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Using geographic profiling to locate elusive nocturnal animals: a case study with spectral tarsiers

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26 Short title

27 Geographic profiling and tarsier sleeping sites

28 Abstract

Estimates of biodiversity, population size, population density and habitat use have important implications for management of both species and habitats, yet are based on census data that can be extremely difficult to collect. Traditional assessment techniques are often limited by time and money, and by the difficulties of working in certain habitats, and species become more difficult to find as population size decreases. Particular difficulties arise when studying elusive species with cryptic behaviours. Here, we show how geographic profiling (GP) - astatistical tool originally developed in criminology to prioritise large lists of suspects in cases of serial crime - can be used to address these problems. We ask whether GP can be used to locate sleeping sites of spectral tarsiers (Tarsius tarsier) in Sulawesi, SE Asia, using as input the positions at which tarsier vocalisations were recorded in the field. This novel application of GP is potentially of value as tarsiers are cryptic and nocturnal and can easily be overlooked in habitat assessments (for example, in dense rainforest). Our results show that GP provides a useful tool for locating sleeping sites of this species, and indeed analysis of a preliminary data set during field work strongly suggested the presence of a sleeping tree at a previously unknown location; two sleeping trees were subsequently found within five metres of the predicted site. We believe that GP can be successfully applied to locating the nests, dens or roosts of elusive animals such as tarsiers, potentially improving estimates of population size, with important implications for management of both species and habitats.

Introduction

The ability to accurately and reliably detect and locate individuals is vital for assessing animal population density and dynamics, habitat use and ranging patterns – crucial information that underpins the development of conservation management plans for both species and their habitat (Tyre et al., 2003). Traditional census and survey techniques are often limited by time constraints, prohibitive costs and the challenging logistics of certain habitats. Particular difficulties arise when studying elusive species with cryptic behaviours (MacKenzie *et al.*, 2005; Neilson *et al.*, 2013), or species with declining populations, since animals become more difficult to find as population size decreases (Neilson *et al.*, 2013; Chades et al., 2008).

Researchers attempting to census such species typically encounter two main problems. First, the overall study area is often too large to explore exhaustively and inferences must therefore be made using a smaller sampling location, for example using a probabilistic sampling method (MacKenzie et al., 2005). Second, variation arises due to detectability, and research must take into account the likelihood that many individuals will go undetected even though they may be present (Neilson et al., 2013; Chades et al., 2008). In this study, we ask whether geographic profiling, a statistical method commonly used in criminology (Rossmo, 2000) and increasingly being applied to biological data (Le Comber et al., 2006; Martin et al., 2009; Raine, Rossmo & Le Comber, 2009; Le Comber et al., 2011; Le Comber & Stevenson, 2012; Stevenson et al., 2012; Papini et al., 2013; Verity et al., 2014), can be used to improve surveys of species that are rare and/or elusive.

In criminology, geographic profiling uses the spatial locations of a series of linked crimes to calculate the probability of offender residence for each location within the study area,

producing a three-dimensional probability surface called a jeopardy surface; overlaid on a map of the study area, this is termed a geoprofile. Suspect sites are prioritised according to their height on the geoprofile (Rossmo, 2000). Geographic profiling was designed to solve the problem of information overload when dealing with cases of serial crime, since such cases typically generate too many suspects rather than too few, and resources will often preclude a detailed investigation of them all: for example, police investigating the case of the Yorkshire Ripper accrued 268,000 suspect names and 5.4 million vehicle registration numbers (Doney, 1990; Rossmo, 2000). Similar constraints – lack of time, lack of resources – will obviously also often apply in conservation. Geographic profiling has been extremely successful in criminology, and is routinely used by organisations including the Royal Canadian Mounted Police, the Bureau of Alcohol, Tobacco, Firearms and Explosives, the Los Angeles Police Department, the National Crime Agency in the UK and the United States Marine Corps (Rossmo, 2012). This success has led to its application to biological data, notably animal foraging (where it can be used to find animal nests or roosts using the locations of foraging sites as input) (Le Comber *et al.*, 2006; Martin et al., 2009; Raine et al., 2009; Le Comber & Stevenson, 2012), epidemiology (identifying disease sources from the addresses of infected individuals) (Le Comber *et al.*, 2011; Le Comber & Stevenson, 2012; Verity et al., 2014) and invasive species biology (using current locations to identify source populations) (Le Comber & Stevenson, 2012; Stevenson

et al., 2012) (Table 1). More recently, a version of the model based on a Dirichlet Process

93 Mixture (DPM) model that outperforms the Criminal Geographic Targeting (CGT) algorithm

94 used in criminology has been developed and applied to biological data (Verity *et al.*, 2014).

Here, we apply this model to a small, cryptic nocturnal primate species, the spectral tarsier *Tarsius tarsier*. There are 10 extant species of tarsier, and eight of these are endemic to the Indonesian island of island of Sulawesi (Shekelle et al., 2008; Merker et al., 2009); however, there may well be many more species that have yet to be described (Shekelle, 2010). Tarsiers are nocturnal, roosting in trees and crevices during the day, but sleeping sites vary depending on forest type. In most cases tarsiers will be found sleeping in the crevices of strangler figs. They are the only extant obligatory carnivorous primates, feeding exclusively on live animals, predominantly insects. Their small size (100-150g), nocturnal lifestyle and ability to leap, almost silently, between branches in the forest make them difficult to locate in the field (MacKinnon & MacKinnon, 1980). Understanding tarsier population dynamics and home ranges is critical to understanding their likely response to habitat change and destruction. However, many tarsier species are either critically endangered or listed by the International Union for Conservation of Nature (IUCN, 2013) as data deficient, meaning that there are insufficient data for a proper IUCN assessment. Many tarsier species have been extensively studied, but much of this relates to aspects of their biology such as their phylogeny (for example, Merker et al., 2014 and Pozzi et al., 2014), and there is less information on their distribution or population size (IUCN, 2013).

Lowland forest is thought to contain the highest diversity and abundance of animal and plant species and, with the exceptionally high biodiversity in SE Asian forests, in conjunction with carbon storage within the peatlands, deforestation of this area is of global concern. Despite this, deforestation is occurring at a rapid rate within Indonesia itself (Whitten, 2000; Whitten, Mustafa & Henderson, 2002; Miettinen *et al.*, 2011a). Globally, Indonesia has exhibited the largest increase in forest loss between 2000 and 2012, with a low of 10,000km² lost per year to a high of over 20,000km². Further analyses of spatial resolution land maps have revealed

an overall yearly decline of 1% of forest cover, with the main destruction occurring within plantations and secondary vegetation. (Hansen *et al.*, 2013; Miettinen *et al.*, 2011a,b). These recent studies show that deforestation is still occurring at a high rate in SE Asia, endangering many endemic forest species, such as the tarsier, and habitat destruction leading to the loss of suitable habitat has led to the IUCN classifying two species of tarsier, the spectral tarsier *Tarsius tarsier* and Dian's tarsier *T. dentatus*, as vulernable. This vulnerable status is primarily driven by habitat loss rather than population number (Shekelle, Merker & Salim, 2008; Shekelle et al., 2008). One way to estimate tarsier numbers is via identification of their roost sites (Fig. 1a). In

practice, though, this is extremely difficult, and is usually carried out by tracking the animals using their duet vocalisations – characteristic calls made prior to dawn each morning as pairs return to their sleeping sites (MacKinnon & MacKinnon, 1980). However, the short overall duration of the duetting period, and rapid sound attenuation in the dense rainforest typical of this species' habitat, mean that actually locating individuals from their duets is at best difficult and time consuming, and at worst impossible. Other methods of estimating population numbers, such as camera trapping, are arguably less labour intensive but perhaps less effective (Foster & Harmsen, 2012) and in any case also present logistical difficulties due to the dense habitat (Fig. 1b); camera trapping is also expensive.

Here, we use the DPM implementation of the geographic profiling model (Verity *et al.*, 2014) to identify likely sleeping sites, with locations of duet vocalisations representing 'crime sites' and the sleeping sites analagous to an offender's 'anchor point'. To test this model, we take a retrospective approach, using data on vocalisations and sleeping trees that were collected in a previous study. We suggest that this approach has the potential to provide a more efficient

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way to identify physical locations of elusive, cryptic species such as the spectral tarsier, and
to improve estimates of population size, population density and home range size for such
species.

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151 Methods

152 <u>Study area</u>

153 This project was conducted on Buton Island, Southeast Sulawesi, Indonesia (longitude

154 123°12' E-122° 33'E and latitude 5°44' S-4° 21' S; Fig. 2). Buton has a length of 100 km and

is 42 km at its widest point, and an area of approx. 4,520 km² (Priston *et al.*, 2011). The

156 forest where sampling took place is split into two reserves, separated only by a small road:

157 Kakanauwe Nature Reserve (810 ha) and Lambusango Wildlife reserve (28,500 ha) (Martin

4 158 & Blackburn, 2010). Buton Island experiences a tropical climate, with a pronounced dry

season between August and October, and a wet season between October and April; there is

160 variable rainfall between May and July each year (Whitten 2000; Whitten *et al.*, 2002;

161 Gillespie *et al.*, 2004). The traditional economy is based on subsistence farming, arising from

slash and burn agriculture (Priston *et al.*, 2011). The main anthropogenic impacts on the

163 Buton rainforest are forest clearance for land use such as subsistence farming, illegal logging,

asphalt mining and rattan collection (Priston *et al.*, 2001).

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166 Field data collection

Research was undertaken between May and August 2013. Surveys started before 05:00 each
morning, and continued until approximately 06:00. Before dawn, between 05:00 and 06:15,
mated pairs of tarsiers make shrill, sexually dimorphic vocalisations that last up to four

170 minutes as they are returning to roost; these are repeated as the animals move closer to the

sleeping sites, covering in total a period of around 20 minutes (Faulkner, pers. obs.). Each morning, after the first tarsier was heard, the observer remained static and noted the time of day. GPS data on the location of the observer were recorded, and distance/compass bearing of the vocalising animals from the observer estimated. The observer then attempted to follow the tarsiers to the sleeping tree; where this was possible, its precise location was recorded. A sleeping site was only classed as such if a tarsier or tarsiers were seen entering a tree, vine tangle or rock crevice. A total of 25 sleeping trees were identified during the study, including two located using output from a preliminary GP analysis carried out during data collection; since these were not independent of the model they were excluded from the final analysis.

181 <u>Geographic profiling</u>

The DPM model of geographic profiling, which is fully described in Verity *et al.* (2014), provides a mathematically robust method of estimating source locations from the spatial locations of the observed crime sites. Conceptually the method can be split into two parts. First, the crime sites are partitioned into distinct clusters, with crimes that are close to one another being more likely to end up in the same cluster. It is assumed that all points within a cluster originated from the same source, while points in different clusters originated from different sources. Second, conditional on a particular partition of the data into clusters, the posterior distribution of the unknown source locations is calculated using a method analogous to that described by O'Leary (2010). By alternating between these two steps using standard Markov Chain Monte Carlo (MCMC) methods it is possible to reconstruct the full posterior distribution of the source locations, integrated over all possible partitions of the data into groups.

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195	In our case we were interested in using the spatial locations of tarsier vocalisations as input to
196	the DPM model, and using the resulting geoprofile to construct a prioritised search strategy
197	when looking for sleep sites. By carrying out this analysis retrospectively, on data in which
198	the true sleep sites (or at least a subset of the true sleep sites) are known, we can measure the
199	effectiveness of this search strategy compared with a number of alternative approaches.
200	
201	Finally, we note that although the terminology used in geographic profiling (crime sites,
202	offender residence, etc.) is not always appropriate for use with biological data, for
203	consistency with the criminological literature we will here refer to tarsier sleeping tree sites
204	as anchor points or source locations and vocalisation location sites as crime sites.
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206	Model implementation
207	The DPM model was implemented in R (R Core Team, 2012) using the package Rgeoprofile
208	as described by Verity et al. (2014); this package is available from
209	http://evolve.sbcs.qmul.ac.uk/lecomber, or from the authors on request. Model parameters
210	were set to default values, with the exception of sigma, the distance (in lat/long degrees)
211	representing one standard deviation of the bivariate normal distribution centred on the source.
212	This was set to 0.0009, corresponding to a distance of 100m at the study site location. This is
213	equivalent to stating that 99% of the 'crime sites' are expected to occur within a circle of
214	radius 300m centred on the source. This is consistent with the (admittedly sparse) literature
215	on the dispersal distances of tarsiers, which report them as having nightly path lengths of
216	roughly 1 km (Merker, 2006; Neri-Arboleda et al., 2002).
217	
218	Model evaluation

Model output can be assessed using the hit score, the proportion of the area covering the crimes (in this case, the positions at which tarsiers were recorded, plus a 'guard rail' of 5 % surrounding this) in which the anchor point/s (sleep tree/s) are located. The hit score is calculated by dividing the ranked score by the total search area. The smaller the hit score, the more efficient the search strategy described by the model; a hit score of 0.5 (50%) is what would be expected from a nonprioritised (i.e. random or uniform) search (Rossmo, 2000). Results Field study In total, 190 tarsier call locations were recorded across 45 mornings of sampling, within both the Kakanauwe and Lambusango forest reserves. A total of 15% of the vocalisations were recorded between 05:00 and 05:30, 47% between 05:30 and 05:45, 34% between 05:45 and 06:00 and 4% after 06:00). This follows previously published data on the timing of tarsier calls (Neitsch 1999; MacKinnon & Mackinnon 1980). We identified 25 sleeping sites, mostly large strangler fig trees (Fig. 1a), but dense vine tangles and dead tree trunks were also used. Preliminary analysis Although the analysis here is retrospective, we ran the model on an early partial data set while field work was still in progress. This preliminary analysis strongly suggested the presence of a sleeping tree in the NW part of the study area; two sleeping trees were subsequently found within 5 m of the predicted location (Fig. 3). Since these two sleeping trees were not independent of the model, they were not used to test the model and were excluded from the full analysis reported below.

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244	Full analysis
245	The mean hit score for the 23 sleeping trees identified during field work (excluding an
246	additional two sleeping trees identified in the preliminary analysis) was 0.16 (sd = 0.154); the
247	median hit score was 0.15. The model found 10 of the sleeping trees after searching less than
248	10% of the total map area of 3.4 km^2 , and 16 after searching less than 20% (Fig. 4, Fig. 5).
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251	Discussion
252	These results show that the DPM model of geographic profiling described in Verity et al.
253	(2014) can successfully be used to prioritise the search for tarsier sleeping sites. We suggest
254	that the DPM model could be used to help locate nests, dens or roosts of other rare and hard-
255	to-study animals, potentially improving estimates of population size in these cases, and
256	allowing important management decisions at both the species and habitat level to be based
257	on better data. In fact, although the analysis here is retrospective, the DPM model of
258	geographic profiling also proved useful in practice, with a preliminary analysis successfully
259	predicting the locations of two sleep trees that were subsequently confirmed in the field.
260	While we would be cautious about inferring too much from such a limited example, we note
261	that this is the first time that GP has been used in biology as a prelude to further investigation
262	and at the very least demonstrates the potential of this approach.
263	
264	The ability to locate tarsier roost sites quickly and efficiently is of critical importance if
265	conservation strategies are to be put into place to help conserve this species. Although there is
266	limited destruction occurring on Buton itself in comparison to other areas, and although many
267	tarsier species, including the spectral tarsier, often do prefer secondary forest, possibly due to

268 increased insect abundance arising as a consequence of disturbance, as has been suggested in

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269 other contexts (Zhang et al., 2014) and locomotory aids from smaller trees (Merker et al., 270 2005), there will be a limit to how much disturbance this species can tolerate before 271 population numbers begin to decline. The use of GP to better target behavioural studies and 272 gain more accurate information on the species' ecology could thus be of considerable 273 practical use. 274 Large cavity-bearing trees provide important ecological functions such as nesting and 275 276 denning resources for many species (Lindenmayer *et al.*, 2012). The overall decline in cavity-277 bearing trees such as the strangler fig is an emerging conservation concern, due to the 278 importance of these trees to a variety of cavity-dwelling wildlife including tarsiers, other 279 mammals, birds and invertebrates (Struebig et al., 2013). Forests are not recruiting these 280 trees fast enough due to the extended period required for their replacement once they are 281 destroyed (Lindenmayer et al., 2012). A study by Cockle et al. (2010) showed that logging 282 was reducing the basal area of primary forests by half and therefore reducing the number of 283 trees with suitable cavities for nesting animals. However, there are limited studies on the

availability of these cavity-bearing trees in Southeast Asian ranforests (Cockle *et al.*, 2010;

285 Struebig *et al.*, 2013).

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There are numerous advantages to using GP rather than other more simple measures of spatial tendency such as spatial mean, spatial median and centre of minimum distance. Chief among these is the fact that the DPM model can deal with multiple sources (eg, multiple roost sites in this study), as opposed to providing a single point estimate for a single source or roost site. In criminology, Rossmo & Velarde (2008) made direct comparisons between measures of spatial tendencies and the CGT (Criminal Geographic Targeting) algorithm used in geographic profiling and showed that GP is three times more effective at detecting the anchor

294	points of serial offenders, while in ecology, in a study looking at source populations of
295	invasive species, Stevenson et al. (2012) found that the CGT algorithm outperformed other
296	measures of spatial central tendency (spatial mean, spatial median, centre of minimum
297	distance and a kernel density model) in 52 of the 53 species studied.
298	
299	Although the results from this study are highly promising, geographic profiling is still in the
300	initial stages of application to the field of biology. For example, not all species will offer a
301	conspicuous vocalisation like the elusive tarsier; however, other measurable parameters
302	abound. These include sightings, scat evidence or GPS data from radio collars, for example,
303	all of which could potentially be used as 'crime sites' to help locate the animals' anchor
304	points (nests, dens or roosts). However, it is striking how well even this simple model
305	performs: using other dispersal distributions (eg Cauchy distributions) or incoporating more
306	complex priors based on habitat information could all add power to the model.
307	
308	In conclusion, this study suggests that GP could be useful when searching for elusive and rare
309	species such as tarsiers, increasing search efficiency, improving estimates of population
310	numbers and range size and leading to more efficient use of scarce resources such as time,
311	money and personnel.
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FIGURE LEGENDS

419	
420	Figure 1 (a) A sleeping tree; (b) Typical habitat within the study site.
421	
422	Figure 2 Buton Island. The area in the red square represents the two forested reserves
423	(Kakanauwe and Lambusango) where the study took place.
424	
425	Figure 3 Geoprofile showing the results of the preliminary analysis. Red circles show the
426	positions of the observer when tarsier vocalisations were recorded, and blue squares the two
427	sleeping trees whose locations were successfully predicted in this analysis. Contours show
428	bands of 5%, with lighter colours corresponding to higher parts of the geoprofile.
429	
430	Figure 4 (a) Geoprofile showing the results of the final analysis. As before, red circles show
431	the positions of the observer when tarsier vocalisations were recorded, and blue squares the
432	sleeping trees. Contours show 5% increments. (b) The raw probability scores (p) underlying
433	the geoprofile in (a).
434	
435	Figure 5 Histogram showing the hit scores for all 23 sleeping trees in the final analysis.
436	

Table 1 Geographic profiling's application in criminology, biology and epidemiology

Field	Crime sites	Suspect sites	References
Criminology			
Murder, rape, burglary,	Spatial locations of	Areas likely to be	Rossmo 2000 and
arson	linked crime sites (eg	associated with the	many others
	murders)	offender (eg a home or	
		workplace)	
Biology			
Animal foraging	Spatial locations of	Possible nests, roosts,	Le Comber et al.,
	foraging sites	dens etc	2006; Martin et al
			2009; Raine <i>et al.</i>
			2009
Invasion biology	Spatial locations of	Areas associated with	Stevenson et al.,
	current populations of	source populations	2012; Papini et al.
	invasive species		2013
Epidemiology			
Malaria, cholera	Spatial locations of	Vector breeding sites or	Buscema et al.,
	infected individuals	other sources of	2009; Le Comber
		infection (eg	et al., 2011; Verit
		contaminated water)	et al., 2014

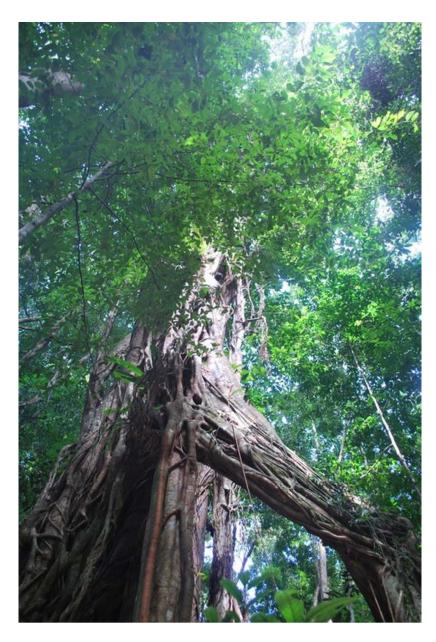


Figure 1 (a) A sleeping tree; (b) Typical habitat within the study site. 189x282mm (72 x 72 DPI)

 $\begin{array}{r} 47\\ 48\\ 49\\ 50\\ 51\\ 52\\ 53\\ 54\\ 55\\ 56\\ 57\\ 58\\ 59\\ 60\\ \end{array}$



Figure 1 (a) A sleeping tree; (b) Typical habitat within the study site. 189x282mm (72 x 72 DPI)



Figure 2 Buton Island. The highlighted area represents the two forested reserves (Kakanauwe and Lambusango) where the study took place. 418x304mm (72 x 72 DPI)

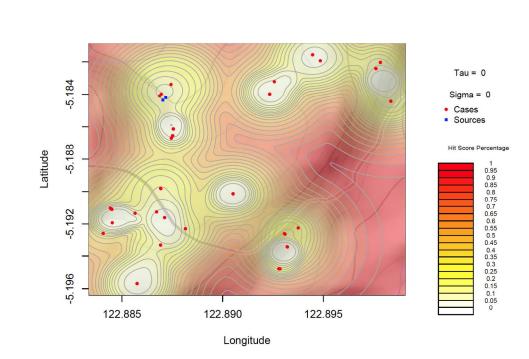


Figure 3 Geoprofile showing the results of the preliminary analysis. Red circles show the positions of the observer when tarsier vocalisations were recorded, and blue squares the two sleeping trees whose locations were successfully predicted in this analysis. Contours show bands of 5%, with lighter colours corresponding to higher parts of the geoprofile.

614x451mm (72 x 72 DPI)

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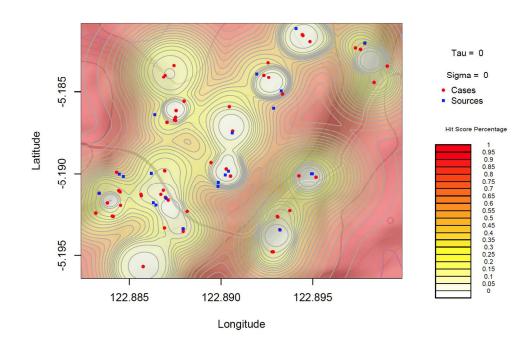


Figure 4 (a) Geoprofile showing the results of the final analysis. As before, red circles show the positions of the observer when tarsier vocalisations were recorded, and blue squares the sleeping trees. Contours show 5% increments. (b) The raw probability scores underlying the geoprofile in (a).

606x452mm (72 x 72 DPI)

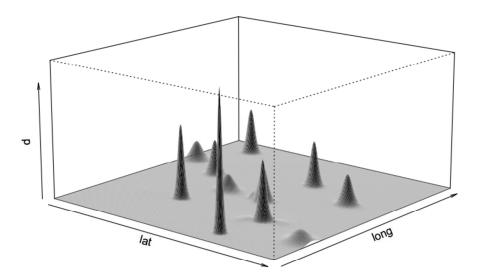


Figure 4 (a) Geoprofile showing the results of the final analysis. As before, red circles show the positions of the observer when tarsier vocalisations were recorded, and blue squares the sleeping trees. Contours show 5% increments. (b) The raw probability scores underlying the geoprofile in (a). 287x196mm (72 x 72 DPI)

