Bringing clarity to the clouded leopard *Neofelis diardi*: first density estimates from Sumatra

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SUPPLEMENTARY MATERIAL 1 Parameterization and implementation of spatial capture–recapture models

Spatial capture–recapture models assume that each individual in the study population, *i*, has an activity (or home range) centre, s_i, and that the encounter rate of individual *i* at a given camera-trap *j*, λ_{ij}, declines with increasing distance to s_i, d_{ij}. We can model this decline in encounter rate using a half-normal function, which has two parameters: λ_0 is the baseline encounter rate at $d_{ij} = 0$ (the expected encounter rate at a hypothetical trap located at an individual's home range centre), and σ is the scale parameter, which is related to home range radius and governs how quickly the encounter rate declines with d_{ij}.

Abundance is defined as the number of activity centres s_i in the state-space *S*, which is an area including the trapping array that is chosen to be large enough that it contains all individuals that could have potentially been exposed to trapping. We defined *S* by buffering the outermost trap coordinates of each trap array by 13 km. We estimated abundance using data augmentation (Royle & Dorazio, 2012), where the observed encounter histories are augmented with a large number of all-zero encounter histories. We then introduce an individual covariate, z_i, which is modelled as a Bernoulli random variable that takes on the value of 1 if an animal is part of the population, and 0 if it is not:

$$z_i \;\; Bernoulli(\psi),$$

where ψ is the probability than an individual is part of the population. *N* is the sum over all *s*, and density *D* can be derived by dividing *N* by the area of *S*, (A(*S*)).

Two of the four surveys (Bungo and Ipuh) in the present study lasted 8 and 7 months, respectively (Table 1). To approximate population closure we subdivided these surveys and considered the data sets for the resulting shorter time intervals as independent; i.e. we do not keep track of whether individuals from survey 1 appear again in survey 2, treating the two sets of individuals as independent from each other. We assumed, however, that, density remained constant across these sub-surveys. This approach allows turnover in individuals, as well as changes/shifts in activity centres in the population without introducing an additional density parameter. Such a model can be implemented by jointly analysing data from both shorter time intervals, augmenting data sets to the same size *M* and having them share a single inclusion probability parameter ψ. Note that this approach keeps the expected value of density (defined as ψ * *M*/A(*S*)) constant, but realized densities (*N*/A(*S*)) may still differ slightly. A single combined density estimate for both intervals can be calculated as the mean of both estimates of realized density.

We implemented the model in a Bayesian framework using *JAGS* (Plummer, 2003) accessed through *R v. 3.0.1* (R Core Team, 2013), running three parallel Markov chains with 50,000 iterations, following a burn-in of 200 iterations. We checked for chain convergence using the Gelman–Rubin statistic (Gelman et al., 2004); values < 1.1 indicate convergence, and all parameters in the present model had a value < 1.1.