proportion of the area sampled and C is the count. In call-up surveys response likelihood is equivalent to \hat{p} in the canonical estimator and $\hat{\alpha}$ is the total sampling area (area sampled per station multiplied by the number of stations) divided by the larger area of inference. The product of $\hat{\alpha}\hat{p}$ then is essentially the probability of observing an individual lion within a given area. However, variation in $\hat{\alpha}$ or \hat{p} between call-in stations spatially and within call-in stations temporally, will produce considerable variation in the observed count, which will also be the case if the product of $\hat{\alpha}\hat{p}$ is very low. As such, all the statistical conclusions about induced overdispersion in abundance estimation will occur (Gopalaswamy et al. 2015; Gopalaswamy 2015) and the confidence intervals will frequently

be too large to enable meaningful assessment of trends over time (e.g. Ogutu et al. 2005).

More recently, surveys of other African predators (O'Brien & Kinnaird 2011), African

lions (Rosenblatt et al. 2014; Blackburn et al. 2016) and Asiatic lions (P. l. persica; Banerjee
et al. 2013) have made great advancements over traditional approaches, and provide more
reliable estimates. Of particular note, Rosenblatt et al. (2014) and Blackburn et al. (2016)
utilized a mark-recapture framework to produce estimates of African lions over a 4-5 year
period and provide estimates of survival and age-sex structure. In the present study, we aim
to improve upon four limitations of those studies: (i) They were not spatially explicit
(implying that the estimating model fails to characterize the spacing rules governing
carnivore populations (Sandell 1989) despite Blackburn et al. (2016) specifically recognizing
that lions are territorial); (ii) They did not account for effort (implying that there might be
biases associated with individual capture rates); (iii) They were conducted over extended
intervals (potentially violating demographic and geographic closure (Karanth & Nichols
1998)); (iv) The conventional capture-recapture models they employed estimate abundance
and did not permit them to directly estimate lion density, which is the principal parameter of
interest. The first three limitations are particularly severe using conventional capture-
recapture approaches as these, essentially multinomial likelihoods (Amstrup et al. 2010), can
be very sensitive to model violations.
To improve on these methods we use a repeatable field method, established within a
spatially explicit mark-recapture framework (Royle et al. 2013), to provide robust density
estimates across the study site. In addition we estimate parameters such as sex ratios, while
accounting for effort and estimating detection probability. This methodology will lay the

foundation for long-term, spatially explicit monitoring and allow for an evaluation of

methodology will join seamlessly with long-term, in-depth studies, enabling a better

ecological determinants of spatial heterogeneity in lion density. Furthermore, our

understanding of the link between individuals and populations and is applicable to other study sites and species.

Methods

Study area

The study area (~2,398km²) was located in southwestern Kenya (centered at 1°S, 35°E), in the MMNR (including the Mara Triangle), Ol Kinyei, Naboisho, Olare Motorogi, Mara North, Lemek and Ol Chorro conservancies (Fig. 1). The area is characterised by open, rolling grasslands interspersed with woodlands and shrublands. Surface water is available from numerous permanent and seasonal rivers that are filled by seasonal rainfall which is bimodal: a short rainy season between November and December, and a long rainy season between March and June. Mean annual rainfall is variable across the study area, with the eastern edge of the study area receiving ~877mm compared to ~1300mm on the western edge (Ogutu et al. 2011). The ecosystem supports large numbers of resident ungulates, which support high densities of predators. Each year between July and October (or later), large migratory herds of wildebeest (*Connochaetes taurinus*), and zebra (*Equus burchelli*) travel from the Serengeti plains in Tanzania into the study area, resulting in a superabundance of prey.

Data collection

Five observers in vehicles intensively patrolled the study area for 92 days (01 August 2014 - 31 October 2014), during which time they recorded all lion sightings and their exact locations. We chose 92 days as we deemed this to be a short enough time so as not to violate the assumptions of a closed population (Karanth & Nichols 1998), while long enough to obtain a large amount of data. Wherever possible, great care was taken to individually identify all lions at each sighting using whisker vibrissae spots and other distinguishing marks (Pennycuick & Rudnai 1970). Cub mortality is highest during the first year in the

Mara-Serengeti ecosystem (Packer et al. 1988), and thus all lions under the estimated age of one year were excluded from analysis since their inclusion may violate closure. In many instances we first sighted cubs while very young and could accurately determine age, while in other cases we used described field methods (Whitman & Packer 2007). Our effort was continuously recorded using GPS-enabled smartphones, running a customized CyberTracker (www.cybertracker.org) application, set to take a GPS point every ten seconds.

State process

We employed a Bayesian spatial capture-recapture model for our analysis (Royle et al. 2009; Gopalaswamy et al. 2012b). Accordingly, we defined a large statespace S, of $\sim 10,400 \text{km}^2$, represented in discrete form by pixels (0.3975km²). Unsuitable habitat within this statespace was masked out for analysis (Royle et al. 2009; Gopalaswamy et al. 2012b). The statespace encompassed our study area, with the addition of a 15km buffer (Fig. 1). While this buffer size may not be adequately large enough to account for transients, Royle et al. (2016) recently found that spatial capture-recapture density estimates are robust even with a fairly large number of transients during the sampling period. The value of M (the data-augmented value of abundance in the larger statespace) was set at 1,653 ($\eta = 203$ and $\eta_z = 1,450$), which represents the maximum number of lions possible within the statespace. Our expectation was that the estimate of ψ lie between 0.2-0.8 for reliable estimation of the binomial proportion (Gopalaswamy et al. 2012a), since,

Observation process

We envision a standard spatial capture-recapture data set (See Gopalaswamy et al. 2012b for a full example) that is a 3-dimensional matrix, consisting of individuals ($i = 1, 2, 3 \dots N$) x trap locations ($j = 1, 2, 3 \dots J$) x sampling occasions ($k = 1, 2, 3 \dots K$). In our sampling situation, the trap locations are defined by the pixels themselves and we account for

search effort (logarithm of kilometers driven) invested in each pixel per sampling occasion (one day). Since investing more effort in certain pixels compared to others could yield an increased number of detections in highly sampled pixels, we incorporate an additional covariate of search effort per pixel per sampling occasion. As such, we utilize an unstructured spatial capture-recapture sampling design (e.g. Russell et al. 2012).

Male and female carnivores often have different home range sizes (Macdonald 1983), which is likely to influence the observation process in spatial capture-recapture models (Sollmann et al. 2011). We therefore incorporate sex-specific covariates in defining the observation process.

Spatial capture-recapture models employ a variety of detection function models (Royle et al. 2011; Buckland et al. 2001) to define the mechanism of decline in detection probability with increasing distance between the activity center of an animal and a trap location (in our case, the centroid of a search pixel). Rather than testing various detection function models we explicitly estimate parameter θ and consider an infinite number of possibilities between a perfect Gaussian detection function ($\theta = 1$) and a perfect negative exponential detection function ($\theta = 0.5$; Royle et al. 2009). Thus, θ defines the shape of the detection function, and is indicative of resource utilization.

Hence, the probability of detecting a lion i, in sampling occasion k at pixel j, π_{ijk} is defined by a complementary log-log function of covariates. The below represents the full model in our analysis (see section on Candidate models below).

$$c \log \log(\pi_{ijk}) = \log \lambda_0 + \beta_{eff} [\log(EFFORT_{jk})] + \beta_{sex}(SEX) - f[dist(i, j | \theta, \sigma_{sex})]$$

Candidate models

We defined the following *a priori* models.

Model 1: $[\beta_{sex}, \theta(.)]$ - Full model assumes that detection probability is sex-specific and the detection function is estimated (defined by θ)

Conservation Biology

Model 2: $[\beta_{sex} = 0(fixed), \theta(.)]$ - Assumes detection probability is independent of sex. Rate 194 of decline in detection probability (σ) remains sex-specific, since this parameter is also 195 196 related to animal movement. Model 3: $[\beta_{sex} = 0 (fixed), \theta = 0.75 (fixed)]$ - Detection probability is independent of sex 197 and detection function shape, defined by θ , is fixed to a certain value. 198 Model 4: $[\beta_{sex}, \theta = 0.75]$ – Detection probability is sex-specific but the shape of the 199 200 detection function is fixed. 201 *Implementation of the model* 202 The above set of models were implemented using an adaptation of the package 203 SCRbayes (https://github.com/jaroyle/SCRbayes) in the programming environment R (R-204 Development-Core-Team 2015). The models were implemented using the Bayesian Markov 205 Chain Monte Carle (MCMC) simulation using the Metropolis-Hastings algorithm (Tierney 206 1994). We set each model for 11,000 iterations with a burn-in period of 1,000 iterations. We 207 refined the burn-in period during later stages of an analysis if we found evidence that we had 208 not arrived at a stationary distribution. As a result we had 10,000 posterior samples for each 209 chain. A total of four chains were set to run for each model. 210 Model checking 211 Each model was subsequently checked for adequacy utilizing the Bayesian p-value 212 assessment (Royle et al. 2009; Gopalaswamy et al. 2012a). Although there are a few different 213 test statistics available for the Bayesian p-value assessment (Gopalaswamy et al. 2012a; 214 Royle et al. 2009; Royle et al. 2013), we implemented the test statistic based on individual 215 encounters as suggested in Royle et al. (2009). All R scripts for our analyses can be found in 216 the supplementary materials (S1).

Posterior mean abundance

While we were principally interested in estimating density, in order to discuss our results more fully we computed posterior mean abundance across the study area and within different management areas. For each iteration of the MCMC model we took the sum of all pixels within each area of interest and computed posterior mean abundance and posterior standard deviation.

Results

During the 92 days of sampling we drove a total of 8,397kms and recorded 817 captures (sightings) of individual lions. It was not always possible to identify every individual at each sighting due to environmental variables and 165 lion captures could not be identified and thus were excluded from the analysis. We then removed 214 captures of lions estimated at <1 yr of age, leaving a total of 438 lion captures. Of these, 203 were unique individuals over the (estimated) age of one year, equating to a capture success rate of 2.4 lions identified per 100km of search effort. Of the 203 individuals, 66 were male and 137 were female. Capture history varied with 77 individuals captured only once, 71 individuals twice, 28 individuals three times, 11 individuals four times, nine individuals five times, three individuals six times and four individuals seven times.

Model diagnostics

Bayesian p-value was estimated between 0.6-0.7 for all models, thus indicating that they were all adequate, since this value lies well within the extremities (0.15-0.85). We assessed the MCMC chain convergence for all the models using the Gelman-Rubin diagnostic (Gelman & Rubin 1992) and all models had a shrink reduction factor of less than 1.2 for each parameter. Furthermore, all four models produced very similar posterior mean estimates and levels of precision. Since there was such little variation between the models, and the full model contained the most information, we report the posterior

estimates of the parameters in Model 1 here (Table 1), with the remaining models reported in the supplementary materials (S2).

Posterior mean density estimates

Lion density within our study area was estimated at 16.85 (PSD = 1.30) individuals >1yr per 100km^2 . The posterior density estimates for each pixel (0.3975km^2) ranged from 0.0003 to 4.011 lions/km², revealing the heterogeneous distribution of lions across space (Fig. 2). Mean pixel density for all the conservancies combined (0.175) was higher than that of the MMNR (0.167), illustrating the conservation importance of these newly established protected areas. The sex ratio, as estimated by ψ_{sex} , was calculated to be 2.2?:13.

Posterior mean abundance estimates

Posterior mean abundance for the entire study area was estimated at 419.89 (PSD=29.25) lions >1yr (see Table 2 for a breakdown of abundance and density estimates per protected area).

Discussion

Our methodology and results demonstrate that an unstructured spatial capture-recapture sampling design can produce tight estimates of population parameters while estimating detection probability. This makes our approach robust in the context of varying detection probabilities (Hayward et al. 2015). By including effort and incorporating a spatial design, we were able to explicitly estimate detection probability and measure density on a fine spatial scale. Furthermore, the estimates were obtained over a relatively short survey period (three months), reducing concerns over population closure (Karanth & Nichols 1998). Our methodology thus improves upon other unstructured designs (e.g. Rosenblatt et al. 2014; Blackburn et al. 2016) and will enable long-term population monitoring with an evaluation of the ecological determinants of lion density at a fine spatial scale. It will also allow for an

Conservation Biology

analysis of spatial demographic trends over time, thereby identifying spatial areas of concern and demographics of concern. However, our methodology would benefit from the following improvements: (a) incorporate how an individual is found; (b) build in those individuals that were not identified, which may not necessarily change the density estimate, but will reduce the variance; (c) split the demographics to include sub-adults; (d) account for opportunistically detected mortalities.

267

268

269

270

271

272

273

274

275

276

277

278

279

280

281

282

283

284

285

286

287

288

289

290

Although lion sex ratios are frequently equal at birth (Schaller 1972), our estimates show that by one year the ratio was 2.2 ?:1 \circlearrowleft . It is likely that the number of male lions decline due to intra-sexual competition for pride tenure and our results are consistent with average sex ratios in lions (2.33 ?:1 ?) reported in a review of 40 scientific papers (Périquet et al. 2014). The difference between σ_F and σ_M was relatively small (Table 1), indicating that males move slightly more than females. Although a previous study reported larger differences in movement between demographics (Elliot et al. 2014), that study utilized data over a five year period, compared to three months in the current study. It is therefore likely that while male lions do move more than females, as they more actively patrol their larger territories (Schaller 1972), this becomes increasingly evident over larger time scales. Our estimate of θ , which is indicative of resource utilization, was 0.512 (Table 1), a near perfect negative exponential function. This suggests that a negative exponential function may be more appropriate than the traditional Gaussian function when calculating lion home ranges for short time periods. The estimate of parameter $\beta_{\rm eff}$ was slightly negative (Table 1), which is counter-intuitive since more effort should result in more sightings. However, the posterior standard deviation was extremely high relative to the estimate, making inference problematic. It is also noted that additional information went into some sightings, which was not accounted for in the models. For instance, if a field observer followed up on a report of a lion

292

293

294

295

296

297

298

299

300

301

302

303

304

305

306

307

308

309

310

311

312

313

314

315

or spotted tourist vehicles grouped around a sighting, this would influence the effort in that cell. Future models should have a conditional probability built in to account for this.

Two previous surveys (Dloniak 2006; Ogutu & Dublin 1998) have recently been used in high profile studies that suggest a drastic decline of lions in the MMNR (Packer et al. 2013; Bauer et al. 2015a; Bauer et al. 2015b). Ogutu & Dublin (1998) and Dloniak (2006) provided estimates for those studies based on whole counts conducted in 1991-1992 and 2005 respectively. The first survey reported 447 lions >1yr while the second survey reported 269 lions >1 yr. These data were utilized in a study that reported rapid declines across Africa (Bauer et al. 2015b), which were later contested (Bauer et al. 2015c; Riggio et al. 2015). The same data were used in another paper highlighting the costs of lion conservation and concluding that fences are the best means of conserving lions (Packer et al. 2013). These data were also used in the most recent IUCN classification, which, based on an inferred population trend, estimated a 54% reduction in lion numbers between 1993 and 2014 (Bauer et al. 2015a). In the present study, our spatially explicit density estimates translate to an expected abundance of 250 (PSD=19.95) lions >1 yr in the MMNR (Table 2). Although this total is similar to Dloniak's (2006) estimate of 269, we argue that this is pure coincidence and it is worth exploring the two previous surveys in more detail. While the two earlier surveys (Dloniak 2006; Ogutu & Dublin 1998), and the current one, relied on individual identification, several fundamental differences exist, making comparisons and analysis of trends problematic: the 1991-1992 and 2005 surveys were whole counts, employed no statistical analysis, estimation of detection probability or of precision; the 1991-1992 survey was conducted over 20 months (not 12 months as recently suggested; Bauer et al. 2015c), while the 2005 survey took place over 10 months – both time frames potentially violate assumptions of closure (Karanth & Nichols 1998). Given that the first survey was 20 months and the second was 10 months, it is not surprising that a longer survey would yield higher

numbers, since greater effort should return more sightings and more birth, death, immigration
and emigration will occur at longer intervals. To illustrate the point, our monitoring data
shows that during ten months (January-August 2013) we recorded 197 unique individuals
>1yr within MMNR, while we recorded 337 individuals during 20 months (January 2013-
June 2015). Timescale is clearly important and a density estimate should provide a snapshot
that indicates the number of animals present in an area at any one time.
More robust estimates, using mark-recapture, were recently provided for the
surrounding conservancies (Blackburn et al. 2016). However, a simple comparison of
densities reveals very different estimates compared to ours: If we compute density per
conservancy from our spatial analysis (see Table 2) we estimate the following expected
density of lions >1yr per 100km ² , compared to that of Blackburn et al. (2016) in brackets –
Mara North 16.97 (8.15), Naboisho 14.57 (9.54), Lemek 17.15 (8.62), OOC 31.27 (20.36).
However, comparison is problematic since Blackburn et al. (2016) did not account for search
effort, the study was not spatially explicit and potentially violated assumptions of closure
(Karanth & Nichols 1998). Similarly, comparing our estimates or those of Blackburn et al.
(2016) to those of Ogutu et al. (2005), who estimated lion density within the conservancies
from a 2003 call-up survey, despite not seeing a lion in the area, is problematic. This is
because fundamental methodological differences exist and therefore fluctuations are not
necessarily because the state variable of interest (lion density) is fluctuating, but because we
detect lions differentially due to many uncontrollable factors. We therefore caution against

unified framework to assess lion densities across their range to allow for accurate population assessments and trend analyses.

methodologies in order to inform management and policy decisions. Instead, we call for a

Blackburn et al. 2016; Ogutu & Dublin 1998; Dloniak 2006) or pooling of data from differing

comparing our estimates to those of previous surveys in this area (Ogutu et al. 2005;

Conservation Biology

While we acknowledge that the Maasai Mara is unique in that it is possible to sight a large number of lions in a relatively short time period, our approach performs well with small sample sizes and can be used to concurrently estimate density of other species that can be individually identified. For example, the field work presented here was used by Broekhuis and Gopalaswamy (2016) to simultaneously, and accurately, estimated cheetah (*Acinonyx jubatus*) density from just 59 sightings of 25 individuals. In areas where capture success may be even lower, our approach is flexible enough to incorporate data from multiple sources such as camera traps, telemetry, genetics or call back surveys where individuals are recognizable. Our methods are therefore applicable to a wide range of species, including Asiatic lions.

Given the importance of accurate density estimates to our understanding of ecological processes, management decisions and international classification, we recommend that spatially-explicit capture recapture methods are widely adopted to census African carnivores and that more traditional methods, such as spoor and call-back surveys (unless utilized within a mark-recapture framework), be abandoned for estimating density at all important lion source populations. We also discourage extrapolations based on faulty predictions from linear regression based index-calibration experiments.

References

- Amstrup, S. C., T. L. McDonald, and B. F. Manly 2010. Handbook of capture-recapture
- analysis. Princeton University Press.
- Anderson, D. R. 2001. The need to get the basics right in wildlife field studies. Wildlife
- 363 Society Bulletin:1294-1297.
- Banerjee, K., Y. V. Jhala, K. S. Chauhan, and C. V. Dave. 2013. Living with Lions: The
- Economics of Coexistence in the Gir Forests, India. PLoS ONE **8**:e49457.
- Bauer, H., and S. van der Merwe. 2004. Inventory of free-ranging lions, *Panthera leo*, in
- 367 Africa Oryx **38**:26-31.
- Bauer, H., C. Packer, P. F. Funston, P. Henschel, and K. Nowell. 2015a. Panthera leo. The
- 369 IUCN Red List of Threatened Species 2015: e.T15951A79929984. IUCN 2015.
- Bauer, H., G. Chapron, K. Nowell, P. Henschel, P. Funston, L. T. Hunter, D. W. Macdonald,
- and C. Packer. 2015b. Lion (Panthera leo) populations are declining rapidly across Africa,
- 372 except in intensively managed areas. Proceedings of the National Academy of Sciences
- **112**:14894-14899.
- Bauer, H., G. Chapron, K. Nowell, P. Henschel, P. Funston, L. T. Hunter, D. W. Macdonald,
- S. M. Dloniak, and C. Packer. 2015c. Reply to Riggio et al.: Ongoing lion declines across
- most of Africa warrant urgent action. Proceedings of the National Academy of
- 377 Sciences:201522741.
- Blackburn, S., J. G. C. Hopcraft, J. O. Ogutu, J. Matthiopoulos, and L. Frank. 2016. Human-
- wildlife conflict, benefit sharing and the survival of lions in pastoralist community-based
- conservancies. Journal of Applied Ecology:10.1111/1365-2664.12632.
- Broekhuis, F., and A. M. Gopalaswamy. 2016. Counting Cats: Spatially Explicit Population
- Estimates of Cheetah (Acinonyx jubatus) Using Unstructured Sampling Data. PLoS ONE
- **11**:e0153875.

- Buckland, S. T., D. R. Anderson, K. P. Burnham, J. L. Laake, D. L. Borchers, and L. Thomas
- 2001. Introduction to Distance Sampling: estimating abundance of biological populations.
- 386 Oxford University Press, Oxford.
- Chardonnet, P. 2002. Conservation of the African Lion: Contribution to a status survey in P.
- Chardonnet, editor. Conservation of the African Lion: Contribution to a status survey.
- International Foundation for the Conservation of Wildlife, France & Conservation Force,
- 390 USA.
- Creel, S., and E. Rosenblatt. 2013. Using pedigree reconstruction to estimate population size:
- 392 genotypes are more than individually unique marks. Ecology and Evolution:n/a-n/a.
- Croes, B. M., P. J. Funston, G. Rasmussen, R. Buij, A. Saleh, P. N. Tumenta, and H. H. de
- 394 Iongh. 2011. The impact of trophy hunting on lions (Panthera leo) and other large carnivores
- in the Bénoué Complex, northern Cameroon. Biological Conservation **144**:3064-3072.
- Cusack, J. J., A. Swanson, T. Coulson, C. Packer, C. Carbone, A. J. Dickman, M. Kosmala,
- 397 C. Lintott, and J. M. Roweliffe. 2015. Applying a random encounter model to estimate lion
- density from camera traps in Serengeti National Park, Tanzania. The Journal of Wildlife
- 399 Management **79**:1014-1021.
- 400 Dloniak, S. M. 2006. Masai Mara Predator Research Project, Masai Mara National Reserve,
- 401 Kenya: Annual Report of Research Activities, 2005.
- Durant, S. M., M. E. Craft, R. Hilborn, S. Bashir, J. Hando, and L. Thomas. 2011. Long-term
- trends in carnivore abundance using distance sampling in Serengeti National Park, Tanzania.
- 404 Journal of Applied Ecology **48**:1490-1500.
- Eberhardt, L., and M. Simmons. 1987. Calibrating population indices by double sampling.
- The Journal of Wildlife Management: 665-675.

- 407 Elliot, N. B., S. A. Cushman, A. J. Loveridge, G. Mtare, and D. W. Macdonald. 2014.
- 408 Movements vary according to dispersal stage, group size, and rainfall: the case of the African
- 409 lion. Ecology **95**:2860-2869.
- 410 Funston, P. J., L. Frank, T. Stephens, Z. Davidson, A. Loveridge, D. M. Macdonald, S.
- Durant, C. Packer, A. Mosser, and S. M. Ferreira. 2010. Substrate and species constraints on
- the use of track incidences to estimate African large carnivore abundance. Journal of
- 413 Zoology. **281**:56-65.
- Gelman, A., and D. B. Rubin. 1992. Inference from iterative simulation using multiple
- sequences. Statistical Science: 457-472.
- Gopalaswamy, A. M., J. A. Royle, M. Delampady, J. D. Nichols, K. U. Karanth, and D. W.
- 417 Macdonald. 2012a. Density estimation in tiger populations: combining information for strong
- 418 inference. Ecology **93**:1741-1751.
- Gopalaswamy, A. M., J. A. Royle, J. E. Hines, P. Singh, D. Jathanna, N. S. Kumar, and K. U.
- 420 Karanth. 2012b. Program SPACECAP: software for estimating animal density using spatially
- 421 explicit capture–recapture models. Methods in Ecology and Evolution 3:1067-1072.
- 422 Gopalaswamy, A. M., M. Delampady, K. U. Karanth, N. S. Kumar, and D. W. Macdonald.
- 423 2015. An examination of index-calibration experiments: counting tigers at macroecological
- scales. Methods in Ecology and Evolution **6**:1055-1066.
- Gopalaswamy, A. M. 2015. Corrigendum. Methods in Ecology and Evolution 6:1067-1068.
- 426 Hayward, M. W., L. Boitani, N. D. Burrows, P. J. Funston, K. U. Karanth, D. I. MacKenzie,
- 427 K. H. Pollock, and R. W. Yarnell. 2015. FORUM: Ecologists need robust survey designs,
- sampling and analytical methods. Journal of Applied Ecology **52**:286-290.
- 429 Karanth, K. U., and J. D. Nichols. 1998. Estimating Tiger Densities in India Using
- 430 Photographic Captures and Recaptures. Ecology **79**:2852 2862.

- Kenya Large Carnivore Taskforce. 2009. Conservation and management strategy for lions
- and spotted hyaenas in Kenya, 2009–2014.
- 433 Macdonald, D. W. 1983. The ecology of carnivore social behaviour. Nature **301**:379 384.
- May, R. 1999. Unanswered questions in ecology. Philosophical Transactions of the Royal
- 435 Society of London B: Biological Sciences **354**:1951-1959.
- 436 Midlane, N., M. Justin O'Riain, G. Balme, and L. B. Hunter. 2015. To track or to call:
- comparing methods for estimating population abundance of African lions Panthera leo in
- 438 Kafue National Park. Biodiversity and Conservation **24**:1311-1327.
- Miller, S. M., and P. J. Funston. 2014. Rapid growth rates of lion (*Panthera leo*) populations
- in small, fenced reserves in South Africa: a management dilemma. Pages 43-55.
- Mosser, A., J. M. Fryxell, L. Eberly, and C. Packer. 2009. Serengeti real estate: density vs.
- fitness-based indicators of lion habitat quality. Ecology Letters 12:1050-1060.
- O'Brien, T. G., and M. F. Kinnaird. 2011. Density estimation of sympatric carnivores using
- spatially explicit capture–recapture methods and standard trapping grid. Ecological
- 445 Applications **21**:2908-2916.
- Ogutu, J. O., and H. T. Dublin. 1998. The response of lions and spotted hyaenas to sound
- playbacks as a technique for estimating population size. African Journal of Ecology **36**:83-95.
- Ogutu, J. O., N. Bhola, and R. Reid. 2005. The effects of pastoralism and protection on the
- density and distribution of carnivores and their prey in the Mara ecosystem of Kenya. Journal
- 450 of Zoology **265**:281-293.
- Ogutu, J. O., N. Owen-Smith, H. P. Piepho, and M. Y. Said. 2011. Continuing wildlife
- 452 population declines and range contraction in the Mara region of Kenya during 1977–2009.
- 453 Journal of Zoology **285**:99-109.
- Packer, C., L. Herbst, A. E. Pusey, J. D. Bygott, J. P. Hanby, S. J. Cairns, and M. Borgerhoff-
- 455 Mulder. 1988. Reproductive success in lions. Pages 363 383 in T. H. Clutton-Brock, editor.

- Reproductive Success: Studies of individual variation in crossbreeding systems. University of
- 457 Chicago Press, Chicago.
- Packer, C., A. Loveridge, S. Canney, T. Caro, S. Garnett, M. Pfeifer, K. Zander, A. Swanson,
- D. MacNulty, and G. Balme. 2013. Conserving large carnivores: dollars and fence. Ecology
- 460 Letters **16**:635-641.
- Pennycuick, C. J., and J. Rudnai. 1970. A method of identifying individual lions (*Panthera*
- *leo*), with an analysis of reliability of identification. Journal of Zoology **160**:497-508.
- Périquet, S., H. Fritz, and E. Revilla. 2014. The Lion King and the Hyaena Queen: large
- carnivore interactions and coexistence. Biological Reviews **90**:1197-1214.
- 465 R-Development-Core-Team. 2015. R: A language and environment for statistical computing
- in R. D. C. Team, editor, Vienna, Austria.
- Riggio, J., A. Jacobson, L. Dollar, H. Bauer, M. Becker, A. Dickman, P. Funston, R. Groom,
- P. Henschel, H. Iongh, L. Lichtenfeld, and S. Pimm. 2013. The size of savannah Africa: a
- lion's (*Panthera leo*) view. Biodiversity and Conservation **22**:17-35.
- Riggio, J., T. Caro, L. Dollar, S. M. Durant, A. P. Jacobson, C. Kiffner, S. L. Pimm, and R. J.
- van Aarde. 2015. Lion populations may be declining in Africa but not as Bauer et al. suggest.
- 472 Proceedings of the National Academy of Sciences:201521506.
- Rosenblatt, E., M. S. Becker, S. Creel, E. Droge, T. Mweetwa, P. A. Schuette, F. Watson, J.
- Merkle, and H. Mwape. 2014. Detecting declines of apex carnivores and evaluating their
- causes: An example with Zambian lions. Biological Conservation **180**:176-186.
- 476 Royle, J. A., K. U. Karanth, A. M. Gopalaswamy, and N. S. Kumar. 2009. Bayesian
- 477 inference in camera trapping studies for a class of spatial capture-recapture models. Ecology
- **90**:3233-3244.
- Royle, J. A., M. Kery, and J. Guelat. 2011. Spatial capture-recapture models for search-
- encounter data. Methods in Ecology and Evolution 2:602-611.

- Royle, J. A., R. B. Chandler, R. Sollmann, and B. Gardner 2013. Spatial capture-recapture.
- 482 Academic Press.
- Royle, J. A., A. K. Fuller, and C. Sutherland. 2016. Spatial capture–recapture models
- allowing Markovian transience or dispersal. Population Ecology **58**:53-62.
- Russell, R. E., J. A. Royle, R. Desimone, M. K. Schwartz, V. L. Edwards, K. P. Pilgrim, and
- 486 K. S. Mckelvey. 2012. Estimating abundance of mountain lions from unstructured spatial
- sampling. The Journal of Wildlife Management **76**:1551-1561.
- Sandell, M. 1989. The mating tactics and spacing patterns of solitary carnivores. Pages 164-
- 489 182. Carnivore behavior, ecology, and evolution. Springer.
- 490 Schaller, G. B. 1972. The Serengeti Lion. University of Chicago Press, Chicago.
- 491 Sollmann, R., M. M. Furtado, B. Gardner, H. Hofer, A. T. Jácomo, N. M. Tôrres, and L.
- 492 Silveira. 2011. Improving density estimates for elusive carnivores: accounting for sex-
- 493 specific detection and movements using spatial capture–recapture models for jaguars in
- 494 central Brazil. Biological Conservation **144**:1017-1024.
- Tierney, L. 1994. Markov chains for exploring posterior distributions. the Annals of
- 496 Statistics:1701-1728.
- Whitman, K. L., and C. Packer. 2007. A Hunter's Guide to Aging Lions in Eastern and
- 498 Southern Africa, Long Beach, CA.
- Williams, B. K., J. D. Nichols, and M. J. Conroy 2002. Analysis and management of animal
- 500 populations. Academic Press.

Table 1. Posterior summaries from Bayesian spatially explicit capture-recapture (SECR) of parameters estimate using Model 1 [β_{sex} , θ (.)]. Number of posterior samples used was 10,000. Bayesian P-value = 0.6397.

Parameter	Posterior	Posterior	Definition
	mean	standard	
		deviation	
			Rate of decline in detection probability as a female lion's
$\sigma_{\scriptscriptstyle F}$	0.700	0.044	activity center increases as a function of her distance from
-			the centroid of a grid cell
			Rate of decline in detection probability as a male lion's
$\sigma_{_{\! M}}$	0.790	0.059	activity center increases as a function of his distance from
			the centroid of a grid cell
eta_{sex}	-0.360	0.235	The difference of the complementary log-log value of
P_{sex}	-0.360	0.235	detection probability between a male and female lion
			The rate of change in the complementary log-log value of
$eta_{\!\scriptscriptstyle e\!f\!f}$	-0.0034	0.004	detection probability as the (log) effort changes by one
-			unit (one kilometer of drive effort)
λ_0	0.055	0.008	The basal encounter rate of a lion whose activity center is
70	0.033	0.008	located exactly at the centroid of a grid cell
			The ratio of the true number of individuals in the
Ψ	0.590	0.047	population compared to the data augmented population
			M
N_{super}	970.7	75.000	The total number of lions in the larger state space S
			The proportion of lions that are female.
ψ_{sex}	0.314	0.038	$Sex ratio = \frac{1 - \psi_{sex}}{1 - \psi_{sex}}$
r sex	3.31	2.330	$Sex \ ratio = \frac{\gamma}{\psi_{sex}}$
			Determines the shape of the estimated detection
θ	0.512	0.019	
0	0.512	0.019	function. The value of θ ranges from 0.5 (exponential form) to 1 (Gaussian)
D	16 0/75	1.3017	form) to 1 (Gaussian) The estimated density of lions /100km²
D	16.8475	1.301/	The estimated density of lions/100km ²

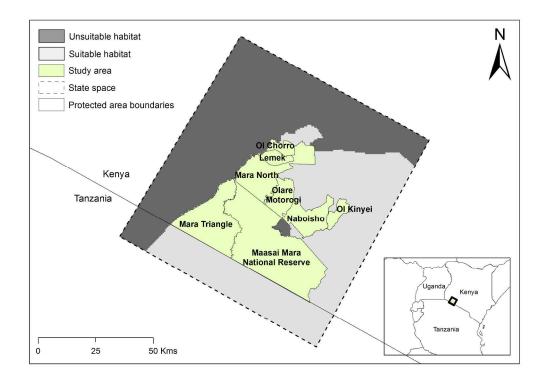
Table 2. Posterior mean abundance and density estimates split according to protected areas.

Protected Area	Posterior mean abundance	Posterior standard deviation	Posterior mean density	Posterior standard deviation
Olare Motorogi	44.51	3.29	32.11	2.38
Olare (excluding Motorogi)	29.80	3.01	31.27	3.16
Ol Chorro	11.22	3.02	20.96	5.64
Ol Kinyei	14.33	2.43	22.50	3.81
Lemek	10.66	2.95	17.15	4.75
MMNR	174.59	14.17	16.64	1.35
Mara north	58.59	8.04	16.97	2.33
Mara Triangle	75.31	9.32	15.82	1.96
Naboisho	30.69	3.75	14.57	1.78
MMNR + Mara Triangle	249.90	19.95	16.38	1.31
All conservancies combined	170.00	12.79	19.46	1.46

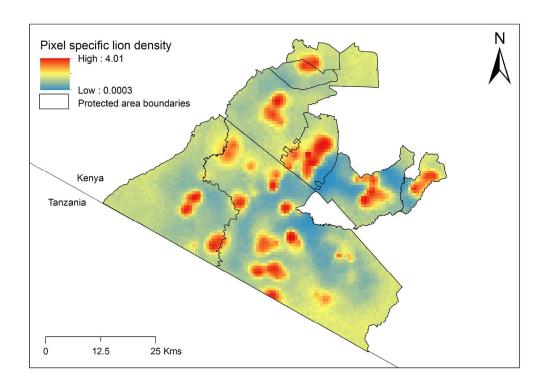
Figure Legends	Figur	e Le	egends
----------------	-------	------	--------

Fig. 1. The larger states space (~10,400km²) was defined by a 15km buffer around the study
area (2,398km²). Unsuitable habitat was masked out prior to analysis. Names of each
protected area under different management regimes are included for reference.
Fig. 2. Pixel specific (0.3975km2) lion density as predicted by Model 1: $[\beta_{sex}, \theta(.)]$ - Full
model. Our unstructured spatial-recapture sampling design accounted for effort (in
kilometres) per pixel per sampling occasion (one day). Map depicts the Maasai Mara

National Reserve and surrounding conservancies, Kenya.



297x210mm (300 x 300 DPI)



297x210mm (300 x 300 DPI)