USING A SPECIES DISTRIBUTION MODEL TO GUIDE NSW SURVEYS OF THE LONG-FOOTED POTOROO *(POTOROUS LONGIPES)*

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To the examiners,

This thesis is written in the form of a journal article from Animal Conservation. Author guidelines for Animal Conservation can be found at the end of this paper. Any deviations from this journal style are in accordance with the Macquarie University Masters of Research thesis guidelines.

Declaration

I certify that the research presented in this thesis is my original work. However, this research project could not have been undertaken without the greatly appreciated assistance of my two Macquarie University supervisors, Dr. Linda Beaumont and Dr. David Nipperess, and adjunct supervisor, Dr. Joss Bentley, of the NSW Office of Environment and Heritage (OEH). Linda Beaumont and Postdoctoral Research Fellow, John Baumgartner, assisted with the species distribution modelling data preparation and interpretation. David Nipperess assisted with microhabitat experimental design, data collection and analysis. Joss Bentley assisted with the species distribution modelling, camera trapping experimental design, camera and microhabitat data collection and analysis. My supervisors have also provided invaluable, ongoing feedback on this thesis.

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Abstract

Current knowledge on threatened species' distributions is essential for effective conservation decision-making. Species distribution models (SDM) are widely used to map species geographic ranges and identify new areas of suitable habitat. This paper uses a SDM to identify regions in NSW that may have suitable habitat for the long-footed potoroo (*Potorous longipes*) and guide the selection of field survey sites. In NSW, there are grave doubts surrounding the persistence of this critically endangered species and identification of occupied sites is a high priority for its conservation. The SDM, Maxent, had strong predictive performance (AUC: 0.94 to 0.95) and enabled identification of new areas of climatically suitable habitat, beyond areas of known occurrence in NSW and prior survey locations. Importantly, ground-validation of the SDM output was undertaken and showed that projected habitat suitability values were: a) significantly higher at independent presence locations than absence locations (H=55.61, DF=1, P=0.000); and b) correlated with six out of ten microhabitat variables. However, baited camera trapping, undertaken at 58 sites in NSW, did not detect any long-footed potoroos. Refinement of binary regression models found that the combination of connectivity, i.e. larger, connected areas of climatically suitable habitat (χ^2=5.51, P=0.019), understorey cover (χ^2=6.86, P=0.009) and soil moisture (χ^2=7.6, P=0.006) best predicted this species presence. If the long-footed potoroo remains extant in NSW, it is extremely rare. The findings indicate that, in addition to climatic factors, microhabitat features and connectivity are important predictors of presence of the long-footed potoroo and should be incorporated into any future distribution modelling and survey site selection.

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INTRODUCTION

Naturalists have long been fascinated by species' distribution across space and time, and understanding the relationship between distribution and the environment. An early example is Grinnell (1904) describing the distribution of morphological variations in the Chestnut-backed chickadee (*Parus rufescens*) in relation to an environmental gradient: atmospheric humidity. Accurate information regarding species' distributions is critical to numerous conservation and land management decisions. Many studies on species distributions have been undertaken to deliver conservation outcomes across multiple spatial scales (Guillera-Arroita, Lahoz-Monfort, Elith *et al.*, 2015, Guisan and Thuiller, 2005). For instance, knowledge regarding species' distributions has aided biodiversity hotspot identification (Myers, 1988); guided protected area identification and reserve design decisions (Kirkpatrick, 1983, Loyn, McNabb, Volodina *et al.*, 2001, Pearce, Ferrier and Scotts, 2001) and enabled identification of biological invasion risks (Thuiller, Richardson, Pysek *et al.*, 2005). Furthermore, this information is critical for the conservation of threatened species. Extinction risk is often associated with range size, whereby significant reductions in the size of a species' distribution is a key element in determining its conservation status and required management actions (Mace, Collar, Gaston *et al.*, 2008, Purvis, Gittleman, Cowlishaw *et al.*, 2000).

A key challenge with establishing a species' distribution is identifying and understanding its geographical range limits (Geber, 2011). Multiple factors can limit a species' distribution, including habitat suitability (e.g. abiotic factors, resources, biotic interactions, disturbance and behaviour), history and geography of the species' origin, dispersal opportunities and barriers and ecological and evolutionary dynamics (Geber, 2011, Hoffmann and Blows, 1994). The importance of the effect of climate in explaining species' distributions has been recognised by early, largely qualitative, studies linking biological patterns to observed environmental gradients (Grinnell, 1904, Murray, 1866). For instance, global vegetation patterns have been explained by correlations with climate and other environmental variables (Salisbury, 1926, Woodward and Williams, 1987). Humboldt's (1807) "Essay on the Geography of Plants" was one of the earliest papers on this topic. These early studies, confirming that organisms tend to occupy distinct zones, generated further questions regarding species' associations and, ultimately, what determines a species' range limits (Parmesan, Gaines, Gonzalez *et al.*, 2005).

Descriptive approaches, such as comparative or correlative studies, can identify which environmental factors e.g. climate, resources or biotic interactions, are important in the determination of a species' distribution (Hoffmann and Blows, 1994). For example, Leishman and Wild (2001) found that the distribution of lichen in the Antarctic was positively correlated with soil total nitrogen and phosphorus, suggesting nutrients may be important limiting factors. In a comparative study of the distributions of three kangaroo species across Australia, Caughley, Short, Grigg *et al.* (1987) found that climate variables, such as mean annual temperature and mean annual precipitation, can characterise each species' distribution. Manipulative experiments, such as those involving transplants can test whether a species can persist beyond its current range and may highlight important abiotic factors or biotic interactions that influence its distribution. Transplant studies can also aid investigation into whether absence from an area is due to dispersal limitations or limited adaptation (Geber, 2011, Sexton, McIntyre, Angert *et al.*, 2009). For example, in a long-running transplant experiment, Van der Veken, Rogister, Verheyen *et al.* (2007) found that plant performance was lower for transplanted plants than those in 'origin' populations, and that significant drivers of plant extinction were soil disturbance and forest management. Over the past two decades, however, the number of correlative studies has rapidly increased with the advent of computer-based species distribution models, emerging as essential tools for evaluating and defining species' distributions (Guisan and Thuiller, 2005, Sexton *et al.*, 2009).

Species Distribution Models

Correlative species distribution models (SDMs) are statistical tools that combine observations of species occurrence/absence with environmental estimates to model the distribution of suitable habitat under past, current or future conditions (Booth, Nix, Busby *et al.*, 2014, Elith and Leathwick, 2009, Monnet, Hardouin, Robert *et al.*, 2015). These tools emerged from the parallel development of i) statistical methods (e.g. generalised linear regression models (GLMs)); ii) geographical datasets (e.g. data from digital elevation models (DEM), interpolation of climate parameters); and iii) geographical systems, chiefly the advent of Geographic Information Systems (GIS) (Elith and Leathwick, 2009).

Computer-based predictive modelling of species distributions originated in the mid-1970s using simple geographic envelopes and convex hulls within GIS (Elith and Leathwick, 2009). One of the earliest SDMs developed was BIOCLIM, which predicts suitable conditions in a "bioclimatic envelope", which consists of a rectilinear region in environmental space that corresponds to the range (or percentile range) of values of the bioclimatic variables at known locations of the species' occurrence (Booth *et al.*, 2014, Nix, 1986). BIOCLIM has been used to predict distributions for a variety of Australian fauna, such as the Leadbeaters possum (*Gymnobelideus leadbeateri*) (Lindenmayer, Nix, McMahon *et al.*, 1991), the mountain brushtail possum (*Trichosurus caninus*) (Fischer, Lindenmayer, Nix *et al.*, 2001), the long-footed potoroo (Claridge, 2002) and multiple Australian butterfly species (Beaumont and Hughes, 2002) and flora such as eucalypt species (Booth, Nix, Hutchinson *et al.*, 1988, Lindenmayer, Mackey and Nix, 1996).

Although still in use, these earlier models were succeeded in the early 1980s by the pioneering simulations of Ferrier (1984), who used GLMs based upon field observations to predict the distribution of the rufous scrub-bird (*Atrichornis rufescens)*. There is now a proliferation of SDMs in use, including regression-based models (e.g. Generalized Linear Models (GLM), Generalised Additive Models (GAMs), Resource Selection Function (RSF)), Bayesian models and algorithmic modeling based on machine learning (e.g. Artificial Neural Networks, Classification And Regression Trees, Maximum Entropy (Maxent)) (Elith, Graham, Anderson *et al.*, 2006, Fourcade, Engler, Rödder *et al.*, 2014, Phillips, Anderson and Schapire, 2006).

Interpretation of SDMs relies upon environmental niche theory, whereby a higher probability of species occupancy is expected to occur in geographic areas at the centre of a species' environmental niche rather than at the edges (Bean, Prugh, Stafford *et al.*, 2014, Guisan and Zimmermann, 2000). The concept of the "fundamental" ("Grinellian") ecological niche was first defined by Hutchinson (1957) as an "n-dimensional hypervolume" which corresponds to an environmental state that permits a species to persist indefinitely. Hutchinson (1957) also noted, however, that a species will not typically utilise its entire fundamental niche, but rather a smaller area where it is competitively dominant: its "realised" niche. Pulliam (2000) identified two further possible niche states: i) a metapopulation 'source-sink' concept whereby a species, through immigration processes, may occur in sink locations that by definition would not be suitable for the species' persistence, and ii) dispersal limited, whereby a species may be absent from suitable habitat as they cannot reach it. Differentiating between these concepts is important as the data used in predictive SDMs can have implications depending upon which niche concept is assumed to underlie the model. Guisan and Thuiller (2005) highlighted that SDM studies frequently assume the quantification of the realised niche, often on the basis that the observed distributions are "already constrained by biotic interactions and limiting resources". This assumption is considered appropriate for static predictive models that use large datasets of field-derived observations (Guisan and Zimmermann, 2000).

The type of species location data available is a key factor in model selection. In many instances, only occurrence (i.e. presence) data are readily available from online biodiversity atlases (e.g. Atlas of Living Australia (ALA)). In this instance, Maxent has become a widely used model, due to its superior predictive capacity compared to other presence-only models (Elith *et al.*, 2006, Hernandez, Graham, Master *et al.*, 2006). Elith *et al.* (2006) compared 16 presence-only modelling methods, over 226 species, and found that novel methods, including Maxent, consistently outperformed more established methods, including BIOCLIM.

Maxent

Maxent is a machine learning technique based on the maximum entropy method for modelling habitat suitability with a species' presence-only data (Phillips *et al.*, 2006). The goal of Maxent is to estimate a distribution that agrees with what is known and avoids assumptions unsupported by the data (Pearson, 2008). Thus Maxent estimates a target probability distribution of maximum entropy (i.e. closest to uniform/most spread out), subject to a set of constraints (e.g. the mean of the estimated probability distribution of a covariate must equal the covariate's mean value at presence location) (Phillips *et al.*, 2006). Maxent is capable of modelling complex, non-linear relationships, as well as, incorporating both continuous and categorical environmental covariates (Elith, Phillips, Hastie *et al.*, 2011, Merow, Smith and Silander, 2013, Phillips *et al.*, 2006). Furthermore, Maxent is less sensitive to small sample sizes, overfitting can be reduced using L_1-regularisation, and the output is continuous, allowing fine distinctions to be made between projected suitability of different areas (Elith *et al.*, 2006, Phillips *et al.*, 2006, Wisz, Hijmans, Li *et al.*, 2008). These elements are key differentiators from the BIOCLIM model (Booth *et al.*, 2014).

Species Distribution Models: Applications

Species distribution models are a valuable tool for multiple scientific disciplines, including ecology, wildlife management, conservation biology and biogeography. These models have, and continue to be, widely used to identify factors influencing a species' distribution (Hayward, de Tores, Dillon *et al.*, 2007, Lindenmayer, Ritman, Cunningham *et al.*, 1995). Nevertheless, since the uptake of SDMs in the 1970s/1980s there has been a subtle shift in their purpose: from seeking an understanding of factors delineating species' distributions to predicting distributions (Elith and Leathwick, 2009). As such, they have become widely used to map potential geographic ranges, assess climate change impacts on species distributions

(Adams-Hosking, Grantham, Rhodes *et al.*, 2011, Beaumont, Gallagher, Leishman *et al.*, 2014), identify gaps in protected areas (Catullo, Masi, Falcucci *et al.*, 2008, Pearlstine, Smith, Brandt *et al.*, 2002), predict the effects of human impacts (Seoane, Justribó, García *et al.*, 2006, Yates, McNeill, Elith *et al.*, 2010), and locate new populations (McCune, 2016, Mizsei, Uveges, Vagi *et al.*, 2016). Hence, SDMs have become an essential tool, providing input for conservation planning, assessing risk and directing surveys (VanDerWal et al. 2009b, Elith et al. 2011, Aizpurua et al. 2015).

Guillera-Arroita et al. (2015) conducted a review of the use of SDMs over the period 2008 to 2014, which revealed that the most common motivation for using SDMs is management of threatened species (16%), prediction of climate change impacts (13%), and exploring phylogenetic patterns (9%). These themes persist in recent peer-reviewed literature. An updated review of journal articles in Web of Science, using the same topic search terms as Guillera-Arroita et al. (2015) (i.e. “species distribution model”; “ecological niche model” and “habitat model”) for the period 2014 to June 2017, produced 1,323 article results, a two-fold increase since the Guillera-Arroita et al. (2015) study. A random selection of 20 articles highlights the diversity of current SDM applications (Table 1).

There are several reasons for the uptake and usefulness of SDMs. When information on a geographic distribution is biased or incomplete, field surveys to further assess species’ distributions can be challenging, requiring large amounts of human effort and financial/capital expenditure (Le Lay, Engler, Franc *et al.*, 2010). SDMs can be used at the desktop to fill in these distribution gaps by extrapolating habitat specific information from one area to another to identify suitable areas for a species and infer a likelihood of presence under both current conditions and future climate scenarios (Beaumont et al. 2005, Fourcade et al. 2014).

Table 1 : Summary of Current SDM Uses

SDM Uses	Author	Model(s) Presence-Absence (PA); Presence Background (PB); Presence-Only (PO)
Refugia identification a) Identified habitat refugia for the pink-footed goose (*Anser brachyrhynchus*) b) Located climate refugia for koalas (*Phascolarctos cinereus*) c) Identified critical areas for protection and monitoring for the Orinoco crocodile (*Crocodylus intermedius*) d) Identified habitat and protected area needs of soft corals.	a) Baveco, Bergjord, Bjerke *et al.* (2017) b) Briscoe, Kearney, Taylor *et al.* (2016) c) Balaguera-Reina, Espinosa-Blanco, Morales-Betancourt *et al.* (2017) d) Poulos, Gallen, Davis *et al.* (2016)	a) GLM (PA) b) Maxent (PB); NicheMapper c) Maxent (PB) d) Resource Selection Function (PO)
Assessing human impacts a) Cetaceans (multiple species) – mapping distributions and fisheries overlap. b) Bird - Bachman's sparrow (*Peucaea aestivalis*) – identified restoration areas and interaction with urban growth impacts.	a) Breen, Brown, Reid *et al.* (2016) b) Pickens, Marcus, Carpenter *et al.* (2017)	a) Maxent (PB) b) Maxent (PB)
Threatened species conservation a) Blanding's turtle (*Emydoidea blandingii*) b) Swift parrot (*Lathamus discolour)* c) Pine marten *(Martes martes)*	a)Stryszowska, Johnson, Mendoza *et al.* (2016) b) Webb, Wotherspoon, Stojanovic *et al.* (2014) c) O'Mahony (2017)	a) Maxent (PB); GLM (PA) b) GAM (PA) c) Maxent (PB)
Predicting climate change impacts a) Fish (two species) b) Eucalyptus (16 species) c) Australian Odonata (various spp.) d) Western ringtail possum (*Pseudocheirus occidentals*)	a) Hansen, Read, Hansen *et al.* (2017) b) Hamer, Veneklaas, Poot *et al.* (2015) c) Bush, Nipperess, Duursma *et al.* (2014) d) Molloy, Davis and Van Etten (2014)	a) Random Forests (PA) b) Maxent (PB) c) Maxent (PB) d) Maxent (PB)
Invasive species management a) Invasive plant distributions (Bitou Bush, *Chrysanthemoides monilifera*) b) Mapping distributions of invasive wild pigs (*Sus scrofa*) in Northern Australia c) Predicting the range and abundance of fallow deer (*Dama dama*) in Tasmania	a) Beaumont *et al.* (2014) b) Froese, Smith, Durr *et al.* (2017) c) Potts, Beeton, Bowman *et al.* (2015)	a) Maxent (PB) b) Bayesian network model (PB) c) Maxent (PB)

SDM Uses	Author	Model(s) Presence-Absence (PA); Presence Background (PB); Presence-Only (PO)
Investigation of phylogeographic patterns		
a) Northern red-backed vole, *Myodes rutilus*	a) Kohli, Fedorov, Waltari *et al.* (2015)	a) Maxent (PB)
b) Cactus (seven species in the *Pilosocereus aurisetus* complex)	b) Bonatelli, Perez, Peterson *et al.* (2014)	b) Maxent (PB)
Mapping distribution of disease vectors		
a) Yellow fever mosquito (*Aedes aegypti*) and tiger mosquito (*Aedes albopictus)* (for Zika virus)	a) Santos and Meneses (2017)	a) Maxent (PB)
b) Anopheles darlingi (for Malaria in French Guinea)	b) Moua, Roux, Girod *et al.* (2017)	b) Maxent (PB)

Species Distribution Models as a Guide to Field Surveys

An important application of SDMs is predicting where species are likely to occur to facilitate surveys to monitor and study these species. Often knowing where to direct survey effort is hampered by paucity of data regarding species' distributions, biology and ecology. SDMs provide a simple approach to mapping potentially suitable habitat to guide field surveys, and have been used in this manner for a variety of taxa, including marine invertebrates (Rooper, Sigler, Goddard *et al.*, 2016), amphibians (Groff, Marks and Hayes, 2014), reptiles (Stratmann, Barrett and Floyd, 2016), birds (Walker, Hart and Griffin, 2003) and mammals (Lumsden, Nelson, Todd *et al.*, 2013). This approach is appealing as it is likely to be very efficient. For instance, Guisan, Broennimann, Engler *et al.* (2006) found that using an SDM to guide field surveys may save up to 70% of the time spent in the field relative to a random sampling approach.

Surveying for rare and endangered species is essential for monitoring populations and supporting positive conservation outcomes. Research has demonstrated that detection of rare species is greatly improved when surveys are guided by SDMs (Guisan *et al.*, 2006, Le Lay *et al.*, 2010). Guisan *et al.* (2006) used a GAM to guide "model based" random-stratified sampling of a rare plant species (*Eryngium alpinum*) and successfully discovered seven new populations. McCune (2016) undertook forest surveys for eight rare plants guided by a Maxent SDM, which led to the discovery of new populations for four species, with no target species found in sites predicted as being "unsuitable". Furthermore, five of the eight study species had significantly higher relative abundance in areas predicted by Maxent to be suitable rather than unsuitable (McCune, 2016).

Surveys directed by SDMs have been found to be efficient and equally, or more, effective at locating the target species than other approaches (e.g. random sampling, expert guidance) (Aizpurua, Cantú-Salazar, San Martin *et al.*, 2015, Guisan *et al.*, 2006). For instance, Crall, Jarnevich, Panke *et al.* (2013) found that detection of three invasive plant species in western USA using Maxent output was significantly more successful than a non-model based survey approach. Wang, Zachmann, Sesnie *et al.* (2014) also utilised Maxent output to identify high habitat suitability sites (i.e. 90^{th} percentile) for invasive species: field surveys went on to locate the species at 70% of previously-unsampled sites. Guisan *et al.* (2006) compared a GAM model based survey approach to random sampling using an iterative, virtual simulation. This study found that the number of new presences was approximately four times higher when using the model approach as compared to simple random sampling (Guisan *et al.*, 2006). Similarly, Le Lay *et al.* (2010) compared GAM and ecological niche factor analysis (ENFA) SDMs for eight native plant species to a random sampling approach and found that for six out of eight target species, the model approach was significantly more efficient than random sampling for finding new populations.

Surveys predicated upon a method of random site selection, however, are not the only alternative to model based site selection. For example, Aizpurua *et al.* (2015) compared surveys based on a SDM (Maxent) to surveys based on: i) a random sample approach, or ii) expert-opinion. Their study found 95 new shrike territories during ground validation surveys using Maxent compared to 72 with expert-based sampling and only 11 new territories using a random sampling strategy (Aizpurua *et al.*, 2015). Furthermore, a GLM analysis confirmed that “sampling strategy” was the only significant factor explaining this variation in new territories found (Aizpurua *et al.*, 2015). These studies highlight the important role that SDMs can play in guiding field surveys, whilst also recognising that the best outcomes are achieved when there is expert input into modelling (Aizpurua *et al.*, 2015).

The positive outcomes from model based surveys are not universal. Some studies found new populations of some, but not all, target species (McCune, 2016), or the overestimation of suitable habitat (Stratmann *et al.*, 2016). Ultimately, however, there is sufficient evidence that the use of SDMs to guide field surveys can avoid inefficiencies of random, haphazard searches, even in fragmented landscapes (Aizpurua *et al.*, 2015, McCune, 2016, Stratmann *et al.*, 2016).

Ground validation of species distribution models

Model output is considered a useful index of habitat quality, implicitly assuming that locations with higher predicted habitat suitability have higher quality habitat, resulting in greater species abundance and probability of persistence (Bean *et al.*, 2014). However, an SDM may correctly identify suitable habitat at a regional scale, yet fail to capture the fine-scale ecological requirements of a species or predict local variations in habitat suitability (Le Lay *et al.*, 2010). Studies evaluating the relationship between SDM output and habitat quality have predominantly focused upon abundance measures (see Weber, Stevens, Diniz-Filho *et al.* (2016) for a comprehensive review). Recent studies have confirmed that Maxent's predicted habitat suitability values are positively related to the abundance of various species, e.g. 10 bird species and eight butterfly species in the UK (Oliver, Gillings, Girardello *et al.*, 2012); 84% of 69 rainforest vertebrate species in the wet tropics of Australia (VanDerWal, Shoo, Johnson *et al.*, 2009b); and 19 of 21 bird species on La Palma Island (Spain) (Carrascal, Aragón, Palomino *et al.*, 2015).

Other studies have evaluated this relationship using density (Torres, Virgos, Santos *et al.*, 2012) or proxy measures of habitat quality (Bean *et al.*, 2014). For instance, Bean *et al.* (2014) compared Maxent predictions for the Giant Kangaroo Rat (*Dipodomys ingens*) with three proxy measures of habitat quality: survival, abundance and body condition, finding a positive correlation with abundance. In contrast, Giovannini, Seglie and Giacoma (2014), found a positive, significant, relationship between regions predicted to have high suitability for a European amphibian, *Pelobates fuscus insubricus,* and the species persistence. Overall, studies suggest that SDMs are effective at predicting habitat quality on the ground. However, research investigating the relationship between SDMs and finer scale habitat attributes remains limited (Bean *et al.*, 2014, Gogol-Prokurat, 2011).

The ability of an SDM to identify the appropriate fine-scale requirements may be of significance if microhabitat characteristics are an important factor limiting the species' distribution (Claridge, 2002, Gogol-Prokurat, 2011). Many studies have highlighted the importance of microhabitat factors, such as vegetation cover, different plant species, ground cover and logs, for the abundance and distribution of a variety of small Australian mammals (Bennett, 1993, Graham, Blackwell and Hochuli, 2005, Pizzuto, Finlayson, Crowther *et al.*, 2007, Tulloch and Dickman, 2007, Vernes, 2003). For instance, Tulloch and Dickman (2007) investigated whether differences in local attributes (e.g. vegetation types, site fire history, floristics, vegetation structure) influenced the abundance and distribution of the eastern pygmy-possum (*Cercartetus nanus*). The capture rate of *C. nanus* was found to differ between vegetation types and site fire history, with more individuals captured in "unburnt woodland" than other vegetation types (Tulloch and Dickman, 2007). There was also a strong association between *C. nanus* and certain plant species, including *Banksia serrata, B. ericifolia and Xanthorrhoea* species, which are thought to represent important food resources for this species (Tulloch and Dickman, 2007). Vernes (2003) undertook multiple regression modelling to investigate relationships between mammal capture success for several small mammals and 21 fine-scale habitat features. The highest northern bettong (*Bettongia tropica*) captures occurred in areas of Eucalyptus woodland with sparser ground cover density, a variety of tree sizes, fewer pig diggings, and low density of blady and molasses grass (Vernes, 2003). In contrast, northern brown bandicoot (*Isoodon macrourus*), captures were found to be higher in both *Eucalyptus* and *Allocasuarina* forest types with dense ground cover, higher density of blady and molasses grasses, and wetter gullies. The differences in microhabitat preferences of these two mammals provides an example of the high degree of microhabitat partitioning that can arise between species.

The relationship between the distribution and abundance of numerous small ground-dwelling mammals and microhabitat variables (e.g. canopy cover, shrub cover, ground vegetation cover, ground cover type, moisture, basal area of canopy tress and logged stumps and foliage nutrients) have been examined in detail by Catling, Burt and Forrester (2000) (north-eastern NSW) and Catling, Burt and Forrester (1998) (south-eastern NSW). In south-eastern NSW, GLMs were fit for three small mammal species, brown antechinus (*Antechinus stuartii*), bush rat (*Rattus fuscipes*) and dusky antechinus (*Antechinus swainsonii*). The microhabitat variables selected in the best performing model for each species were highly varied. For example, the abundance of the dusky antechinus was positively related to tree cover, groundcover, rainfall and foliage magnesium and potassium, whereas, the abundance of the brown antechinus was positively related to community type (i.e. *Eucalyptus gummifera* community), leaf litter depth and shrub cover.

In contrast, Bennett (1993) was not able to find a strong relationship between capture rates of the long-nosed potoroo (*Potorous tridactylus*) and selected floristic and vegetation structural measures. Overall, however, studies highlight the important role played by microhabitat features in the local distribution of many small mammals.

A Case Study: The NSW distribution of the long-footed potoroo *(Potorous longipes)*

Ecology of the long-footed potoroo

The endangered long-footed potoroo (*Potorous longipes*) is a small marsupial rat kangaroo (1.5-2.3 kg) (Scotts and Seebeck 1989). Rare and elusive, it was first described as a separate species in 1980 (Seebeck and Johnston 1980). Since then, three small, disjunct, populations have been located: two in north-eastern Victoria (Department of Sustainability and Environment (DSE) 2009), and one in south-eastern NSW (National Parks and Wildlife Service (NPWS) 2002), with a combined population size estimated at 10,000 individuals (DSE 2009). However, the recently updated IUCN listing notes the total population size is less than a few thousand individuals (Woinarski and Burbidge, 2016). Furthermore, at the East Gippsland Bellbird study site (Victoria), the population is likely in decline, with an estimated long-term average annual proportional population growth rate of 0.94 (Chick *et al*. 2006; DSE 2009; Lumsden *et al*. 2013).

Knowledge of the biology and ecology of the long-footed potoroo comes from studies conducted in Victoria. The long-footed potoroo has been found across various ecological vegetation classes, altitudes (150 - 1370 m), topographic types (from creeks to ridge tops) and forest age classes (e.g. eight-year regrowth post-timber harvesting to old growth forests) (Scotts and Seeback 1989; Green *et al.* 1998, Chick *et al.* 2006; Elsner *et al.* 2012). Preferred habitat, however, appears to be areas with moist soils and sheltered aspects, likely due to the species' relationship with fungal food sources (DSE 2009; NPWS 2002). Indeed, the long-footed potoroo is the most fungi-dependent mammal in Australia: on average, 91% of its diet comprises truffle-like fungi with the remainder consisting of invertebrates and plants (Green *et al.* 1999). As such, year-round fungal abundance and diversity is likely a key requirement for the species (NPWS 2002).

The home range of the long-footed potoroo is estimated to be between 14-59.9ha (95% Minimum convex polygon (MCP)), with range widths between 527-1193m (average = 710m) (Green, Mitchell and Tennant, 1998). Green *et al.* (1998) radio-tracked 17 individuals at two separate locations in Victoria (Bellbird (11) and Riley (6)). Individuals in Riley were found to have significantly smaller home ranges (14.3-22.7 ha) than individuals in Bellbird (22.3-59.9 ha), ascribed to relatively better habitat quality at Riley.

Survey History

All known records of long-footed potoroos in New South Wales occur within the boundaries of the South-East Forests National Park (SEFNP). In NSW, multiple, intensive surveys have been undertaken to evaluate the species' distribution and patterns of occupancy. Hair tubing and scat surveys in 1986 and 1989 confirmed the presence of the species within the Sheep Station Creek catchment of SEFNP (Claridge 2002; NPWS 2002). These records, along with existing records from Victoria, were used in BIOCLIM modelling, which formed the basis of extensive live-trap and hair tube surveys conducted between 1990-1995 (Figure 1). This effort yielded less than ten definitive records (Claridge 2002). The most recent survey undertaken in 2008/09 used scat searches, hair tubes and low-intensity camera traps and yielded no new findings (pers. comms. Joss Bentley, Office of Environment and Heritage (OEH), 14 July 2015). Furthermore, ongoing sand plot monitoring in Sheep Station Creek, NSW has yielded no results (pers. comms. Franz Peters, NPWS, 18 September 2014). In NSW, there has never been a live capture or direct observation (Claridge 2002; NPWS 2002).

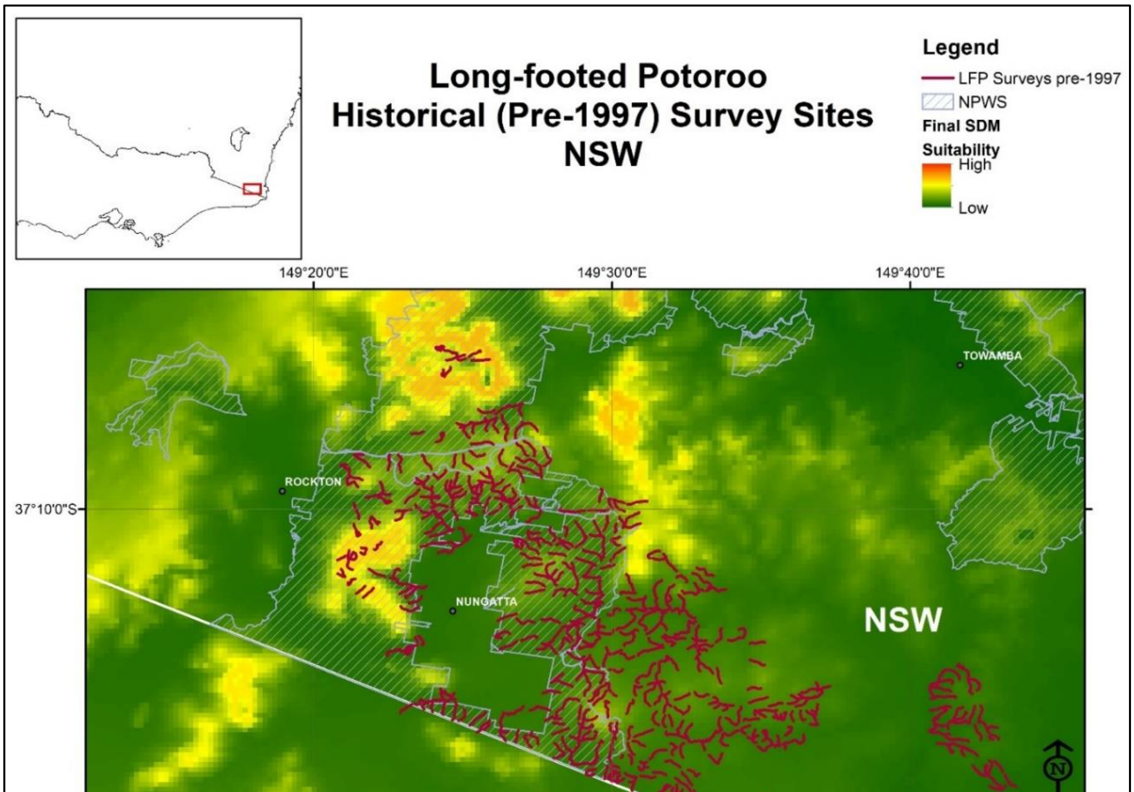

Figure 1: Historical long-footed potoroo survey transects (red lines) as at 1997 (transect data courtesy of Dr. Joss Bentley, OEH) overlayed on the pre-survey Maxent SDM output whereby orange areas have relatively higher habitat suitability values and green areas have lower habitat suitability values.

In Victoria, however, surveys for the long-footed potoroo have been vastly different, with recent camera surveys being highly successful in detecting the long-footed potoroo. In 2011, a multi-year survey program commenced using baited camera traps at 13 sites spread across 10,000 hectares west of the Snowy River (pers. comm. Marc Perri, DELWP 21 February 2017). Although no long-footed potoroos were detected in 2011, three sites yielded detections in 2012, increasing to 13 sites by 2016 (pers. comm. Marc Perri, DELWP 21 February 2017). These represented the first records of the species in the Gippsland area west of the Snowy River (Lumsden *et al.*, 2013). In a separate study, a SDM was utilised to guide a field survey for the species in Gippsland during April to August 2012. Camera surveys were undertaken across 170 sites that fell across four zones: i) the existing known range of long-footed potoroo, ii) a 5km buffer around the known range, iii) a 10km buffer around the known range and iv) east of the 10km buffer and north of the Princes Highway to the New South Wales border, an area predicted by the study's SDM to have suitable habitat (Lumsden *et al.*, 2013). Baited cameras were left *in situ* for three weeks. Long-footed potoroos were detected at 41 sites. While several were new records outside the known range, the majority (88%) were within the previously known range (Lumsden *et al.*, 2013). Possible factors contributing to increased detection over time are the long-footed potoroo's response to predator control (fox baiting) in these areas; a post-drought response to the 2002-2010 drought; and extension of surveys into these new areas.

Most recently, camera surveys undertaken between July and October 2016, as part of the Southern Ark Program (monitoring fox control) in Victoria, gave rise to 67 new long-footed potoroo camera detections across 35 locations (pers. comm. Andy Murray, DELWP, 1 December 2016). On nearly all camera traps the long-footed potoroos provided several unambiguous photos on (usually) multiple visits, thus confirming presence (pers. comm. Andy Murray, DELWP, 1 December 2016).

The unsuccessful resurveying efforts of regions in NSW where the species was originally detected, raise concerns about possible extirpation in NSW. Alternatively, these findings might suggest: 1) past survey methods do not reliably census the species, 2) the long-footed potoroo is present at extremely low density, or 3) sampling is occurring in the wrong locations. If the long-footed potoroo persists, however, its distribution and population size in NSW is unclear. These concerns are echoed in the recent decision to change the species' conservation status in NSW to critically endangered (NSW Scientific Committee (NSW SC) 2015). Further field surveys, covering both known and new locations, were proposed to establish the species' persistence, distribution and population size in NSW (pers. comm.

Joss Bentley 14 August 2015). This information is critical to recovery planning for the species, and the effective management of its habitat.

In NSW, predictions from the SDM BIOCLIM have previously been used to direct long-footed potoroo survey efforts (Claridge, 2002, Saxon and Noble, 1993). However, modelling has not been updated in NSW since Claridge (2002) (pers. comm. Joss Bentley, 14 July 2015). Since then, new occurrence data have become available from the Victorian surveys expanding the long-footed potoroo's distribution and discovering populations in new habitat types, e.g. drier coastal (Cape Conran) and hinterland habitat types (Lumsden *et al.* 2013; Elsner *et al*. 2012; pers. comm. Joss Bentley, 8 July 2015). Furthermore, the availability of environmental data and SDM techniques has advanced considerably, e.g. Maxent (Phillips *et al.* 2006; Elith *et al.* 2006; Merow *et al.* 2013).

The objective of the current study is to determine the long-footed potoroo's current distribution and persistence in NSW using targeted camera surveys based upon an updated SDM. Further, in the absence of detailed data on abundance or other proxy measures of long-footed potoroo habitat quality in NSW, this study proposes to use field surveys and microhabitat assessments to ground-truth the SDM predictions. Thus, this paper seeks to answer the following questions: i) what is the current distribution of the long-footed potoroo in NSW? ii) does the SDM accurately predict the presence of the long-footed potoroo? iii) is the species' preferred microhabitat characteristics encompassed by the SDM prediction of suitable habitat? and iv) to what extent do climate suitability and various microhabitat variables, in combination, predict the occurrence of the LFP? This information is critical to assess the likelihood that long-footed potoroo populations remain extant in NSW and, if so, aid with the development of recovery planning for the species and effective management of its habitat. This research will also contribute towards establishing the usefulness of SDMs in guiding future field surveys.

METHODOLOGY

Species Distribution Modelling - Maxent

To establish the long-footed potoroo's current distribution in NSW, species distribution modelling was undertaken to identify areas of potentially suitable habitat. Maxent (Version 3.3.3k) was used as it does not require absence data, which was unavailable pre-field survey, and due to its well-recognised high predictive performance (Elith *et al.*, 2006).

A description of the Maxent model and program, including the procedure for determining the logistic output for habitat suitability, has been outlined by various authors (Elith *et al.*, 2011, Phillips *et al.*, 2006, Phillips and Dudík, 2008). The program requires up to three key data inputs: locations of species occurrences, environmental variable grids and an optional sampling bias grid (Syfert, Smith and Coomes, 2013). In brief, several model iterations were run using Maxent's default settings with two exceptions relating to the background file and feature selection (outlined below), to investigate the impact of different covariate combinations on model predictions.

i) Locality data

Locality data were obtained from occurrence records in the Atlas of Living Australia (ALA) database (http://www.ala.org.au). The initial 531 occurrence records were examined to identify definitive records of the species (i.e. locations where the animals were live-trapped, camera-trapped, had hair in hair-tubes; and/or had reliable expert observers). Spatially invalid, duplicate records or those that were poorly geocoded (i.e. coordinate uncertainty greater than 1000m) were deleted. As the long-footed potoroo was identified as a distinct species in 1980, records with dates stated as 'first of the century' (i.e. 1900) or before 1980 and that were based upon human observation were deleted as they are potentially less reliable. There were 341 occurrence records remaining; 34 from NSW and 307 from Victoria.

The coordinates of cleansed occurrence records were projected to the Australian Albers Equal Area (EPSG:3577) coordinate system and reduced to one record per grid cell (250m resolution) using custom code in the R statistical computing environment (v3.1.1) (R Development Core Team, 2015).

ii) Background Grids

By default, Maxent randomly samples 10,000 background locations from covariate layers, to which it compares the characteristics of occurrence data. This approach assumes that the occurrence records are also a random sample from the landscape (Elith *et al.*, 2011).

However, sampling bias is likely to be present in the occurrence data because of the *ad hoc* nature of many of these collections. Accounting for sampling bias is critical to the accuracy of SDMs generated from presence-only datasets, and failure to correct for it can result in predictions that reflect sampling effort rather than true distributions (Phillips, Dudík, Elith *et al.*, 2009, Syfert *et al.*, 2013, VanDerWal, Shoo, Graham *et al.*, 2009a). Hence, to reduce sampling bias, we followed the approach outlined by Elith *et al.* (2011) and generated background data with similar biases to those in the presence data. Using R (v3.1.1) we generated a background file of all mammal records in ALA, that were recorded from the four IBRA (Interim Bioregionalisation of Australia) regions within which the long-footed potoroo occurs (Australian Alps, South East Coastal Plain, South East Corner, South Eastern Highlands) (Figure 2).

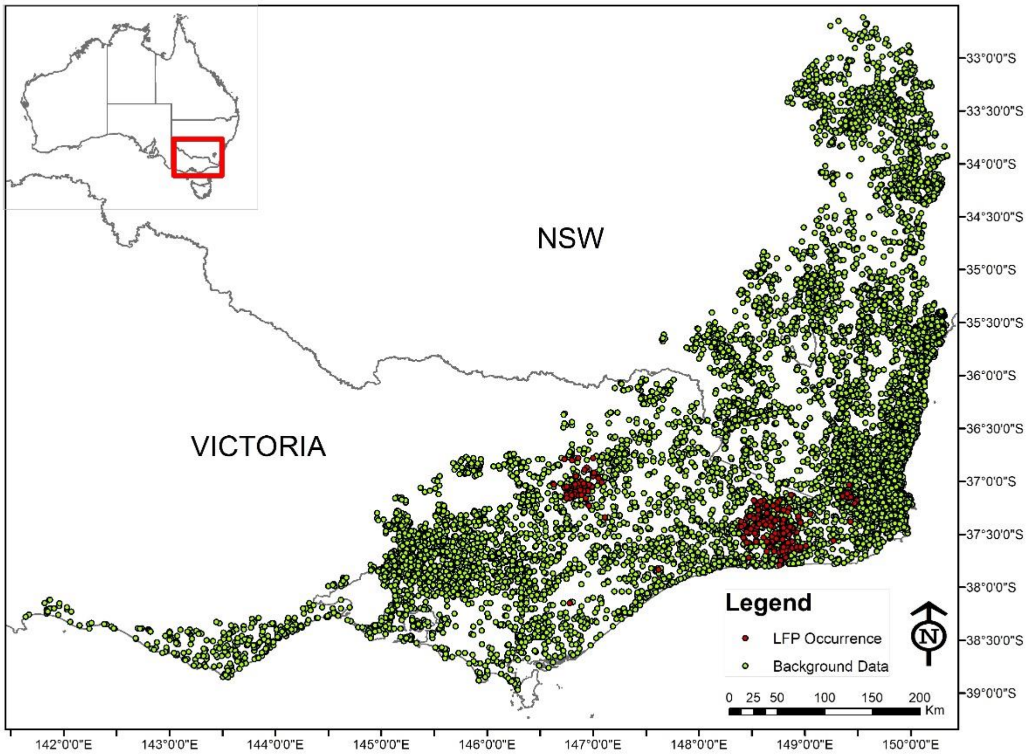

Figure 2: Distribution of 10,000 randomly selected ALA mammal records that were used to generate a background file for use in Maxent (green circles), overlayed with the LFP occurrence records (red circles).

iii) Environmental Variables (Covariates)

A number of variables pertaining to climate, topography and vegetation, were considered for inclusion in the Maxent models. Climate data were obtained from the baseline data (1990-2009) generated as part of the NSW and ACT Regional Climate Modelling (NARCliM) project (Evans, Ji, Lee *et al.*, 2014). These data represented a set of 35 bioclimatic variables generated by M. Hutchinson (ANU) using ANUCLIM version 6.1.1., at a spatial resolution of

~250 x 250m. (Supplementary Material - SM 1). The Geoscience Australia 9 second DEM was used as the basis for deriving slope and aspect variables. The spatial data were projected to Australian Albers Equal Area projection, with gridded raster data resampled by cubic spline to a resolution of 250 x 250m Slope and aspect (both measured in degrees) were calculated using the gdaldem function provided by the gdalUtils R package (Greenberg and Mattiuzzi, 2015). Aspect was then transformed to two separate variables expressing the northness and eastness. National Vegetation Information System (NVIS) vegetation categories were generated from NVIS Major Vegetation Subgroups (Version 4.1) (Department of Sustainability Environment Water Population and Communities, 2015) data that was originally at 100 x 100m, resampled to 250 x 250m, assigning the most common cell value to the whole 250m cell. There was a total of 39 environmental variables included, prior to variable selection.

With respect to variable selection, it is recommended that they be ecologically relevant, and while correlations should be minimised Maxent is considered robust to correlated variables (Elith *et al.*, 2011, Guisan and Zimmermann, 2000, Merow *et al.*, 2013). Thus, variable selection proceeded as follows: i) a correlation analysis was generated in R (v3.1.1) to identify highly correlated variables; and ii) a model with all variables was run to identify variables that did not make a significant contribution to the model (SM 2,SM 3). Next, a set of 10 variables was put forward for discussion with an expert (BIOCLIM 5, 6,14,16, 21, 22, 23, 30, 31, 34 and vegetation) following which two sets of variables were selected (see Table 2 – “Select Variables A” and “Select Variables A_No VEG”). Maps were produced for these two datasets, evaluated for ecological relevance and variables were discussed again with an expert, giving rise to the “Final” model (Table 2). Maxent was calibrated with each of the three variable sets, using five-fold cross validation. The use of a single dataset to calibrate and evaluate each model was necessary due to the small size of the presence dataset and desire to use as many of these observations as possible for model calibration (Guisan and Zimmermann, 2000).

Table 2: Summary of the Maxent SDMs evaluated

Model Name	Covariates	AUC (Average across 5-fold cross validation)
Maxent		
1. All Variables	BIOCLIM 1 to 35, NVIS (vegetation), aspect	0.959 (std. dev +/- 0.01)
2. Select Variables A	BIOCLIM 5, 14, 21, 22, 23, 30, 31 and NVIS (vegetation)	0.954 (std. dev +/- 0.008)
3. Select Variables A_NO VEG	BIOCLIM 5, 14, 21, 22, 23, 30, 31	0.953 (std. dev +/- 0.007)
4. Final model = ‘pre-survey’ model	**BIOCLIM 5, 14, 21, 22, 30, 32, 33**	**0.941 (std. dev +/- 0.011)**

Model Settings and Evaluation

Maxent’s default setting is to apply five feature types to covariates, enabling the model to fit complex, non-linear functions (Merow *et al.*, 2013, Phillips *et al.*, 2006). However, simpler models are worth considering if ecological relationships can be met (Syfert *et al.*, 2013). For this study, only linear, quadratic, product and categorical binary features were used as these capture likely ecological relationships.

Maxent obtains a solution by maximising the ‘gain function’, which corresponds to finding a model that can best distinguish between sites associated with presences and background locations (Merow *et al.*, 2013, Syfert *et al.*, 2013). This study used five-fold cross-validation to define training and test data sets used to fit the models and to enable evaluation of model performance using the Area Under the Curve (AUC) metric. An AUC value close to 1 represents excellent predictive power and 0.5 or less is considered no better than random (Syfert *et al.*, 2013). In addition, a visual comparison of areas projected by each model to contain suitable habitat was undertaken to identify differences (Elith *et al.*, 2011).

Long-footed potoroo Field Survey

Study Location

The study area was located in South-East Forests National Park (SEFNP), south-east New South Wales (NSW), and across four sites in north-east Victoria: Errinundra National Park (NP), Arte Flora Reserve, Bemm State Forest (SF) and Murrungower SF, within the box 148”40’0”E and 149”37’0”E and 36”51’0”S and 37”40’0”S (Figure 3). The SEFNP is 115,499ha, consisting of several sections that are mostly joined to form a narrow park with a very long perimeter (National Parks and Wildlife Services (N.P.W.S.), 2006). NSW survey sites were located on seven vegetation classes, including South East Dry Sclerophyll Forests, Southern Hinterland Dry Sclerophyll Forests, Southern Escarpment Wet Sclerophyll Forests and South Coast Wet Sclerophyll (Office of Environment and Heritage, 2012). Sites ranged from being open, dry sclerophyll forests, with varying understorey and groundstorey species, to wet sclerophyll with a more rainforest understorey (Figure 4). In contrast, the vegetation across Errinundra NP and Murrungower SF is dominated by tall, wet eucalypt forests, with Errinundra NP protecting the largest contiguous area of Cool Temperate Rainforest in Victoria (Parks Victoria, 2016). Several survey sites in this study are located in, or close to, well studied areas, such as the Bellbird Grid, for which an area description can be found in Green *et al.* (1998). Elevation across sites ranged from 170m to 1144m a.s.l. Both National Parks are bounded predominantly by areas of State Forest and private agricultural land-holdings.

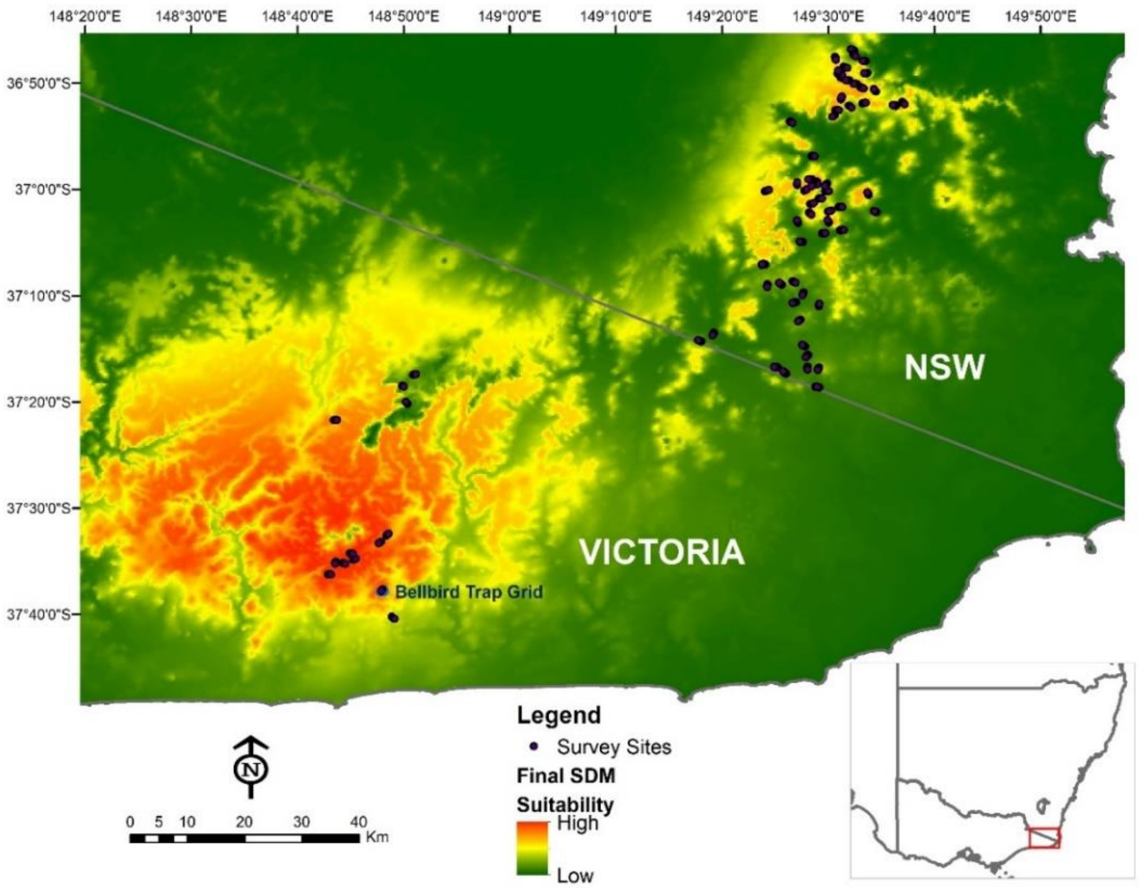

Figure 3: Map of study area. 2016/2017 field survey sites (dark circles) are located across the habitat suitability gradient predicted by the Maxent pre-survey model.

Figure 4: Sites surveyed for the long-footed potoroo in New South Wales and Victoria ranged from being open, dry sclerophyll forests, with varied understorey and groundstorey species including various Acacia sp., Persoonia linearis, Leucopogon lanceolatus, Lomandra longifolia, Ghania sp., Dianella sp,. Pteridium sp., and Hibbertia sp. *(e.g. site 30, 24, 37, 49, 55, 29), to wet sclerophyll, with understorey characterised by* Bedfordia arborescens, Dicksonia antartica, Olearia argophylla and Pomaderris sp*. and various groundstorey ferns (e.g.* Blechnam sp.*) (e.g. sites 5,54). Dominant eucalypt species across all sites included* Eucalyptus cypellocarpa, E. sieberi, E. obliqua, E. fastigata, E. dives, E radiata and E. viminalis*.*

Site Selection

Survey sites in NSW and Victoria were selected using a random stratified sampling approach based upon the Maxent output of the pre-survey model. To ensure sites were stratified across the predicted habitat suitability (HS) gradient, model output was arranged into four climate suitability bands that were loosely based upon the range of predicted SDM HS values at known long-footed potoroo locations:

a) Low: 0-0.13 (unsuitable) (i.e. equal sensitivity and specificity binary threshold)
b) Low-Moderate: 0.131 to 0.61 (worse than the 50^{th} percentile of known records)
c) Moderate: 0.611 to 0.89 (better than the 50^{th} percentile of known records)
d) High: >0.891 (better than known occurrences)

In NSW, 58 field sites were surveyed across the predicted HS gradient for camera surveys and microhabitat assessments. Sites were randomly located on moderate topography, within 40-100m of the nearest access track, and (mostly) within SEFNP boundaries. In NSW, there were no sites in the 'High' HS value. There was roughly equal coverage of sites across the three HS value bands present in NSW (Moderate: n = 15; Moderate-Low: n = 23; Low: n = 20) (Figure 3 and see SM 5 for detailed maps). Selection of areas with moderate slope and proximity to tracks enabled reduced effort to access sites and increased the number of sites sampled. As the long-footed potoroo's range has been estimated to be between 22-100ha, sites were located a minimum of 1km apart to ensure independence (Green et al., 1998; pers. comm. Andy Murray, DELWP, 1 December 2016). In Victoria, 13 sites, situated across the HS gradient were selected for microhabitat assessments only (High: n=4, Moderate: n = 3; Moderate-Low: n = 4; Low: n = 2). Most sites were within 1km of a long-footed potoroo occurrence record, at least 30m from the nearest road, at least 1km from other sites, and within either National Park or State Forest. Overall, sites were generally located in areas that had not been logged or exposed to fire for greater than 25 years, giving sufficient time for forest succession to occur and deliver greater habitat complexity (Coops and Catling, 2000). Exceptions, encompassing all sites in NSW and Victoria, were seven sites and two sites in locations that had been exposed to fire or logging for less than 25 years, respectively.

NSW LFP Survey: Camera Trapping

Due to the likely low population density and patchy distribution of the long-footed potoroo in NSW, individuals may be difficult to detect using traditional survey methods, e.g. live trapping and hair tubing. As such, camera trapping is likely the most effective survey technique (Scroggie, Henry and Lumsden, 2011). Camera trapping has seen an exponential uptake in wildlife research and monitoring both in Australia and overseas (Claridge, Paull and Barry, 2010, Meek, Ballard, Vernes *et al.*, 2015). It is considered a preferred survey technique as it is less invasive, enables remote monitoring for prolonged periods and is more cost effective (De Bondi, White, Stevens *et al.*, 2010, Paull, Claridge and Cunningham, 2012). Further, multiple studies have found camera surveys to be more effective than other survey techniques (Driessen and Jarman, 2015, Paull *et al.*, 2012, Welbourne, MacGregor, Paull *et al.*, 2015), and recent camera trapping in Victoria has been highly successful for detecting the long-footed potoroo (pers. comm. Andy Murray, 1 December 2016, and Marc Perri, 6 December 2016).

Camera surveys in NSW took place across six field trips between April 2016 to May 2017. Up to 10 sites were completed every trip and at each site between six to eight baited cameras were deployed along a 500m transect, 100m apart. Cameras were mounted on a tree (40-80cm above-ground depending on site topography) at a distance of 1.5-2m from the bait station and left in-situ for up to 63 days (Claridge *et al.*, 2010, Taylor, Goldingay and Lindsay, 2014) (Figure 5). This extended deployment time, which is more than double the recommended number of days required to give rise to 95% detectability (Scroggie *et al.*, 2011), was considered necessary to maximise detection probability in NSW. Baits contained either peanut butter and oats (fieldtrip 1) or only peanut butter (fieldtrips 2 to 6) and were suspended approximately 20 to 30cm above the ground (Claridge, Paull and Cunningham, 2016, Paull, Claridge and Barry, 2011).

Two types of passive infrared (PIR) cameras were used: Reconyx Hyperfire HC600 (hereafter “Reconyx”) and Scoutguard DTC-530V (hereafter “Scoutguard”). A mix of both camera types were consistently placed along transects. The infrared motion detection trigger settings for each camera were: i) Reconyx: “High” sensitivity, 5 images per trigger event, 1 second delay between triggers and 1 minute quiet period; ii) Scoutguard: “High” sensitivity, 3 images per trigger, 5M resolution (highest resolution setting) and 1 minute quiet period. Camera images were reviewed by myself and Office of Environment and Heritage (OEH) experts. Data on species occurrences will be incorporated into the NSW BioNet: the Atlas of NSW Wildlife.

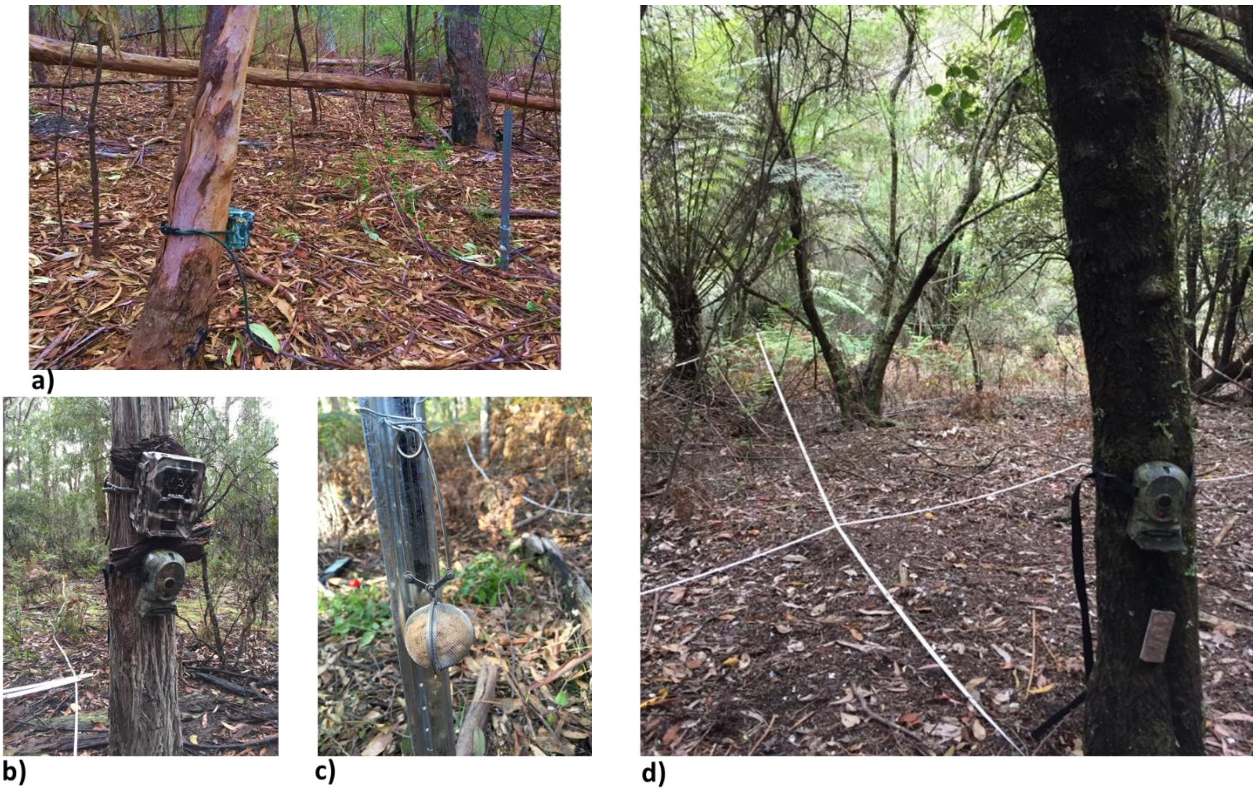

Figure 5: Photo of a) camera set up and bait station; b) double camera set-up; c) bait station; d) microhabitat 20mx20m plot set up.

Microhabitat assessments

Microhabitat data was collected at both NSW and Victorian sites. At three locations along a transect (approx. 200m apart), microhabitat features were measured within a 20 x 20m plot (Figure 5d) using a modified form of the habitat complexity method developed by Newsome and Catling (1979). The method typically involves assigning habitat complexity scores based on field estimates of percentage cover of five habitat attributes, then assigning these attributes a score of 0–3 and tallying the resultant scores to derive an overall “habitat complexity score” (Catling and Burt, 1995, Catling, Coops and Burt, 2001). Therefore, lower tallied scores (4-5) are “*indicative of lower habitat complexity (poor structure, few understorey shrubs and little groundcover),* whereas anything above 9 is considered *“high habitat complexity (thick understorey, good ground and litter cover)”* (Coops and Catling, 2000). Studies applying this methodology have found that there is a positive significant relationship between habitat complexity scores and potoroo abundance (Catling *et al.*, 2001) as well as abundance of other small mammals (e.g. brown antechinus (*Antechinus stuarrtii*), dusky antechinus (*Antechinus swainsonii*), and bush rat (*Rattus fuscipes*) (Catling and Burt, 1995)).

For this study, the five microhabitat attributes of the Habitat Complexity Score were measured (Table 3). However, original values for data gathered on each attribute was maintained for data analysis purposes (i.e. there was no conversion to a “complexity score”). With respect to understorey and groundstorey cover measures, two approaches were initially trialled: i) whiteboard cover % (Robley, Woodford, Lindeman et al., 2013), whereby a photo was taken of vegetation against a 1.7 x1m whiteboard and the percentage cover was computed using HabitApp software (Scrufster, 2016); and ii) pole intercept touches (Nipperess, Beattie, Faith et al., 2012). A comparison of these measures found them to be significantly, positively correlated (Pearsons $r = 0.77$; $P<0.001$) (SM 6). Consequently, the pole intercept method was used on future fieldtrips as it was less difficult to implement in the field. For one site, number 26, a site revisit to obtain raw pole intercept data was not possible due to time constraints. As such, interpolated intercept values, based upon a linear regression model, were calculated.

Table 3: Explanatory variables used to investigate the relationship between SDM predicted values and microhabitat features.

Variable Name	Description
Upper canopy cover (% cover)	Cover was estimated via a visual assessment at 5 locations within each 20x20m plot. HabitApp software (Scrufster, 2016) was used to calculate the percentage cover using a photo of the canopy and a smart device as a coverage measurement tool. Using an image of the canopy, HabitApp converts the pixels to black and white and the percentage cover is calculated from the number of black pixels in the resulting image.
Understorey cover (Total # intercept points)	A relative measure of density was calculated as follows: at 20 locations within each plot, the number of plants touching against a 1.17m pole (above 30cm to the top of the pole) were tallied.
Groundstorey cover (Total # intercept points)	A relative measure of density was calculated as follows: at 20 locations within each plot, the number of plants touching against a 1.17m pole from the ground 0cm to 30cm marker on the pole were tallied.
Groundcover Type (% cover)	Every 2m, along the two 20m tape measures, one of five ground cover types at that point was recorded: forbs/grasses, rock, bare ground, leaf litter, or logs. The total percentage for each category was calculated.
Soil moisture (%)	A soil moisture probe (MPM-160) was used to measure soil moisture (millivolts and %) at 5 locations within each 20mx20m plot, and average soil moisture values were calculated.
Leaf litter depth (cm)	The leaf litter depth was measured using a ruler at 5 locations within each plot and average values were calculated.

Data Analysis

Relating model predictions to field survey findings

Modelling species' distributions is an iterative process and models can be assessed and recalibrated as new information, e.g. new presence and absence data, becomes available. To determine whether the SDM accurately predicts the presence of the long-footed potoroo, the approach applied used long-footed potoroo presence/absence datasets that were independent of those data used in the pre-survey Maxent model that guided the current field survey. The datasets were: i) absence data generated from the current NSW field survey (n=58), and presence data associated with the Victorian microhabitat field sites (n=13 sites, of which nine sites were within 1km of an occurrence record and, of these nine sites, six sites were within 1km of an "independent record" i.e. not utilised in the pre-survey Maxent model); ii) presence data from Victorian camera trap surveys conducted during 2012-2016 (n=91), but not incorporated in the Victorian Biodiversity Atlas at the time of Maxent modelling (data courtesy of Marc Perri, DELWP, 6 December 2016); and iii) absence data from Victorian camera trap surveys conducted in 2012 (n= 128) (data courtesy of Jenny Nelson, DELWP, 5 July 2017, refer to Lumsden *et al.* (2013) for further details on survey methodology).

Data analysis involved a comparison of the median values of predicted habitat suitability scores for absence and presence sites using all three independent datasets noted above. To evaluate whether there was a difference between these two groups a Kruskal-Wallis H Test was undertaken (Bennett, 1993) in Minitab® Statistical Software (Version 17) (Minitab Inc, 2014).

Relating model predictions to microhabitat

The microhabitat data gathered during the field survey were used to investigate whether the SDM predictions encompassed the species' preferred microhabitat characteristics. Prior to analysis, the microhabitat data gathered at the three assessment locations per transect were pooled and averaged to obtain a site-level value. Furthermore, analysis required evaluation of data points collected across a 10-month period. Most of the variables are unlikely to be significantly impacted by short-term temporal changes in environmental factors (e.g. daily weather). However, upper layer soil moisture conditions are primarily controlled by precipitation (Entekhabi and Rodriguez-Iturbe, 1994, Pan, Peters-Lidard and Sale, 2003). To enable comparison of soil moisture values across all study periods, an alternative variable "Soil moisture residual" was calculated to account for rainfall impacts close to, or during, the study periods. This alternative variable is the difference between: i) actual soil moisture values and ii) soil moisture values predicted by a simple linear regression model of soil moisture based upon total rainfall (mm) 14 days prior to surveying (SM 7). Rainfall data was obtained from rain stations located nearby and/or at similar elevation to survey locations (NSW: Cathcart (Mt Darragh), Bombala (Therry St), Eden (Timbillica); Victoria: Goongerah, Club Terrace and Cabbage Tree Creek, sourced from Bureau of Meteorology's Climate Data, http://www.bom.gov.au/climate/data/ accessed on 1 April 2017).

Regression analyses of HS values with individual microhabitat variables was carried out in Minitab® Statistical Software (Version 17) (Minitab Inc, 2014) to identify whether SDM predicted "HS value" was a statistically significant predictor of the microhabitat feature. In addition, to test whether there were significant differences in microhabitat variables in sites where the long-footed potoroo is present versus absent, a one-way ANOSIM (Analysis of Similarities) was computed in Past (v3.14) (Hammer, Harper and Ryan, 2001) with Euclidean distances of microhabitat variables and a one-tailed significance test computed by permutation of group membership, with 9,999 replicates. An ANOSIM can determine whether there is a significant difference between two or more groups using a distance-based measure (Clarke, 1993). The output is the test statistic R, whereby a large positive R (up to 1) signifies distinct groups (i.e. dissimilarity between groups), and values close to 0 suggest there are no well-defined groups, i.e. close to random (Hammer, 2016). As the microhabitat data are in different units, data were transformed using the normalising equation (x_i-$\bar{x}$/ σ) prior to analyses.

Model Refinement

Species Distribution Modelling (Post Field Survey)

i) Binary Logistic Regression

Binary logistic regression modelling was carried out to investigate the extent to which climate suitability in combination with additional variables, such as microhabitat, disturbance and connectivity, predicts the presence of the long-footed potoroo. These additional variables are ecologically important and hence it is worthwhile investigating their statistical significance for predicting long-footed potoroo presence (see SM 8 for a list of variables and data sources and SM 9 for raw data).

Binary logistic regression models were carried out in Minitab® Statistical Software (Version 17) (Minitab Inc, 2014), using default settings (i.e. logit link function). Models were derived using two datasets: i) “current survey” dataset that incorporated data associated with sites from the current survey (i.e. presence sites in Victoria within 1km of an occurrence record (n=9) and absence sites (n=58)) and utilised the full suite of variables outlined in SM 8 and SM 9; and ii) an “extended” dataset that incorporated presence sites (n=100) and absence sites (n=186) associated with the current field survey data, as well as the newly acquired Victorian presence and absence data (refer to datasets noted under *“Relating model predictions to field survey findings*”). With respect to the ‘extended’ data, as microhabitat surveys were not conducted across all these locations, only a subset of variables (climate suitability, connectivity, and disturbance (time since fire / time since logging)) were able to be analysed in the models.

Ideally correlation between variables should be minimised in additive models. Therefore, prior to modelling, a Principle Component Analysis (PCA) and *Pearsons r* correlation analysis were computed using Past (v3.15) to aid initial variable selection. A principal components analysis (PCA) finds hypothetical variables (components) accounting for as much of the variance in a multivariate dataset as possible (Davis and Sampson, 1986). A PCA can also be used to reduce the data set to fewer, e.g. two variables, for plotting purposes (Hammer, 2016). A PCA can aid identification of microhabitat variables that are driving the variability across the dataset, identify highly correlated variables, and provide an overall measure of variability. Additionally, binary fitted line plots were carried out for each variable in Minitab® Statistical Software (Version 17) (Minitab Inc, 2014) to evaluate fit. Several variables, e.g. rock, log, bare ground percentage cover variables, had poor fit. Therefore, ARCSINE transformations of these select variables was conducted prior to inclusion in the logistic model.

Following initial variable selection, logistic models were evaluated using forward stepwise selection procedures, applying α=0.25 for variable entry and compared using Adjusted-R^2 and Akaike Information Criterion (AIC). The AIC is a measure of the amount of information lost in an estimating model, effectively measuring the trade-off between model complexity (number of variables) and model fit (precision) (Burnham and Anderson, 2003).

ii) Maxent

New observations may help to refine a species realised niche or aid removal of bias (Guisan et al., 2006). Data availability at the time of initial modelling meant that the NSW field survey was informed by presence-only modelling techniques and expert opinion. Updated 'post-survey' Maxent species distribution modelling was undertaken that incorporated the new occurrence records from Victoria spanning the period 2012-2016 (refer to presence datasets under: "Relating model predictions to field survey findings"). The same Maxent program, settings, background file and pre-survey model covariates, as noted previously, were applied. The post-survey model output was contrasted against the pre-survey model used to guide the survey using a difference map generated via the Raster Calculator function in ArcMap10.5.

RESULTS

Pre-Survey: Maxent Species Distribution Model

Models generated had average AUC values ranging from 0.953+/- 0.007 to 0.941 +/- 0.011, suggesting that changing the number of covariates did not greatly change predictive performance (Table 2). Based upon this evaluation, each of the modelled outcomes could be considered potentially useful (Phillips and Dudík, 2008).

The core areas of predicted high habitat suitability (HS) (red-orange pixels in the maps) were almost identical across models and aligned with areas containing the majority of long-footed potoroo occurrence records (Figure 6). However, differences in predicted HS emerged around the periphery of core areas and models with fewer, ecologically relevant, covariates had larger areas of relatively higher HS values (i.e. a greater area covered in yellow to red coloured pixels), with the pre-survey model appearing to have the most extensive areas of higher HS. This finding is consistent with overfitting concepts, whereby reducing the number of variables can enable the model to better generalise to the landscape (Beaumont, Hughes and Poulsen, 2005).

All model maps were discussed with experts and the pre-survey model map was determined to be the most biologically realistic. The pre-survey model included seven covariates: maximum temperature of warmest period, precipitation of the driest period, highest period radiation, lowest period radiation, lowest period moisture index, moisture index of highest quarter, moisture index of lowest quarter. These variables were based upon expert opinion and are considered ecologically relevant due to their ability to influence the species' primary limiting factor: fungi availability; in that hotter, drier conditions will likely affect soil and vegetation characteristics and the associated presence, diversity and abundance of hypogeal fungi (Claridge, Barry, Cork *et al.*, 2000). It is noted that this model included two highly correlated variables (BIOCLIM 30, 33), however, one variable (BIOCLIM 30) contributed almost nothing to the model. Although aspect and slope are ecologically important, these were found to have low variable importance in early model runs (SM 2, SM 3). Also, although the vegetation covariate (NVIS sub-categories) appeared to be important in early model runs (SM 2, SM 3), the predicted distributions of models with and without vegetation were visually very similar (Figure 6) suggesting that climate covariates are driving the prediction. Therefore, vegetation was not included in the pre-survey model.

The most important variables for the pre-survey model were moisture index of the lowest quarter (29.7%), maximum temperature of warmest period (24%) and moisture index of lowest quarter (19.9%) (SM 4). Also, covariate response curves indicated that the highest predicted HS values are in areas with higher moisture (SM 4).

The pre-survey Maxent model projects a large, contiguous area in Victoria to have the highest HS values, consistent with the locations of known populations (Figure 7). In comparison, there is relatively little area projected to be suitable in south-eastern NSW and, where higher HS areas do occur (yellow to dark orange areas), they appear patchy, indicative of more marginal habitat (Figure 7). In NSW, many of the areas projected to have higher HS are located at higher elevations and along the sides of ridgelines, on steeper slopes. Only 2 out of 34 known occurrence records in NSW are in higher HS areas: the remaining 32 records are located on flatter areas that are predicted to be low HS. There are, therefore, areas predicted to have relatively high HS that do not have any known occurrence records in NSW, for example, areas around Candelo Creek, Back Creek, Basin Creek, and Reedy Creek, providing numerous candidate locations for survey work. Other areas predicted to have high HS are within the SEFNP and State Forest areas, of which the latter is subject to active logging and is less likely to provide suitable habitat conditions. Areas adjacent to the coast that are considered by experts to be survey candidates, e.g. Nadgee Nature Reserve (pers. comm. Mike Saxon and Joss Bentley, 13 October 2015), were predicted to be relatively unsuitable.

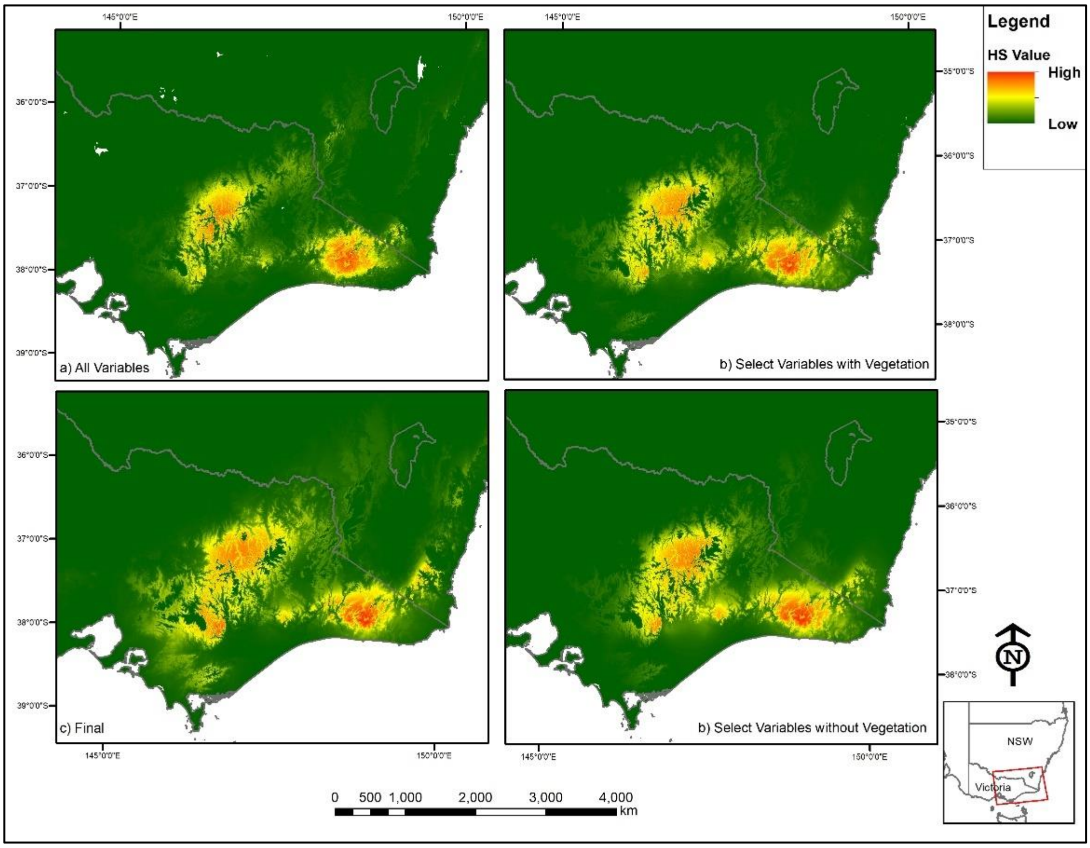

Figure 6: Maxent predictions for the four logistic models per Table 2: a) All variables; b) Select Variables A with vegetation; c) Final 'pre-survey' Model and d) Select Variables – No Vegetation. Warmer colours show areas predicted to have more suitable environmental conditions.

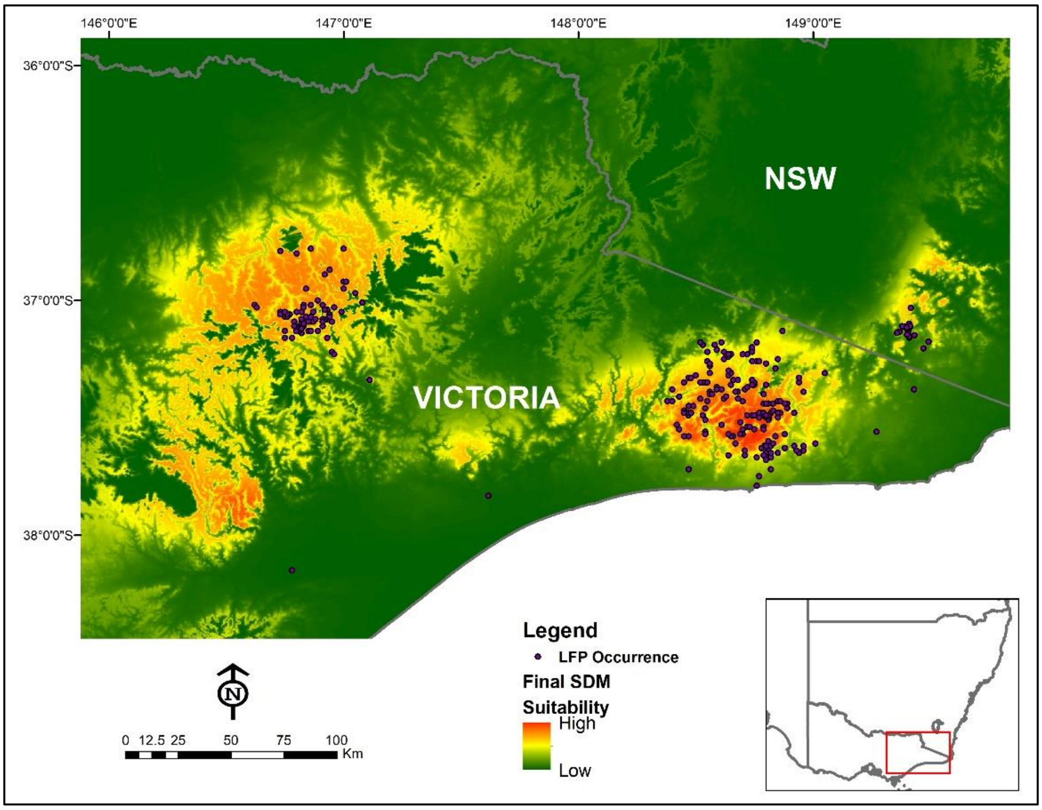

Figure 7: Map of Maxent predictions for the pre-survey model and long-footed potoroo occurrence records. Warmer colours show areas predicted to have more suitable environmental conditions. Core (red/orange) areas of high habitat suitability appear to closely intersect with existing occurrence records.

Camera Survey

A total of 215,759 images capturing 43 species from 58 transect sites (or 431 individual camera sites) were recorded during this study from 25,120 camera trap nights. Incorrect camera settings (e.g. time lapse / video) on four cameras (28.3, 29.3, 29.5, and 41.2) generated a large number of images (102,412), of which, only night images were reviewed in detail.

Fifteen native mammal species, 22 bird species and one reptile species were detected. Seven introduced mammal species were also detected. Two mammal species: long-nosed potoroo (*Potorous tridactylus*) and southern brown bandicoot (*Isoodon obesulus*) are listed as 'Vulnerable' and 'Endangered' (respectively) under the *Environment Protection and Biodiversity Conservation Act 1999*, and considered at risk from fox and cat predation. Of concern for native small- to medium -sized mammals is the dominance of foxes (*Vulpes vulpes*) and feral cats (*Felis catus*), detected across 28% and 43% of survey sites respectively. A full list of the species detected, the total number of sites occupied and a breakdown by the Maxent model suitability bands can be found in Table 4.

Table 4: List of Species Identified from Camera Traps

Species List	Total Number of Sites	% Sites	Moderate HS Band	Moderate-Low HS Band	Low HS Band
Australian magpie (*Cracticus tibicen*)	1	2%	0	0	1
Bassian thrush (*Zoothera lunulata*)	23	40%	8	11	4
Bushrat *(Rattus fuscipes)*	37	64%	13	14	10
Common brushtail possum *(Trichosurus vulpecula)*	39	67%	6	15	18
Common ringtail possum *(Pseudocheirus peregrinus)*	7	12%	3	3	1
Crimson rosella (*Platycercus elegans)*	1	2%	1	0	0
Dasyurid *(Antechinus sp.*)	37	64%	10	12	15
Dingo / Wild dog (*Canis lupis dingo)*	16	28%	4	5	7
Dusky woodswallow *(Artamus cyanopterus)*	1	2%	0	0	1
Eastern grey kangaroo *(Macropus giganteus)*	11	19%	0	4	7
Eastern pygmy-possum *(Cercartetus nanus)*	2	3%	1	0	1
Eastern whipbird *(Psophodes olivaceus)*	10	17%	5	2	3
Eastern yellow robin *(Eopsaltria australis)*	6	10%	1	3	2
Short-beaked echidna *(Tachyglossus aculeatus)*	32	55%	10	13	9
Grey currawong *(Strepera versicolor)*	14	24%	4	5	5
Grey shrike-thrush *(Colluricincla harmonica)*	21	36%	4	8	9
Lace monitor *(Varanus varius)*	14	24%	1	7	6
Laughing kookaburra *(Dacelo novaeguineae)*	5	9%	3	1	1
Long-nosed bandicoot *(Perameles nasuta)*	27	47%	9	10	8
Long-nosed potoroo *(Potorous tridactylus)**	3	5%	1	1	1
Mountain brushtail possum *(Trichosurus cunninghami)***	32	55%	11	15	6
Olive whistler *(Pachycephala olivacea)*	1	2%	1	0	0
Owlet nightjar *(Aegothelus cristatus)*	1	2%	0	0	1
Pied currawong *(Strepera graculina)*	13	22%	4	5	4
Red-necked wallaby *(Macropus rufogriseus)*	20	34%	0	9	11
Rufous fantail (*Rhipidura rufifrons*)	2	3%	2	0	0
Satin bowerbird *(Ptilonorhynchus violaceus)*	4	7%	1	0	3
Southern brown bandicoot *(Isoodon obesulus)**	5	9%	1	3	1
Spotted harrier *(Circus assimilis)*	1	2%	0	0	1
Spotted quail thrush *(Cinclosoma punctatum)*	10	17%	0	3	7
Superb fairy-wren *(Malurus cyaneus)*	1	2%	0	0	1
Superb lyrebird *(Menura novaehollandiae)*	53	91%	15	20	18
Swamp wallaby *(Wallabia bicolor)*	58	100%	15	23	20
White-browed scrub wren *(Sericornus frontalis)*	13	22%	5	5	3
White throated tree creeper *(Cormobates leucophaea)*	1	2%	0	1	0
White-winged chough *(Corcorax melanorhamphos)*	6	10%	0	3	3
Common wombat *(Vombatus ursinus)*	53	91%	15	20	18
Wonga pigeon *(Leucosarcia melanoleuca)*	15	26%	0	8	7
Introduced Species					
Cat *(Felis catus)*	25	43%	5	11	9
Deer (various sp including Fallow deer (*Cervus dama*), Javan Russa (*C. timoriensis*), Sambar (*C. unicolor*)	5	5%	1	1	3
Fox *(Vulpes vulpes)*	16	28%	3	8	5
Pig (*Sus scrofa*)	8	14%	0	3	5
Rabbit (*Oryctolagus cuniculus*)	7	12%	2	2	3

**Mammal species listed as threatened with extinction under the Environment Protection and Biodiversity Conservation Act 1999*

***The mountain brushtail possum (*Trichosurus cunninghami*) has been separately identified. However, it is noted that the relative distributions of the two brushtail possum species found in this area are not finalised. As such, although it is believed most of the mountain brushtail possums are likely to be* T. cunninghami, *they may be* T. caninus.

Despite these significant efforts, on the completion of the NSW field surveys in 2017, no new long-footed potoroo records were found. The survey sites in NSW with no new long-footed potoroo observations were deemed ‘absences’. This determination was considered appropriate as baited cameras were left in-situ for between 52 to 60 days, almost double the recommended trapping period to attain 95% detectability for the species (Scroggie *et al.*, 2011).

SDM Ground Validation: Relating model predictions to survey findings

The camera survey in this study generated 58 long-footed potoroo absence data points in NSW. In contrast, most of the 13 sites selected for microhabitat surveys in Victoria could be considered presence data points: nine sites were within 1km of a known LFP record, of which six were independent occurrence records, i.e. not included in the “Pre-Survey” model.

A comparison of the interquartile range and 95% confidence intervals (CI) of the median HS values at presence (n=97) and absence (n=186) locations highlights significant variability within groups and some overlap between groups (Figure 8). Furthermore, there are long-footed potoroo absences in areas that may be considered “suitable” when a binary threshold measure, e.g. equal sensitivity and specificity, is applied. Overall, however, the Kruskal-Wallis test of mean ranks revealed that there is a statistically significant difference between HS values at presence and absence locations (H=55.61, DF=1, P=0.000). This result suggests that the pre-survey Maxent model used to conduct the field survey can successfully distinguish between these two groups.

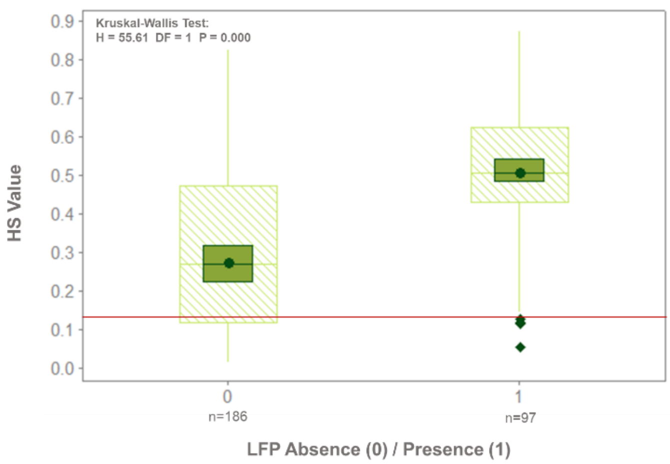

Figure 8: Boxplot of interquartile range (green diagonal lines) and 95% confidence interval (solid green) around median HS values at long-footed potoroo (LFP) presence (1) and absence (0) sites using all independent LFP data. The red line represents the pre-survey SDM “equal sensitivity and specificity” value (0.13), which is a binary (suitable /unsuitable) threshold.

SDM Ground Validation: Relating Model Predictions to Microhabitat

Linear regression analysis of Maxent predicted HS values against individual microhabitat variables identified statistically significant relationships for six out of the ten variables measured (Figure 9). Habitat suitability was found to be a positive predictor for canopy cover, leaf litter depth, understorey cover, soil moisture and log groundcover, and negatively related to grass cover. Although there is significant variability within each variable, these findings indicate that higher HS sites are more likely to have higher canopy, understorey and log cover, greater soil moisture and deeper leaf litter.

This result is consistent with the preferred micro-habitat requirements of this species. For instance, a preferred habitat feature of the long-footed potoroo is dense understorey cover, offering nesting sites and protection from predators (Scotts and Seebeck, 1989). Also, as hypogeal fungivores, sites with moist soils and higher canopy cover are likely to have greater fungal diversity and abundance (higher canopy cover could signal either a larger number of trees closer together or larger (older) trees, which is particularly relevant when these are species that form mycorrhizal relationships with fungi, e.g. *Eucalyptus* and *Acacia*, which were found to dominate many sites surveyed) (Claridge *et al.*, 2000, Green, Tory, Mitchell *et al.*, 1999). Additionally, leaf litter is considered an important foraging substrate for *Potorous* (Claridge and Barry, 2000).

Furthermore, the ANOSIM of all microhabitat variables at presence (n=9) vs absence (n=58) locations generated a statistically significant dissimilarity (R) value of 0.4345 (p(same) = 0.0002), indicating that microhabitat variables are not the same across all sites. This confirms that there are differences between sites where the long-footed potoroo is present as compared to where it is absent, suggesting that microhabitat characteristics are important to the long-footed potoroo.

Overall, these findings suggest that the Maxent model is a good predictor of select microhabitat features on the ground.

Figure 9: Linear regression analysis of predicted habitat suitability values against the six microhabitat variables with statistically significant relationships

Long-footed potoroo Model Refinement

Binary logistic regression

The selection of the variables for logistic regression was guided by a PCA and correlation analysis. A PCA on all site characteristics (i.e. microhabitat, logging and fire history, and connectivity) identified leaf litter depth (cm) as having the highest amount of variance and to be strongly correlated with Principle Component (PC) 1 (Figure 10), followed by connectivity and understorey cover. The PCA suggests that sites with higher understorey cover are better connected to other areas of higher HS, have high soil moisture, but little rock and bare ground. Furthermore, sites with high canopy cover also had high leaf litter cover (%) on the ground and little grass cover (%). Locations where long-footed potoroos were absent (NSW) were more likely to have higher grass, rock and bare ground coverage values than sites where there are known presence records (Victoria) (Figure 10). Principle component 1 may be analogous to an overall “microhabitat” variable. A linear regression analysis suggests that Maxent’s HS values are a statistically significant predictor of “microhabitat” ($t = 6.02$, $P = 0.00$). However, only 45% of the variance in the site characteristics data is explained by the first and second components, which suggests there is complexity in the dataset.

In a PCA of microhabitat variables only, PC1 and PC2 explain 51% of the variability, yet it effectively highlights microhabitat features driving the differences across sites surveyed (Figure 11). This PCA also captures the diversity of vegetation types and structures across sites and elucidates that sites located in Tantawangalo (the northern section of South East Forests NP) had the most similar microhabitat characteristics to those in Victoria (Figure 11).

The *Pearson’s r* correlation analysis identified six microhabitat variables to be significantly correlated ($p<0.05$) to HS values: canopy cover, understorey cover, soil moisture, leaf litter depth, grass cover and log ground cover. Grass cover, bare ground cover and time since logging were the only variables negatively correlated with HS values. This outcome is aligned with *a priori* expectations for grass and bare ground. With respect to time since logging, there is a weak negative correlation, suggesting that areas with higher climate (habitat) suitability were more recently logged. As the correlation is not significant, this result should be interpreted with care.

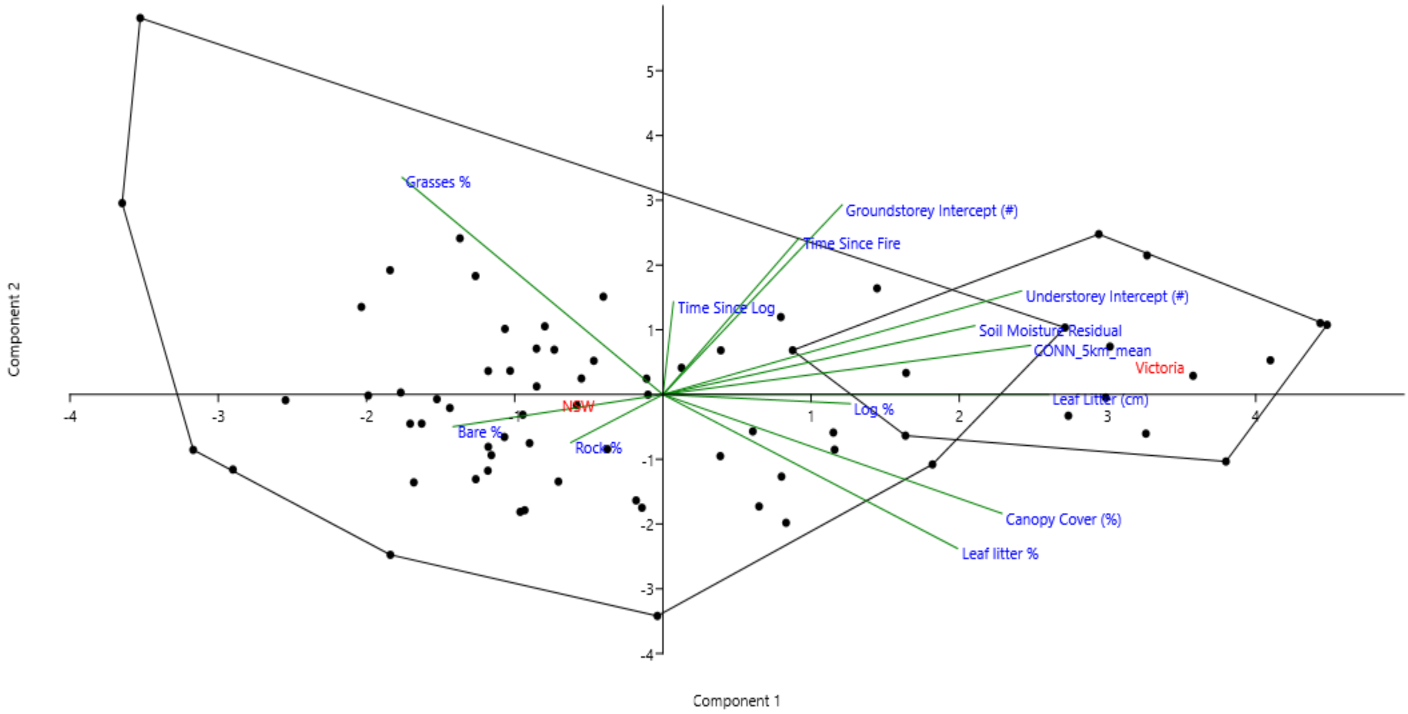

Figure 10: PCA analysis scatter plot for all logistic regression variables. PC1 and PC2 explain 45% of variance in all variables. Convex hulls (black lines) surround each group centroid (NSW and Victoria); whereby the 58 site locations in NSW correspond to absence sites based upon the current survey and the majority of sites in Victoria (9 out of 13 sites) are within 1km of a long-footed potoroo presence record.

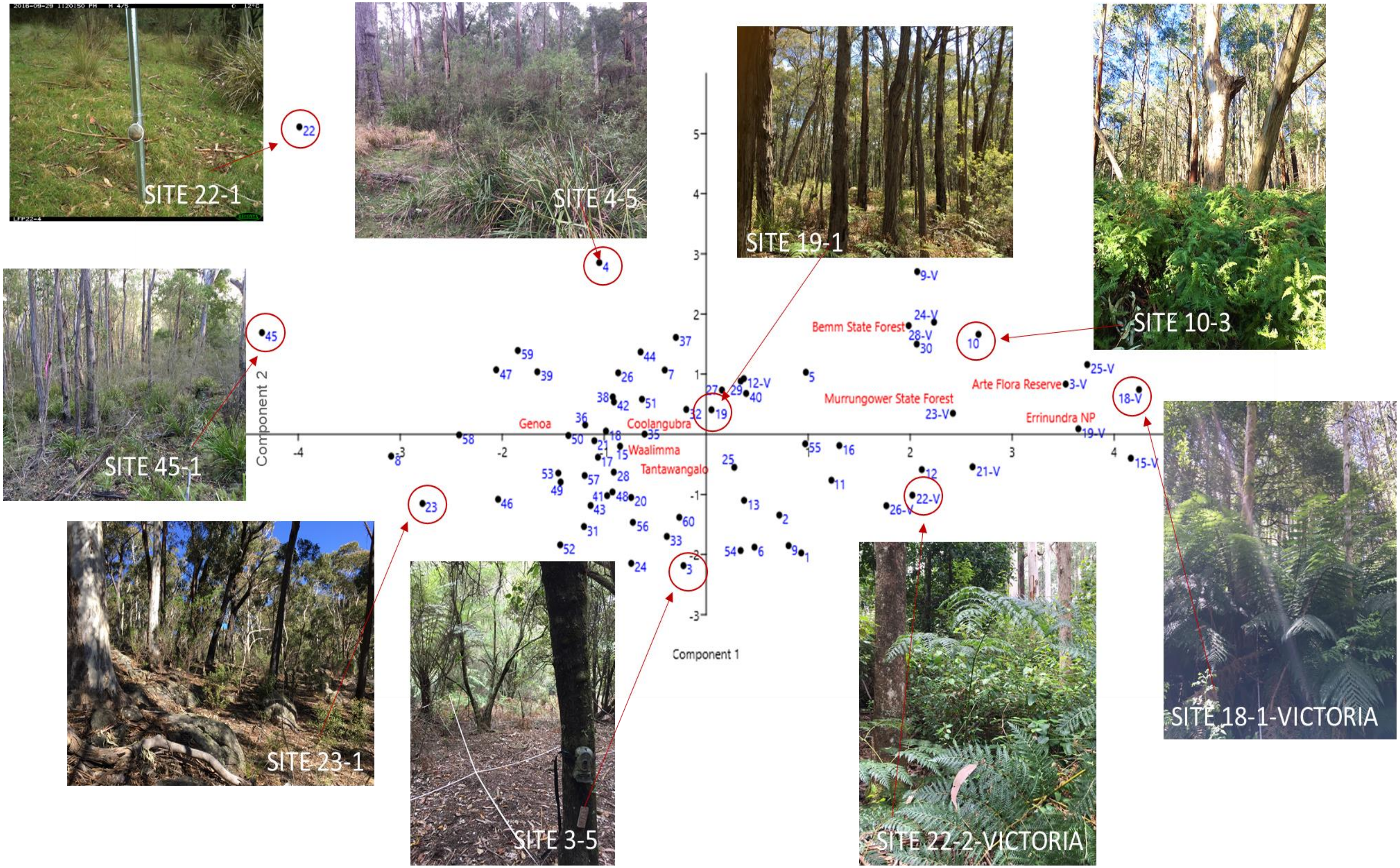

Figure 11: The PCA analysis results for microhabitat data only with images of individual sites spanning the spectrum of PC1 and PC2 values. The first two Principle Components explain 51% of the variance across microhabitat variables and effectively capture the diversity of key microhabitat features driving the variability between sites surveyed. Differences in vegetation and microhabitat at survey sites across NSW and Victoria are also highlighted. Centroids for general "area locations" of survey sites are noted in red.

Multiple binary logistic models were evaluated to identify which other factors, in combination with climate suitability (i.e. HS values), might contribute to predicting the probability of presence of the long-footed potoroo. The five models with the best fit and lowest AIC values are outlined in Table 5. The best overall model included three variables: connectivity (χ^2=5.51, P=0.019), understorey cover (χ^2=6.86, P=0.009) and soil moisture (χ^2=7.6, P=0.006). The probability of presence of the long-footed potoroo is predicted to increase as each of these variables increase. Models that included the connectivity variable were consistently found to outperform models that included climate suitability. Understorey cover and soil moisture were typically selected over other variables when included in a model, and were always statistically significant ($P<0.05$) predictors. Interestingly, when HS was included in a model in combination with understorey or soil moisture it was never selected, suggesting relatively weaker explanatory power.

It was not possible to fit a model that included both connectivity and HS value due to quasi-separation issues. This issue can, however, be resolved by collecting or incorporating more data. Although it was not possible to collect more microhabitat data, it was possible to use the 'extended' dataset to evaluate models with only HS, connectivity and disturbance values (n=186 absences and n=100 presences). A summary of the models evaluated is set out in Table 6. The best overall model included two variables: connectivity (χ^2=100.33, P=0.00) and time since logging (χ^2=25.19, P=0.00) Even when both HS and connectivity variables could be included, connectivity variable provided a better fit model. The disturbance variable, time since logging, was also consistently selected and is a statistically significant predictor in the models, however, time since fire was never selected.

Table 5: Summary of Models Using the 'Survey' Dataset

Model #	Independent Variables	Number of Parameters	Variables Selected / Statistically Significant (p<0.05)*	Adj. R^2 (%)	AIC	Regression Equation P(1) = exp(Y')/(1 + exp(Y')) Y'
1	Connectivity, Understorey, Soil Moisture	3	Connectivity*, Understorey*, Soil Moisture*	72.82	19.37	Y' = -14.54 + 0.0416 Understorey + 0.227 Soil Moisture + 18.3 Connectivity
2	Connectivity, Time Since Logging, Soil Moisture	3	Connectivity*, Time Since Logging*, Soil Moisture*	68.95	21.42	Y' = -1.42 + 20.43 Connectivity - 0.259 Time Since Logging + 0.328 Soil Moisture
3	Connectivity, Canopy, Time Since Fire, Understorey	4	Connectivty*, Canopy*, Understorey*	67.77	22.04	Y' = -23.48 + 18.24 Connectivity + 13.32 Canopy + 0.0522 Understorey
4	HS Value, Understorey, Soil Moisture Residual, Time Since Fire	4	Understorey*, Soil Moisture*	64.3	22.87	Y' = -6.92 + 0.0447 Understorey + 0.1887 Soil Moisture
5	HS Value, Leaf Litter Depth, Understorey, Time Since Logging, Grasses	5	Leaf Litter Depth*, Understorey*	62.28	23.94	Y' = -9.20 + 0.887 Leaf Litter Depth + 0.0413 Understorey

Table 6: Summary of Models using "Extended" presence/absence dataset

Model #	Independent Variables	Number of Parameters	Variables Selected / Statistically Significant (p<0.05)*	Adj. R^2 (%)	AIC	Regression Equation P(1) = exp(Y')/(1 + exp(Y')) Y'
1B	HS Values, Connectivity, Time Since Fire, Time Since Logging	4	Connectivity*, Time since logging*	32.95	252.24	Y' = -1.495-0.0857 Time Since Logging + 10.89 Connectivity
4B	Connectivity, Time Since Fire, Time Since Logging	3	Connectivity*, Time since logging*	32.95	252.24	Y' = -1.495 + 10.89 Connectivity - 0.0857 Time Since Logging
2B	HS Values, Connectivity	2	Connectivity*	26.41	275.43	Y' = -4.566 + 9.98 Connectivity
3B	HS Values, Time Since Fire, Time Since Logging	3	HS Values*, Time since logging*	22.71	290.13	Y' = -0.192 + 5.618 HS Values - 0.0685 Time Since Logging

Post-survey Maxent

Following the initial Maxent model used to guide surveys, additional presence records became available. As such, an updated ‘post survey’ Maxent model was fitted that incorporated an additional 54 long-footed potoroo presence records from Victoria spanning the period 2012-2016 that were not previously included, giving a total of 395 presence records. The post-survey model generated an average AUC value of 0.944+/-0.007, suggesting the modelled outcome is potentially useful (Phillips and Dudík, 2008). This AUC value is within the range of previous models and slightly higher than the pre-survey model used to direct the field survey. BIOCLIM variables Maximum Temperature of the Warmest Period (27.4%), Mean Moisture Index of the Lowest Quarter (22.2%), and Mean Moisture Index of the Highest Quarter (19.9%) were found to provide the greatest contribution to the model. The environmental variable with the highest regularised training gain when used in isolation was Lowest Period Moisture Index, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted was the Lowest Period Radiation, which therefore appears to have the most information that is not present in the other variables.

Comparing the post-survey Maxent model against the pre-survey model used for the current survey identifies several areas as being relatively more (red) or less (blue) suitable (Figure 12). In NSW, there are areas predicted to be relatively more suitable than in the earlier model run. It is unlikely that this would have given rise to significant changes to the selection of survey sites as, in general, areas with highest HS and that were accessible were targeted, and these areas continue to have high HS in the updated model. Of interest, however, is that the interior Genoa area, north of Sheep Station Creek, and the Nungatta Plateau area (adjacent to Nungatta Station) are predicted to be relatively more suitable (as indicated in Figure 12). These areas are relatively remote and difficult to access so were not targeted for the present survey. However, access to Nungatta Plateau and Nalbaugh Plateau via a helicopter was recently organised for OEH staff and camera surveys are now in progress (pers. comm. Joss Bentley, 29 May 2017). However, other nearby areas may also be worthwhile considering for future survey work.

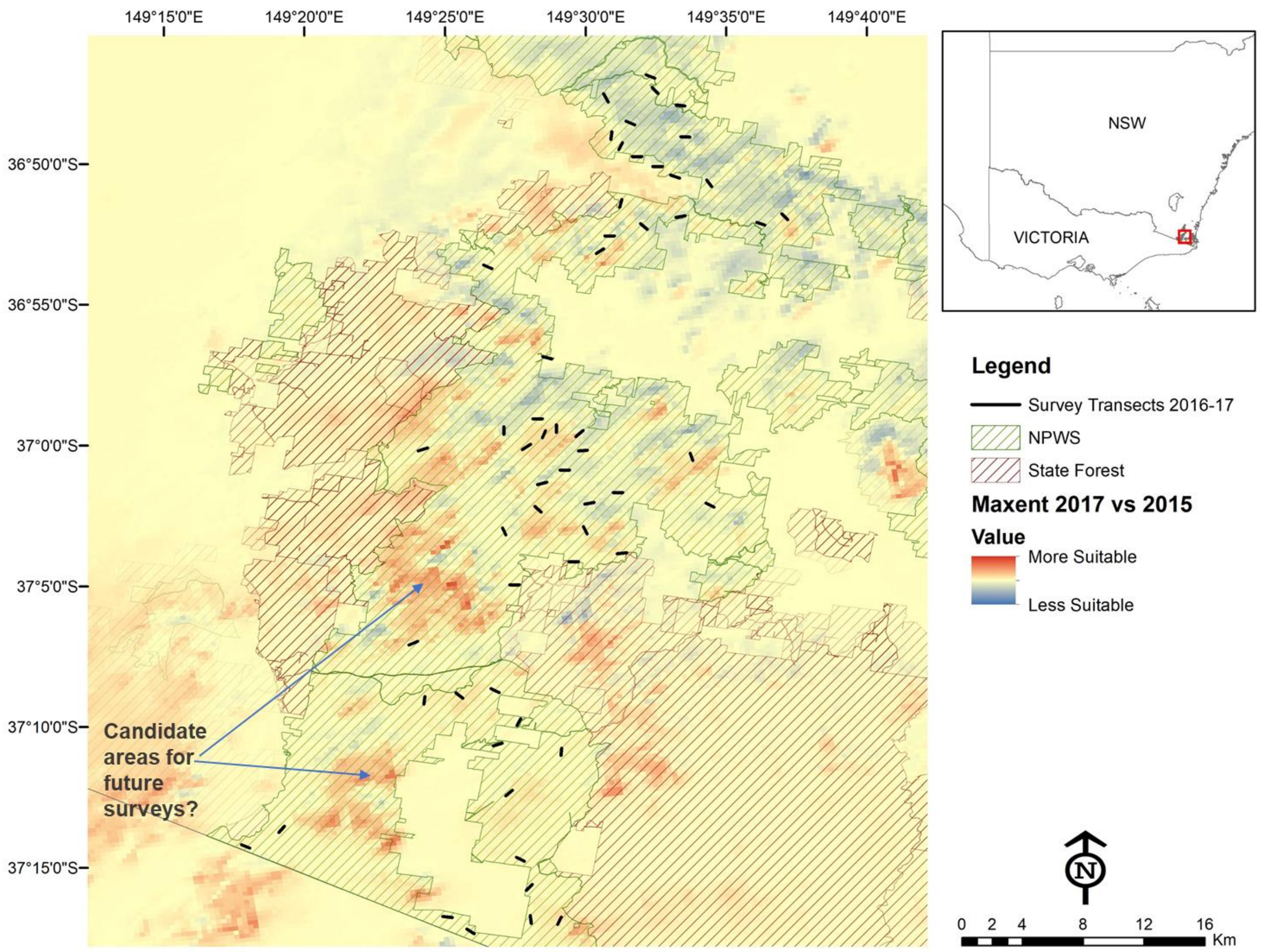

Figure 12: Map of NSW survey transect locations (short dashed lines) overlayed on a difference map of the post-survey Maxent model compared to the model used to guide the survey. Areas in red have higher HS values than the pre-survey model, whereas areas in blue were predicted to have lower HS values than the pre-survey model.

DISCUSSION

The case of the missing potoroo…

Identifying where species occur underpins many conservation management decisions (Guisan, Tingley, Baumgartner *et al.*, 2013) and the use of species distribution models to guide field surveys has proved promising for many species (Aizpurua *et al.*, 2015, Guisan *et al.*, 2006). However, following the completion of model-based field surveys, no long-footed potoroos were detected, despite the models receiving strong evaluation scores (AUC values, Table 2). As such, the distribution of this critically endangered species in NSW remains unclear, founded upon records collected during surveys conducted in the 1990s. Broadly speaking, this result may be due to the species: i) not being present at the sites that were selected for survey; or ii) being present but not detected.

Simply not there?

The survey results highlight that the species was not detected in any areas predicted to have relatively higher HS values, nor even from a wider range of areas that were considered suitable when a binary threshold was applied (Figure 8). Furthermore, the long-footed potoroo was not detected at sites with historical presence records nearby (< 1km). Possible explanations for the species absence at survey sites, include: unsuitable microhabitat, fluctuations in population dynamics, impact of disturbance events (e.g. fire and logging) and presence of introduced predators and competitors.

Microhabitat features are an important factor influencing the distribution of mycophagous mammals, including long-nosed potoroos (Bennett, 1993, Claridge and Barry, 2000, Vernes, 2003). The PCA (Figure 10) highlighted that sites in Victoria, many of which were located within 1km of a presence record, were found to have different microhabitat features to NSW survey sites. Also, microhabitat features, including soil moisture and understorey cover, were found to be statistically significant predictors of presence in binary logistic regression models. Furthermore, logistic regression models that incorporated microhabitat features had better fit than those that included only Maxent HS values and disturbance variables (Table 5,Table 6). Some caution must be born in mind when considering these results given the spatial clustering of presence and absence points.

The Maxent model was successful at identifying some microhabitat features (Figure 9). For instance, sites with higher HS values were more likely to have higher canopy cover, soil moisture, understorey cover, log groundcover and/or leaf litter depth and/or less grass cover, although there was significant variability across the microhabitat attributes. Further, as most sites were situated in areas with relatively lower HS values (particularly when contrasted with HS values in Victoria) it is possible that unsuitable microhabitat contributed to the non-detection of the long-footed potoroo. There were, however, sites where microhabitat appeared to be highly suitable, such as around Tantawangalo (SM 5) and in pockets of temperate rainforest (e.g. site 54). In these instances, it is possible that the long-footed potoroo is locally extinct, or was simply never there, particularly as many of these survey sites were not located close to a historical presence record.

Some sites in NSW may have suitable microhabitat but be unoccupied because either patch size is too small or located too far from known populations to be occupied. Greater connectivity increases species' dispersal capabilities and facilitates gene flow, which is essential for maintaining viable populations (Dixon, Oli, Wooten *et al.*, 2006, Gilbert-Norton, Wilson, Stevens *et al.*, 2010, Šálek, Kreisinger, Sedláček *et al.*, 2009). The areas predicted to be most suitable in NSW were small and patchy (Figure 3). For instance, the area in Tantawangalo with relatively higher predicted HS values was ~9.5km^2 in size and located ~10km from the next patch of suitable HS values at Wog Way, Coolungubra (~7.8km^2). Binary logistic regression models that incorporated a connectivity variable had consistently better fit than other models using HS values alone (Table 5). This suggests that sites that are both climatically suitable and connected to larger suitable patches are important in predicting the presence of the long-footed potoroo.

Habitat fragmentation is likely to further compound the poor connectivity of climatically suitable areas. There has been significant landuse change in the study area over time, with large areas of SEFNP bounded by pine plantations and pastoral lands. Habitat fragmentation disrupts ecological processes and restricts the movement of organisms thereby isolating subpopulations, which increases extinction risk (Gilbert-Norton *et al.*, 2010, Worboys and Pulsford, 2011). Together these factors may hinder the species' dispersal from known populations into NSW, with resulting negative impacts on local population dynamics. As such, poor connectivity of suitable habitat may have contributed to the non-detection of the species, and is an important consideration for future survey site selection.

The presence of feral pigs (*Sus scrofa*), another highly mycophagous species, is a key threatening process for the long-footed potoroo as both species compete directly for their food resource: hypogeal fungi (NPWS 2002). Also, the destructive feeding habits of feral pigs, primarily rooting disturbance, can damage and alter local ecosystems, e.g. reduced plant species richness, cover and regeneration (Barrios-Garcia and Ballari, 2012, Hone, 2002). The camera survey detected evidence of feral pigs at approximately 15% of survey sites. Furthermore, the long-footed potoroo is at risk of predation by foxes and cats, which were detected at nearly 50% of sites. These findings are of concern for the persistence of the long-footed potoroo and a possible factor contributing to its non-detection.

Disturbance events such as logging and fire may negatively impact the long-footed potoroo, for example, through reduced vegetation cover, increased risk of exposure to predators, direct mortality, and disrupted social structure and food availability (Department of Sustainability and Environment (DSE), 2009). In Victoria, surveys taken following the 2006-07 wildfires found that many sites where the long-footed potoroo was recorded were unburnt or experienced low-intensity burning (DSE, 2009). A fire regime encompasses multiple components including the frequency, intensity, seasonality, heterogeneity and size of fires over time (Penman, Christie, Andersen *et al.*, 2011). These components will have varying impacts upon the native vegetation, native fauna, pest species and abiotic factors where they occur. Most of the survey sites were situated in locations that had not experienced any fire or logging for more than 25 years. Data on fire history (i.e. time since fire) was incorporated into binary logistic regression models, and was not found to be a significant predictor of the species' presence. Yet as this data only captures one element of a fire regime, the inclusion of other elements may prove beneficial for fitting future models.

The study area also has a long history of logging. Many occurrence records are located in previously logged forests (including the long-term Bellbird study site), suggesting regrowth forests are utilised by the long-footed potoroo (DSE, 2009). However, long-footed potoroos inhabiting mature, multi-aged and old growth forest tend to forage for shorter periods, have smaller home ranges and are more fecund (Green and Mitchell, 1997, Green *et al.*, 1998). Although many survey sites were in areas that had not been logged for at least 25 years, evidence of past logging was frequently apparent, e.g. felled stumps, log debris covered in vines, large open spaces with dense bracken understoreys, 'matchstick' like regrowth in *E. sieberi* forested areas with minimal understorey. It is possible that the logging history of the area contributed to the species' non-detection via altered vegetation structure and microhabitat features. Time since logging was consistently selected as a statistically significant explanatory variable in the updated regression models (Table 5). However, it had a slight negative impact upon species presence, which is contrary to *a priori* expectations. This may be because of differences in logging data between states. The Victorian dataset represented over 100 years of logging history, however, the data were truncated to align its history with the shorter history of NSW data, potentially reducing "visibility" in the data of much older forests in Victoria. Gaining access to expanded logging datasets from NSW may be worthwhile investigating in future modelling.

Or a clever disappearing act?

It is possible that the long-footed potoroo remained hidden, defying detection in the field surveys due to its likely low population density in NSW. The present study tried to minimise this outcome by using best practice survey methodologies: camera trapping. Camera trapping has been widely used in field surveys for a variety of species, and has been particularly successful for detection of small- to medium-sized mammals, including the long-footed potoroo (Claridge *et al.*, 2010, Paull *et al.*, 2012, Smith and Coulson, 2012, Taylor *et al.*, 2014), and more successful than other methods (e.g. Elliot traps, cage traps and artificial traps) (Welbourne *et al.*, 2015).

The study design applied baited traps and extended deployment times (53 to 60 days), almost double the survey time required to attain 95% detectability for the species (Scroggie *et al.*, 2011) to maximise the chances of detection. Recent camera surveys for the species in Victoria utilised deployment times ranging between 21 days (Lumsden *et al.*, 2013) and 35 days (pers. comms. Andy Murray, 1 December 2016) and successfully recorded the species at 41 sites (out of 170) and 35 sites (out of 85), respectively. However, non-detection due to the survey method cannot be excluded as a factor that may have impacted the results.

Looking forward: ongoing model refinement

The success of a model based survey hinges upon the quality of the underlying SDM. Guisan *et al.* (2006) noted four elements that contribute to the success of a model: i) positional accuracy of species occurrence records; ii) inclusion of only ecologically relevant predictors that are expected to have a physiological effect on the species; iii) use of an appropriate model based on available data; and iv) generation of pseudo-absences from presence sites of other (rare) species when absence data are not available. These elements were considered during the development of the pre-survey Maxent model used to guide field surveys. Cross-validation AUC results (Table 2) suggested good predictive power for the pre-survey model.

The choice of relevant predictors and appropriate resolution for data used in a SDM may invoke a trade-off between using larger, accessible, datasets and spatial accuracy in describing a species-environment relationship (Le Lay *et al.*, 2010). The Maxent models in this paper applied a 250m resolution, thought to be appropriate for capturing the species' environmental-spatial variability and permitting the use of a range of available climate, vegetation and topographic data. The pre-survey Maxent model only incorporated ecologically relevant climate variables that operate over larger scales. Independent model validation found that the pre-survey model could i) successfully distinguish between presences and absences (Figure 8) and ii) identify trends in the long-footed potoroo's realised niche (Figure 9) However, there was significant variability within all datasets and, ultimately, the survey failed to detect the species.

It is possible that the use of climate variables as the sole predictor of suitability may have contributed to sampling failures. Hence, the inclusion of other ecologically important microhabitat features in future SDMs may enhance the ability to identify suitable habitats. Soil type is likely to play an important role in predicting the presence of the species, influencing vegetation type and soil moisture, both of which can impact fungal diversity and abundance. Quantitative soil data may be obtained from direct soil measurements e.g. Australian Classification Soil Type Map for NSW (available at http://data.environment.nsw.gov.au/dataset/australian-soil-classification-asc-soil-type-map-of-nsweaa10). However, these data are available at a high level ("order") and maps are not be available for all locations across NSW, likely due to the large cost and time-consuming nature of soil analyses. Another approach is to derive soil characteristics and composition (e.g. colour, clay mineralogy, organic matter content) from using visible–near infrared (vis–NIR) (400–2500 nm) and mid infrared (mid-IR) (2500–25,000 nm) diffuse reflectance spectra (Rossel and Chen, 2011).

Other structural attributes of the vegetation are also likely to be important. For instance, attributes of eucalypts (diameter at breast height and upper canopy cover) provide measures of potential availability of hosts for hypogeous fungi and, indirectly, the availability of carbohydrates for fungi, because fruiting of hypogeous fungi is related to supply of carbohydrates from hosts to fungi (Claridge *et al.*, 2000). Understorey cover and density is also considered an important feature of primary habitat, providing shelter, nesting sites and protection from predators (Scotts and Seebeck 1989; DSE 2009). Data on these structural attributes may be available by processing LiDAR (Light Detection and Ranging) data, which is acquired by active remote sensing utilising a laser scanning technique. LiDAR data can provide useful information on the spatial extent of habitat types and the vertical height and structure of vegetation, e.g. canopy structure, wood biomass, groundstorey density and the number and height of trees (Tattoni, Rizzolli and Pedrini, 2012). A recent study that incorporated LiDAR derived variables in SDMs found that these variables were: often selected and statistically significant predictors in regression models; improved AUC values of Maxent SDMs; and provided ease of interpretation from an ecological and management perspective (Tattoni *et al.*, 2012).

Incorporation of these variables may improve model performance, yet ultimately may still not be as good as site level variables. Updated SDMs reported in this paper support the incorporation of microhabitat variables operating at a finer scale (20m plots). Habitat features, such as soil moisture, understorey cover, canopy cover and leaf litter depth, in combination with climate suitability, were significant predictors of the long-footed potoroos' presence (Table 5). Furthermore, binary logistic models using the 'extended' dataset, with no microhabitat data, were a poorer fit than all models that used the smaller, 'survey' dataset (Table 5 and Table 6). Even proxies for microhabitat variables may not be as good as actual predictors. For instance, models run using extended datasets that included the 'time since logging" variable, which could be considered a proxy for forest age and vegetation structure, did not have higher fit values than those models using the microhabitat data. This suggests that site-level microhabitat is very important in predicting the presence of the long-footed potoroo. However, this could not be tested directly as microhabitat data for the 'extended' dataset was not available. Overall, future studies may consider using a finer scale resolution or combining models of different spatial scales. For instance, Le Lay *et al.* (2010) combined models at two resolutions: 50m and 1km, to successfully survey for a number of rare and common plant species.

Biotic interactions affect a species' realised niche and thus, are critical to the distribution of a species (Hutchinson, 1957). Fungal availability is likely to be a key limiting factor for the presence of the long-footed potoroo, and, consequently, competition for fungi food resources with feral pigs is a significant threatening process (Department of Sustainability and Environment (DSE), 2009). Bateman, VanDerWal, Williams *et al.* (2012b) outline an SDM approach for another mycophagous species, the northern bettong (*Bettongia tropica*), whereby a resource SDM and competitor SDM were generated. The predicted values from these models were incorporated into an SDM of the target species (i.e. climate + resource + competition variables). They found that incorporating resource related biotic interactions gave rise to models with stronger evaluation measures (AUC), than models utilising climate suitability alone (Bateman *et al.*, 2012b).

Modelled predictions in this paper were based upon long-term climate data (averaged over a 20-year period), producing a static representation of suitable habitat (Bateman, VanDerWal and Johnson, 2012a, Fancourt, Bateman, VanDerWal *et al.*, 2015). Recent studies suggest this may be a weakness when it comes to predicting species distributions, as long-term climate averages do not provide information on the full range of values an organism may experience through its life, or at key life stages crucial to fitness; nor can they capture the impact of short term extreme weather events on species' distribution and abundance (Bateman *et al.*, 2012a, Reside, VanDerWal, Kutt *et al.*, 2010). Weather SDMs have been proposed to provide information on temporal variations in the amount and distribution of climatically suitable space (Fancourt et al., 2015). Studies have found that these models are better able to define habitat suitability than climate models (Reside et al., 2010; Bateman et al., 2012). Seasonal differences in microhabitat use by long-footed potoroos have been detected, with more individuals caught more frequently in moister gully environments in drier spring and summer months, and in mid-slopes and lower slopes during wetter autumn and winter months (Scotts and Seebeck, 1989). As such, future studies investigating the use of weather SDMs may be worthwhile to determine if there are any changes to the extent and location of predicted suitable habitat over different time periods.

The modelling technique chosen is another factor influencing model quality. Studies have compared the success of multiple SDMs (Elith *et al.*, 2006, Elith and Graham, 2009). At this stage, there is no single "best" SDM that can be universally applied. Instead, the optimal choice should depend upon the species' specificities and existing data (Le Lay *et al.*, 2010). For this study, available data meant that the NSW field survey was informed by presence-only modelling techniques and expert opinion. Maxent was selected as it has become one of the most widely used techniques due to a number of factors, including its high predictive capacity, simplicity of use and effectiveness for guiding field surveys (Aizpurua *et al.*, 2015, Elith *et al.*, 2006, Fourcade *et al.*, 2014).

However, models incorporating both presence and absence data have been found to outperform presence-only techniques (Webb *et al.*, 2014). On the completion of the NSW field surveys in 2017, no new records were found and sites with no new long-footed potoroo observations could be deemed 'absences'. This determination may be considered appropriate due to the extended camera deployment period. Also, additional presence and absence data from camera surveys in Victoria from 2012-2016 were obtained after the initial field survey was underway. Thus, moving forward, it would be worthwhile investigating alternative modelling techniques to determine whether any additional areas of suitable habitat are identified that could be candidates for future surveys for the long-footed potoroo.

One possible approach would be regression based SDMs such as Generalised Linear Models (GLM) or Generalised Additive Models (GAM). GLM and GAM have a strong statistical foundation and are able to capture complex ecological relationships, which has resulted in their extensive use for modelling species' distributions (Elith *et al.*, 2006). Guisan, Edwards and Hastie (2002) provide a detailed overview of the use and application of GLM and GAMs, highlighting their use for modelling the distributions of a multitude of species. In GLMs the explanatory variables (i.e. parametric linear predictor) are related to the mean of the response variable (i.e. binary presence/absence) using a link function. As such, GLMs can handle a variety of distributions including Poisson, Binomial, Gaussian or Gamma. They can also incorporate transformations of explanatory variables e.g. quadratic, cubic terms (Guisan and Zimmermann, 2000). In contrast, GAMs fit linear functions using non-parametric smoothers independently to each predictor and additively calculate the component response (Elith *et al.*, 2006, Guisan and Zimmermann, 2000). Both types of regression model can also incorporate additional information on ecological processes, e.g. dispersal or connectivity (Guisan and Zimmermann, 2000).

Another approach is ensemble forecasting, which combines the predictions of multiple modelling techniques into a single projection (Araújo and New, 2007). Although the uptake of this approach has typically been in studies evaluating species' distributions under various climate change scenarios, it may prove to be a useful approach to guide fieldwork. For instance, Le Lay *et al.* (2010) used an ensemble forecasting approach, combining a presence-only and presence/absence model, to guide fieldwork for eight plant species. Sampling guided by the ensemble model was found to be more efficient than random sampling for six out of eight species and enabled the discovery of five new populations of a rare plant species. The ensemble model also had higher predictive accuracy than individual models (based upon AUC and weighted Kappa) (Le Lay *et al.*, 2010).

The benefits of ongoing model refinement are highlighted in the post-survey Maxent model (Figure 12). The inclusion of additional presence records from Victoria has identified several areas as being more suitable than previously predicted. These areas are relatively isolated and inaccessible, but worth considering for future survey work. Prior to conducting further field surveys in this area, the use of new data layers (LiDAR) or technologies, e.g. drones, to capture images of the microhabitat could be considered to identify suitable microhabitat features, ultimately aiding species detection.

In conclusion, the pre-survey Maxent model presented in this paper predicted a distribution that provided insights into a number of new potential survey locations for the long-footed potoroo in NSW. Ground validation of the model using an independent presence/absence dataset and microhabitat variables provided support for the predictive capabilities of the model. However, the field survey was unsuccessful. Model refinement suggests that additional factors, such as, microhabitat and connectivity are also important in predicting the presence of the species. If the long-footed potoroo is still present, it is likely to be extremely rare. Although an extensive survey was conducted, there are still large areas of SEFNP that were not surveyed, either due to time or their relative inaccessibility, as well as areas closer to the coast (e.g. Nadgee Nature Reserve) that may be worth surveying, particularly given recent findings of the species' in more coastal habitats in Victoria.

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SUPPLEMENTARY MATERIAL

SM 1: Summary of BIOCLIM Variables

Temperature Indices
BIOCLIM 1 Annual Mean Temperature
BIOCLIM 2 Mean Diurnal Range(Mean(period max-min))
BIOCLIM 3 Isothermality (P2/P7)
BIOCLIM 4 Temperature Seasonality (Coefficient of Variation)
BIOCLIM 5 Max Temperature of Warmest Period
BIOCLIM 6 Min Temperature of Coldest Period
BIOCLIM 7 Temperature Annual Range (P5-P6)
BIOCLIM 8 Mean Temperature of Wettest Quarter
BIOCLIM 9 Mean Temperature of Driest Quarter
BIOCLIM 10 Mean Temperature of Warmest Quarter
BIOCLIM 11 Mean Temperature of Coldest Quarter

Precipitation Indices
BIOCLIM 12 Annual Precipitation
BIOCLIM 13 Precipitation of Wettest Period
BIOCLIM 14 Precipitation of Driest Period
BIOCLIM 15 Precipitation Seasonality(Coefficient of Variation)
BIOCLIM 16 Precipitation of Wettest Quarter
BIOCLIM 17 Precipitation of Driest Quarter
BIOCLIM 18 Precipitation of Warmest Quarter
BIOCLIM 19 Precipitation of Coldest Quarter
BIOCLIM 20 Annual Mean Radiation

Radiation Indices
BIOCLIM 21 Highest Period Radiation
BIOCLIM 22 Lowest Period Radiation
BIOCLIM 23 Radiation Seasonality (Coefficient of Variation)
BIOCLIM 24 Radiation of Wettest Quarter
BIOCLIM 25 Radiation of Driest Quarter
BIOCLIM 26 Radiation of Warmest Quarter
BIOCLIM 27 Radiation of Coldest Quarter

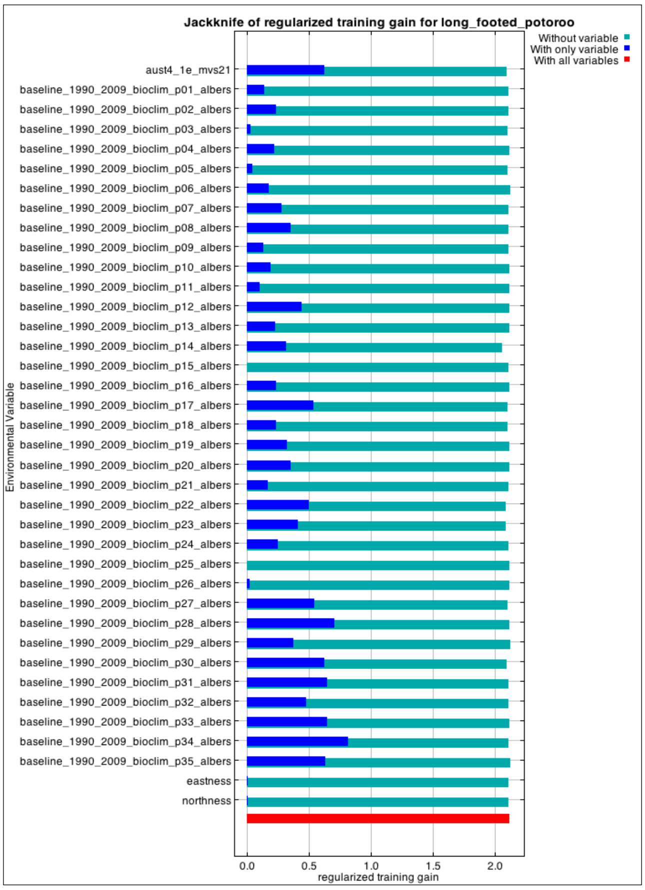
Moisture Indices
BIOCLIM 28 Annual Mean Moisture Index
BIOCLIM 29 Highest Period Moisture Index
BIOCLIM 30 Lowest Period Moisture Index
BIOCLIM 31 Moisture Index Seasonality (Coefficient of Variation)
BIOCLIM 32 Mean Moisture Index of Highest Quarter MI
BIOCLIM 33 Mean Moisture Index of Lowest Quarter MI
BIOCLIM 34 Mean Moisture Index of Warmest Quarter
BIOCLIM 35 Mean Moisture Index of Coldest Quarter

SM 2: Maxent ‘All Variables’ Model Data Output: Jackknife Analysis

The environmental variable with highest gain when used in isolation is Bioclim 34, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is Bioclim 14, which therefore appears to have the most information that isn't present in the other variables. Values shown are averages over replicate runs.

SM 3: Maxent ‘ALL variables’ Model: Variable Contribution Analysis

This table gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. Values shown are averages over 5 replicate runs. The variables with the greatest contribution to the model are Bioclim 34, Bioclim 5 and the NVIS Sub category.

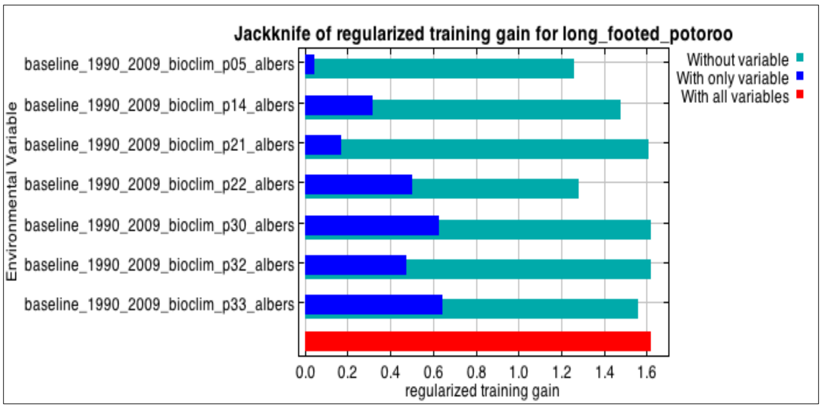


Variable	Percent contribution	Permutation importance
baseline_1990_2009_bioclim_p05_albers	15.8	5.5
baseline_1990_2009_bioclim_p34_albers	13.8	8.8
aust4_1e_mvs21	12.2	0.3
baseline_1990_2009_bioclim_p28_albers	9.7	9.8
baseline_1990_2009_bioclim_p35_albers	5	0.1
baseline_1990_2009_bioclim_p14_albers	4.5	4.8
baseline_1990_2009_bioclim_p09_albers	4.1	5.4
baseline_1990_2009_bioclim_p25_albers	3.7	1.3
baseline_1990_2009_bioclim_p23_albers	2.9	9.1
baseline_1990_2009_bioclim_p24_albers	2.7	2.2
baseline_1990_2009_bioclim_p03_albers	2.2	1.1
baseline_1990_2009_bioclim_p10_albers	2.2	0.2
baseline_1990_2009_bioclim_p29_albers	2.2	0.9
baseline_1990_2009_bioclim_p01_albers	2.1	0.5
baseline_1990_2009_bioclim_p32_albers	1.9	0.4
baseline_1990_2009_bioclim_p27_albers	1.5	1.1
baseline_1990_2009_bioclim_p22_albers	1.4	22.2
baseline_1990_2009_bioclim_p31_albers	1.3	3.8
baseline_1990_2009_bioclim_p08_albers	1.2	5.5
baseline_1990_2009_bioclim_p17_albers	1	11.1
baseline_1990_2009_bioclim_p07_albers	0.9	0.7
baseline_1990_2009_bioclim_p06_albers	0.9	0.1
baseline_1990_2009_bioclim_p30_albers	0.8	2.7
baseline_1990_2009_bioclim_p33_albers	0.8	0.1
baseline_1990_2009_bioclim_p26_albers	0.8	0
baseline_1990_2009_bioclim_p11_albers	0.7	0.1
baseline_1990_2009_bioclim_p18_albers	0.7	0.3
northness	0.5	0
baseline_1990_2009_bioclim_p02_albers	0.5	0.7
baseline_1990_2009_bioclim_p21_albers	0.4	0
baseline_1990_2009_bioclim_p12_albers	0.4	0.1
eastness	0.3	0.1
baseline_1990_2009_bioclim_p13_albers	0.3	0.2
baseline_1990_2009_bioclim_p19_albers	0.2	0.3
baseline_1990_2009_bioclim_p16_albers	0.2	0.1
baseline_1990_2009_bioclim_p20_albers	0.1	0.1
baseline_1990_2009_bioclim_p15_albers	0	0.2
baseline_1990_2009_bioclim_p04_albers	0	0

SM2: Jackknife analysis (left) / SM3: Variable Contribution Analysis (right)

SM 4: Maxent pre-survey Model

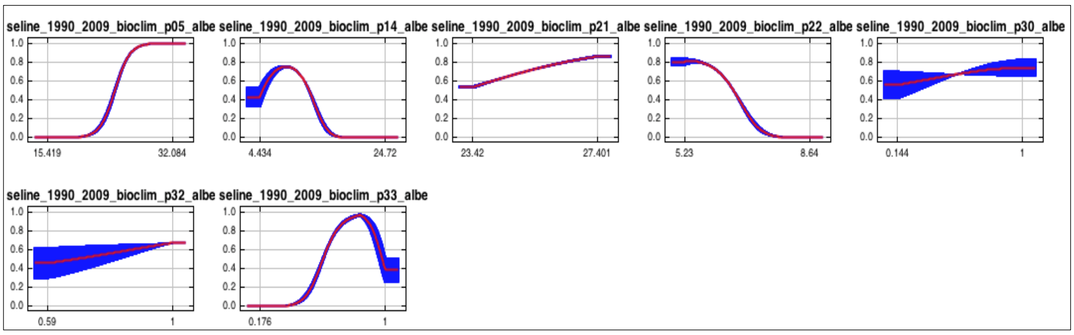
a) Jackknife analysis of variable importance. The environmental variable with highest gain when used in isolation is Bioclim 33, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is Bioclim 5, which therefore appears to have the most information that isn't present in the other variables. Values shown are averages over replicate runs.



b) Variable contribution analysis: The following table gives estimates of relative contributions of the environmental variables to the Maxent model. Bioclim 32 and Bioclim 5 make the greatest contribution to the model predictions.

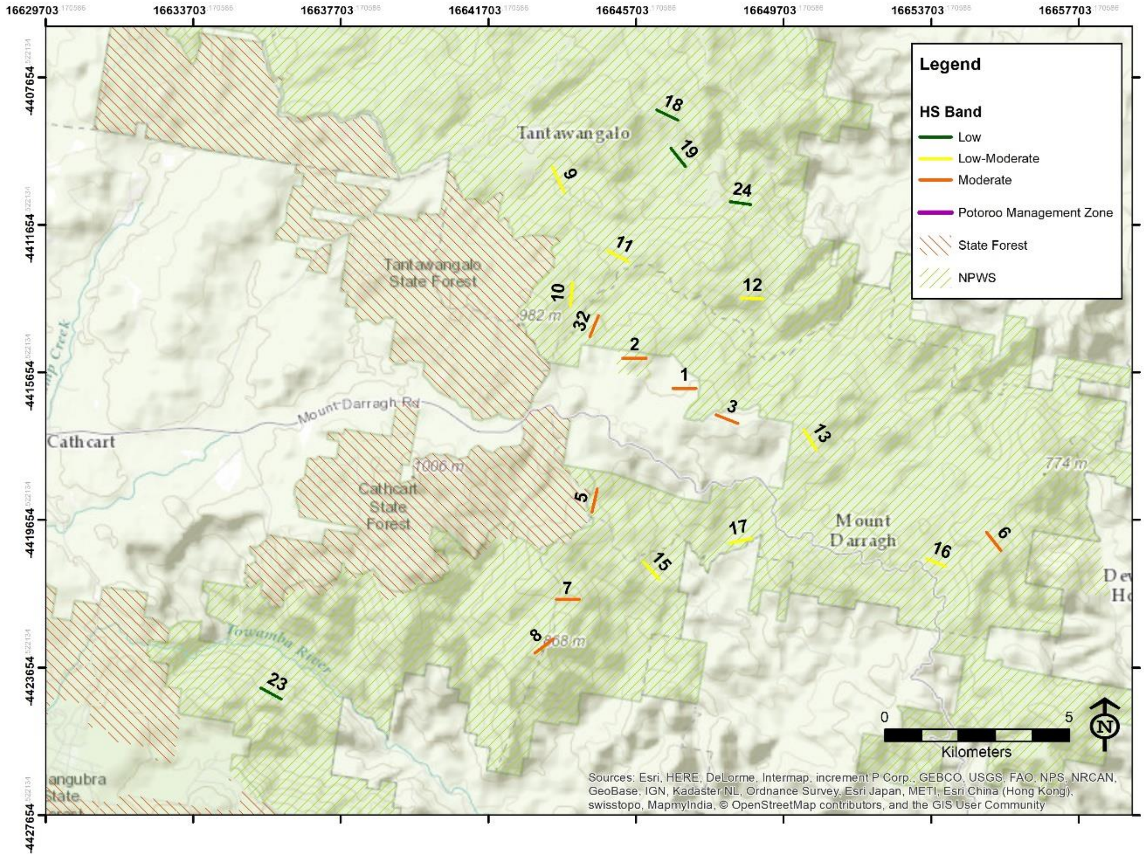
Variable	Percent contribution	Permutation importance
baseline_1990_2009_bioclim_p32_albers	29.7	0.1
baseline_1990_2009_bioclim_p05_albers	24	15.1
baseline_1990_2009_bioclim_p33_albers	19.9	43.3
baseline_1990_2009_bioclim_p14_albers	13.1	8.7
baseline_1990_2009_bioclim_p22_albers	11.5	31.6
baseline_1990_2009_bioclim_p30_albers	1	0.8
baseline_1990_2009_bioclim_p21_albers	0.8	0.4

c) Variable response curves for the Pre-survey model: The curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. The curves show the mean response of the 5 replicate runs. Response curves suggest that the highest predicted habitat suitability tends to be associated with higher moisture index values (see response curves for Bioclim 30, 32 and 33).

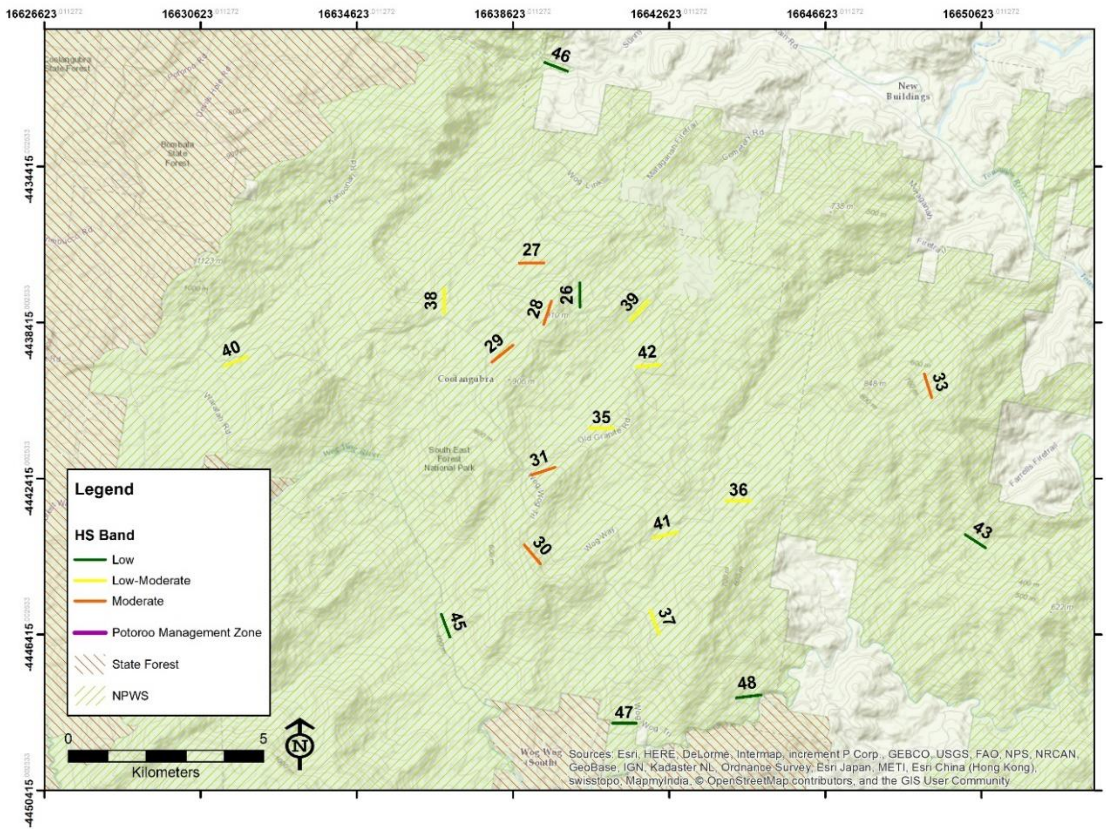


SM 5: Detailed Maps of NSW survey locations

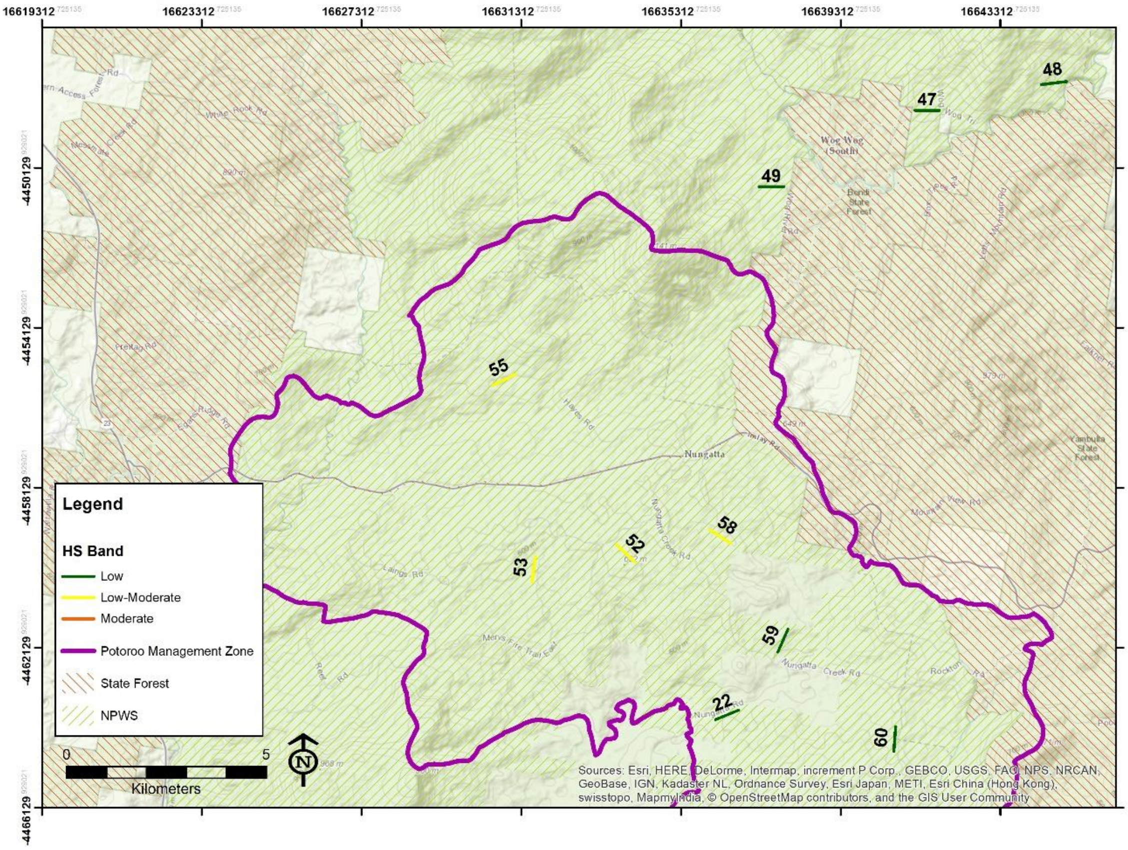
Long-footed potoroo Survey Sites 2016 - 2017: SEFNP - Tantawangalo



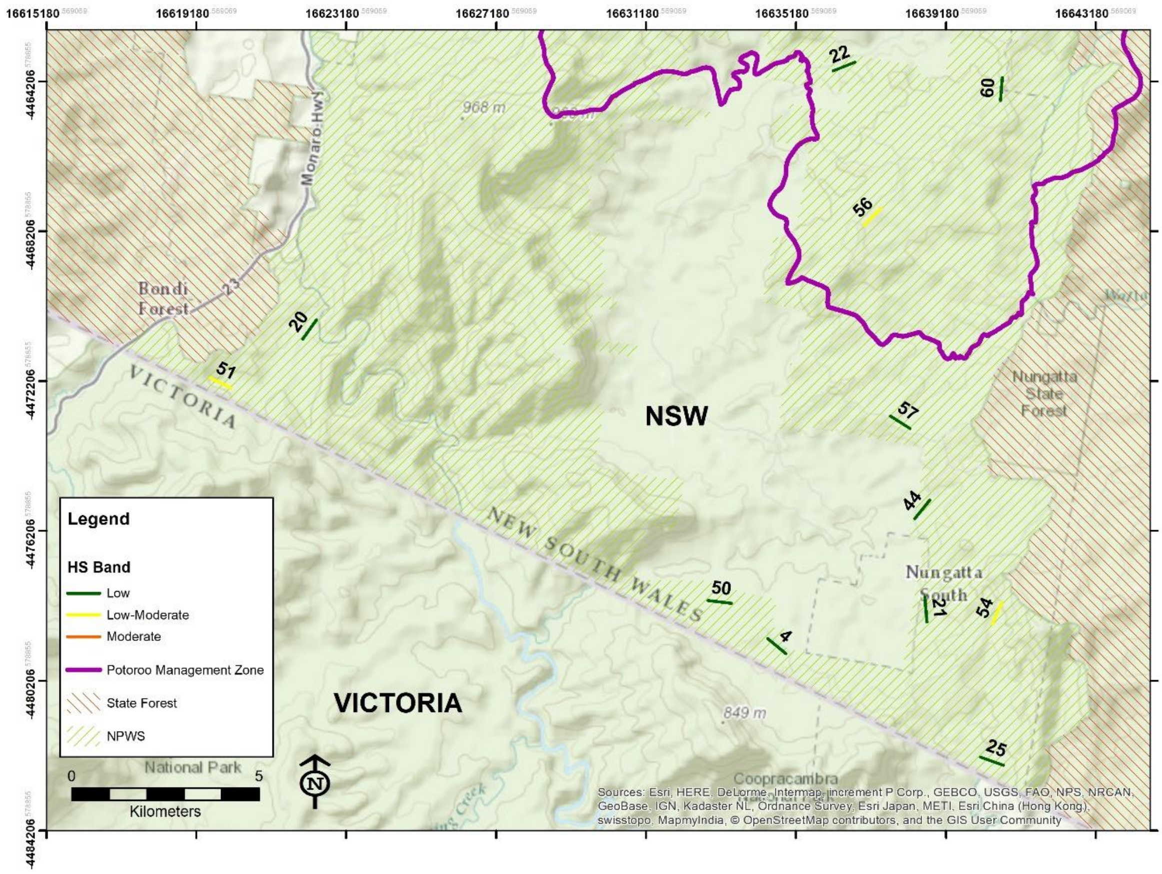
Long-footed potoroo Survey Sites 2016 - 2017: SEFNP - Coolangubra



Long-footed potoroo Survey Sites 2016 - 2017: SEFNP - Genoa



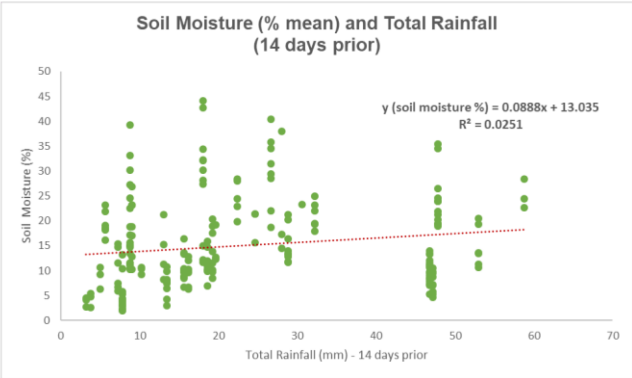
Long-footed potoroo Survey Sites 2016 - 2017: SEFNP - Waalimma



SM 6: Correlation analysis of Understorey and Groundstorey cover estimation methods

Correlation (corr/p(uncorr))	Understorey (Board %)	Understorey (Intercept Points)
Understorey (Board %)		3.79E-05
Understorey (Intercept Points)	0.77431	
Correlation (corr/p(uncorr))	Groundstorey (Board %)	Groundstorey (Intercept #points)
Groundstorey (Board %)		2.71E-05
Groundstorey (Intercept #points)	0.78305	

SM 7: Soil moisture regression model used as the basis for the "Soil moisture residual" variable calculation.



SM 8: Table Summarising Additional Variables considered in Model Refinement: binary logistic regression

Variable	Dataset Name	Data Summary and Source
Time Since Fire	"Time since fire" Data sources: NSW: "Fire_History_Export" VIC: "fire_history"	Time since fire was computed as the difference between i) survey year i.e. 2017 and either ii) date of last fire or iii) in the instance where there was no fire record, the date of oldest record in NSW i.e. 1951). Data Sources: Polygon of fire history data for SE Forest National Park. Oldest record = 1951 Source: NPWS Polygon of fire history data for all of Victoria. Oldest record = 1903 Source:https://www.data.vic.gov.au/data/dataset/fire-history-records-of-fires-primarily-on-public-land Copyright © The State of Victoria, Department of Environment, Land, Water & Planning 2017

Variable	Dataset Name	Data Summary and Source
Time Since Logging	Time since logging Data Sources: NSW:“FNSW_Compartments_Eden 1999_Export all” VIC:“LASTLOG25”	Time since logging was computed as the difference between i) survey year i.e. 2017 and either ii) date of last logging event **or** iii) in the instance where there was no logging event record, the date of oldest record in NSW i.e. 1972). Data Sources: Polygon of logging history data for SE Forest National Park. Oldest record =1972 Source: NPWS Polygon of logging history data for all of Victoria. Oldest record = 1954 Source=http://services.land.vic.gov.au/SpatialDatamart/viewMetadata.html?anzlicId=ANZVI0803002521&extractionProviderId=1 Copyright © The State of Victoria, Department of Environment, Land, Water & Planning 2017.
LFP Connectivity	Connectivity_5km_mean	CONN_5km: Connectivity values were calculated in ArcGIS10.2 using average Maxent predicted HS values within a 5km buffer placed around each study site. A buffered site with a higher mean HS is expected to be better connected and positively impact the long-footed potoroo’s probability of presence.

Microhabitat Variables	• Canopy cover (% cover)
	• Understorey cover (Total # intercept points)
	• Groundstorey cover (Total # intercept points)
	• Groundcover Types:
	  ➢ Leaf litter (% cover)
	  ➢ Rock (% cover)
	  ➢ Bare (% cover)
	  ➢ Log (% cover)
	  ➢ Grasses (% cover)
	• Soil moisture residual
	• Leaf litter depth (cm)
		Obtained during current survey in NSW and Victoria. Refer to microhabitat survey methodology.

SM 9: Raw Data: Aggregated Microhabitat Field Survey Data, Time Since Logging, Time Since Fire and Connectivity

Site #	State	HS Band	HS Value	Field Trip #	Area Name	Season	LFP Presence/ Absence Per 2016/17 Survey	Distance to nearest record (km) (Independent of Maxent / Any Record)	Canopy Cover (%)	Bare Groundcover (%)	Leaf litter Groundcover (%)	Rock Groundcover (%)	Log Groundcover (%)	Grasses Groundcover (%)	Soil moisture (MV)	Leaf Litter Depth (cm)	Understorey Cover (# Intercept)	Groundstorey Cover (# Intercept)	Time Since Fire (Years)	Time Since Logging (Years)	Rainfall Guage Location	Total Rainfall (mm) (14 days prior)	Soil moisture (%)	Predicted Soil Moisture	Soil Moisture Residual	Connectivity (5km Buffer - Average HS Value)
1	NSW	2	0.662988663	4	Tantawangalo	Spring	0	NA	76.40	3.33	86.67	0.00	8.33	1.67	320.20	2.88	31.33	19.00	29	44	Cathcart (Mt Darragh)	19.20	9.93	14.74	-4.81	0.4377798
2	NSW	2	0.644354006	2	Tantawangalo	Winter	0	NA	68.00	6.67	73.33	8.33	10.00	1.67	734.33	2.73	22.67	12.67	29	44	Cathcart (Mt Darragh)	8.80	32.31	13.82	18.49	0.4498567
3	NSW	2	0.663480322	4	Tantawangalo	Spring	0	NA	78.27	11.67	81.67	0.00	3.33	3.33	405.80	1.35	16.33	19.33	36	44	Cathcart (Mt Darragh)	19.20	14.21	14.74	-0.53	0.4259824
4	NSW	4	0.084437365	6	Waalimma	Autumn	0	NA	56.33	0.00	58.33	0.00	6.67	35.00	301.13	2.19	65.33	89.67	35	44	Eden	46.80	8.97	17.19	-8.22	0.1111589
5	NSW	2	0.661044657	2	Tantawangalo	Winter	0	NA	51.93	6.67	70.00	0.00	20.00	3.33	573.80	1.87	112.00	64.33	65	44	Cathcart (Mt Darragh)	9.00	22.92	13.83	9.09	0.4532456
6	NSW	2	0.625395676	5	Tantawangalo	Summer	0	NA	71.53	1.67	88.33	3.33	3.33	3.33	341.87	2.73	16.67	16.00	13	23	Cathcart (Mt Darragh)	7.20	12.29	13.67	-1.38	0.3137881
7	NSW	2	0.645378669	2	Tantawangalo	Winter	0	NA	64.47	5.00	56.67	13.33	5.00	20.00	409.47	3.73	56.00	54.67	11	44	Cathcart (Mt Darragh)	8.80	14.40	13.82	0.58	0.3434770
8	NSW	2	0.652180314	2	Tantawangalo	Winter	0	NA	55.87	20.00	35.00	33.33	5.00	6.67	378.33	1.63	38.33	31.33	4	44	Cathcart (Mt Darragh)	8.80	12.85	13.82	-0.97	0.2769157
9	NSW	3	0.444245666	5	Tantawangalo	Summer	0	NA	77.67	8.33	83.33	0.00	8.33	0.00	296.27	2.67	44.33	27.00	36	44	Cathcart (Mt Darragh)	5.00	8.75	13.48	-4.73	0.3594884
10	NSW	3	0.569702685	2	Tantawangalo	Winter	0	NA	68.93	6.67	71.67	3.33	15.00	3.33	511.47	4.43	154.00	90.00	36	44	Cathcart (Mt Darragh)	8.80	19.50	13.82	5.68	0.4411495
11	NSW	3	0.522070011	6	Tantawangalo	Autumn	0	NA	74.67	5.00	81.67	5.00	8.33	0.00	621.87	2.13	47.33	53.33	35	44	Cathcart (Mt Darragh)	58.80	25.18	18.26	6.92	0.3893027
12	NSW	3	0.383426994	4	Tantawangalo	Spring	0	NA	72.80	1.67	81.67	10.00	6.67	0.00	440.00	5.49	74.67	40.33	36	44	Cathcart (Mt Darragh)	13.00	15.93	14.19	1.74	0.3305199
13	NSW	3	0.58160001	2	Tantawangalo	Winter	0	NA	61.13	1.67	70.00	13.33	15.00	0.00	615.53	2.11	28.00	19.33	36	44	Cathcart (Mt Darragh)	8.87	24.83	13.82	11.01	0.3827315
15	NSW	3	0.527798335	2	Tantawangalo	Winter	0	NA	57.33	11.67	73.33	6.67	1.67	6.67	364.40	2.40	46.33	48.67	65	44	Cathcart (Mt Darragh)	8.80	12.17	13.82	-1.65	0.3861024
16	NSW	3	0.404509008	5	Tantawangalo	Summer	0	NA	67.80	0.00	88.33	0.00	3.33	8.33	286.87	3.66	100.33	41.33	48	37	Cathcart (Mt Darragh)	7.20	8.27	13.67	-5.41	0.3273161
17	NSW	3	0.342623999	2	Tantawangalo	Winter	0	NA	56.53	15.00	68.33	0.00	6.67	10.00	401.60	1.93	52.33	30.67	25	44	Cathcart (Mt Darragh)	9.00	15.41	13.83	1.58	0.4010779
18	NSW	4	0.099031501	4	Tantawangalo	Spring	0	NA	56.80	10.00	75.00	0.00	1.67	13.33	313.40	2.22	50.33	45.67	63	44	Cathcart (Mt Darragh)	13.40	9.63	14.22	-4.60	0.2681490
19	NSW	4	0.073218132	4	Tantawangalo	Spring	0	NA	60.13	5.00	73.33	0.00	10.00	11.67	266.53	3.00	52.67	59.33	36	44	Cathcart (Mt Darragh)	13.40	7.25	14.22	-6.98	0.2867986
20	NSW	4	0.048822834	5	Waalimma	Summer	0	NA	61.00	3.33	78.33	0.00	8.33	10.00	195.93	1.59	31.67	24.33	35	44	Eden	7.80	3.73	13.73	-10.00	0.1654888
21	NSW	4	0.093748669	6	Waalimma	Autumn	0	NA	50.13	3.33	80.00	0.00	5.00	11.67	342.53	1.77	12.33	46.67	39	44	Eden	46.80	11.05	17.19	-6.14	0.1176693
22	NSW	4	0.071202134	3	Genoa	Spring	0	NA	33.53	1.67	28.33	0.00	5.00	65.00	708.87	0.89	9.00	77.33	65	44	Eden	47.80	29.75	17.28	12.47	0.1307967
23	NSW	4	0.051056067	2	Tantawangalo	Winter	0	NA	50.13	16.67	53.33	15.00	6.67	8.33	344.87	1.60	16.00	6.33	15	44	Cathcart (Mt Darragh)	8.80	11.12	13.82	-2.70	0.2649204
24	NSW	4	0.095357602	4	Tantawangalo	Spring	0	NA	67.47	15.00	76.67	0.00	8.33	0.00	224.20	2.19	14.67	18.67	36	44	Cathcart (Mt Darragh)	13.27	5.14	14.21	-9.07	0.2768746
25	NSW	4	0.081444196	6	Waalimma	Autumn	0	NA	62.00	1.67	90.00	1.67	6.67	0.00	276.60	1.63	28.33	69.67	35	44	Eden	46.80	7.75	17.19	-9.44	0.1096330
26	NSW	2	0.636864682	1	Coolangubra	Autumn	0	NA	66.40	5.00	53.33	1.67	10.00	30.00	376.53	2.90	40.48	41.36	35	44	Bombala	15.60	12.75	14.42	-1.67	0.3161081
27	NSW	2	0.629986326	1	Coolangubra	Winter	0	NA	69.27	6.67	56.67	15.00	10.00	11.67	330.40	3.33	89.00	61.33	35	44	Bombala	16.20	10.51	14.47	-3.96	0.3256864
28	NSW	2	0.62898769	1	Coolangubra	Autumn	0	NA	67.60	3.33	51.67	28.33	6.67	10.00	347.25	3.97	8.00	26.33	35	44	Bombala	15.60	11.30	14.42	-3.13	0.3335335
29	NSW	2	0.628592332	1	Coolangubra	Autumn	0	NA	58.47	12.50	60.83	3.33	15.83	7.50	293.20	3.40	126.00	59.67	35	44	Bombala	15.60	8.56	14.42	-5.86	0.3661944
30	NSW	2	0.632524351	3	Coolangubra	Spring	0	NA	58.00	10.00	73.33	3.33	13.33	0.00	487.07	5.40	123.00	88.67	16	44	Bombala	28.80	18.27	15.59	2.68	0.2899736
31	NSW	2	0.63485835	3	Coolangubra	Spring	0	NA	52.27	11.67	71.67	5.00	8.33	3.33	382.07	2.80	13.33	6.33	36	44	Bombala	28.80	13.03	15.59	-2.57	0.3443511
32	NSW	2	0.622247994	4	Tantawangalo	Spring	0	NA	58.60	0.00	73.33	10.00	1.67	15.00	441.93	3.70	23.33	47.67	25	44	Cathcart (Mt Darragh)	19.20	16.02	14.74	1.28	0.4498524
33	NSW	2	0.616669993	5	Coolangubra	Summer	0	NA	56.33	0.00	95.00	0.00	1.67	3.33	206.47	2.35	6.67	18.67	30	44	Bombala	3.80	4.25	13.37	-9.13	0.1705395
35	NSW	3	0.390832335	4	Coolangubra	Summer	0	NA	62.20	3.33	65.00	0.00	15.00	16.67	279.67	1.96	41.67	39.33	36	38	Bombala	47.20	7.91	17.23	-9.32	0.3549568
36	NSW	3	0.163620333	1	Coolangubra	Winter	0	NA	63.73	10.00	58.33	0.00	10.00	21.67	318.00	2.43	32.00	35.00	36	44	Bombala	16.20	9.82	14.47	-4.65	0.2907823
37	NSW	3	0.344951659	3	Coolangubra	Spring	0	NA	50.47	6.67	63.33	0.00	13.33	16.67	494.80	1.53	87.33	63.67	36	44	Bombala	28.00	23.23	15.52	7.71	0.2311603
38	NSW	3	0.439296335	4	Coolangubra	Summer	0	NA	49.67	11.67	66.67	1.67	8.33	11.67	314.33	1.33	160.00	35.33	35	44	Bombala	47.20	9.64	17.23	-7.59	0.3843829
39	NSW	3	0.265493006	1	Coolangubra	Winter	0	NA	59.20	3.33	55.00	6.67	8.33	26.67	365.33	1.33	26.00	51.33	65	44	Bombala	18.60	12.19	14.69	-2.50	0.3198927
40	NSW	3	0.533188005	6	Coolangubra	Autumn	0	NA	67.33	1.67	75.00	3.33	3.33	16.67	510.87	2.78	48.00	60.00	65	44	Bombala	24.60	19.47	15.22	4.25	0.4351392
41	NSW	3	0.276001662	1	Coolangubra	Winter	0	NA	63.27	6.67	63.33	0.00	15.00	15.00	289.73	2.33	6.00	12.33	36	44	Bombala	15.80	8.41	14.44	-6.02	0.2822377
42	NSW	3	0.357470999	4	Coolangubra	Summer	0	NA	56.20	5.00	70.00	3.33	5.00	16.67	226.67	2.36	80.00	48.00	36	37	Bombala	47.20	5.26	17.23	-11.97	0.3599315
43	NSW	4	0.047079667	5	Coolangubra	Summer	0	NA	60.07	8.33	75.00	0.00	8.33	8.33	196.60	1.27	34.00	23.33	19	44	Bombala	3.20	3.75	13.32	-9.57	0.1492999
44	NSW	4	0.088701333	6	Waalimma	Autumn	0	NA	61.87	5.00	71.67	0.00	0.00	23.33	361.33	2.33	65.00	71.67	35	44	Eden	46.80	11.99	17.19	-5.20	0.1106533
45	NSW	4	0.0786021	1	Coolangubra	Winter	0	NA	43.40	16.67	40.00	0.00	0.00	43.33	373.40	0.40	62.33	19.67	65	44	Bombala	18.60	12.63	14.69	-2.06	0.3077074
46	NSW	4	0.0181399	2	Coolangubra	Winter	0	NA	47.07	11.67	73.33	0.00	5.00	10.00	323.53	1.47	15.33	10.67	65	44	Bombala	10.20	10.11	13.94	-3.83	0.1933784
47	NSW	4	0.073555534	1	Genoa	Winter	0	NA	64.47	3.33	53.33	0.00	3.33	40.00	307.13	1.77	35.33	29.33	65	44	Bombala	18.60	9.27	14.69	-5.41	0.2159713
48	NSW	4	0.064225967	1	Genoa	Winter	0	NA	67.60	5.00	65.00	13.33	6.67	10.00	415.75	0.97	51.33	19.00	36	44	Bombala	19.60	14.72	14.78	-0.05	0.1940897
49	NSW	4	0.076605501	3	Genoa	Spring	0	NA	55.20	11.67	68.33	0.00	5.00	15.00	393.60	3.10	10.33	11.33	49	44	Bombala	28.80	13.61	15.59	-1.98	0.2448459
50	NSW	4	0.073465432	6	Waalimma	Autumn	0	NA	63.20	6.67	66.67	0.00	6.67	20.00	306.93	1.67	14.00	44.00	35	44	Eden	46.80	9.28	17.19	-7.91	0.1050578
51	NSW	3	0.144174	5	Waalimma	Summer	0	NA	63.40	0.00	78.33	0.00	0.00	21.67	220.33	1.91	49.33	56.33	36	44	Eden	7.80	4.94	13.73	-8.79	0.1515976
52	NSW	3	0.268910666	3	Genoa	Spring	0	na / 0.462	56.20	13.33	78.33	0.00	6.67	1.67	377.60	1.14	9.67	16.33	34	25	Eden	53.00	12.77	17.74	-4.97	0.1691237
53	NSW	3	0.18346567	3	Genoa	Spring	0	na / 0.131	56.20	10.00	73.33	0.00	3.33	13.33	458.53	1.63	15.67	26.33	34	44	Eden	53.00	16.85	17.74	-0.89	0.1897003
54	NSW	3	0.173326328	5	Waalimma	Summer	0	NA	79.47	8.33	76.67	3.33	10.00	1.67	276.27	1.46	60.00	19.67	44	44	Eden	7.80	8.83	13.73	-4.89	0.1162536
55	NSW	3	0.24539266	6	Genoa	Autumn	0	na / 0	62.93	0.00	86.67	1.67	6.67	5.00	342.87	2.65	100.33	47.00	31	44	Eden	46.80	11.07	17.19	-6.12	0.2727977
56	NSW	3	0.21799167	5	Waalimma	Summer	0	na / 1.2	58.73	5.00	83.33	0.00	6.67	5.00	164.27	1.70	38.33	19.33	38	44	Eden	7.80	2.19	13.73	-11.54	0.1083799
57	NSW	4	0.090574366	5	Waalimma	Summer	0	NA	57.73	0.00	81.67	0.00	3.33	15.00	186.47	1.40	7.00	32.00	44	44	Eden	7.80	3.24	13.73	-10.49	0.1089886
58	NSW	3	0.167127669	3	Genoa	Spring	0	na/ 1.1	60.20	26.67	55.00	0.00	1.67	16.67	548.73	1.28	30.33	42.33	32	37	Eden	47.80	21.37	17.28	4.09	0.1652267
59	NSW	4	0.086846101	3	Genoa	Spring	0	NA	46.27	8.33	58.33	0.00	8.33	25.00	566.47	1.11	44.33	48.33	29	44	Eden	47.80	22.25	17.28	4.97	0.1609042
60	NSW	4	0.120483001	3	Genoa	Spring	0	na / 0.631	64.13	6.67	85.00	0.00	3.33	5.00	587.07	1.45	7.33	25.67	30	44	Eden	47.80	23.29	17.28	6.01	0.1839310
3-V	Victoria	1	0.902762502	5	Arte Flora Reserve	Summer	1	2.6/2.4	78.30	7.50	87.50	0.00	5.00	0.00	795.60	4.70	132.00	79.50	65	44	Cabbage Tree Creek	26.60	34.92	15.40	19.52	0.7879212
9-V	Victoria	2	0.73882101	5	Murrungower SF	Summer	1	2 / 0.684	67.73	0.00	75.00	0.00	1.67	23.33	585.40	4.80	151.00	83.33	49	44	Club Terrace	22.40	23.57	15.02	8.54	0.7564359
12-V	Victoria	2	0.673057	5	Errinundra NP	Summer	1	0/0	58.20	5.00	76.67	0.00	6.67	11.67	381.20	2.73	89.33	65.67	36	41	Goongerah	18.00	12.95	14.63	-1.68	0.6125211
15-V	Victoria	3	0.161689997	5	Errinundra NP	Summer	1	0.15/0.15	76.87	0.00	86.67	0.00	13.33	0.00	791.40	6.40	118.00	22.33	31	44	Goongerah	18.00	35.33	14.63	20.69	0.3657069
18-V	Victoria	4	0.119389666	5	Errinundra NP	Summer	1	0/0	71.40	6.67	80.00	0.00	13.33	0.00	797.33	7.40	158.67	45.33	65	42	Goongerah	18.00	34.99	14.63	20.36	0.2980281
19-V	Victoria	4	0.116217498	5	Errinundra NP	Summer	1	0.894/0.894	75.80	0.00	90.00	0.00	10.00	0.00	723.50	4.80	126.00	49.50	31	44	Goongerah	18.00	30.19	14.63	15.56	0.3332925
21-V	Victoria	1	0.898527662	5	Murrungower SF	Summer	1	1.8/1.8	77.47	0.00	80.00	0.00	20.00	0.00	668.40	2.27	83.00	44.67	65	44	Cabbage Tree Creek	26.60	28.24	15.40	12.84	0.8044410
22-V	Victoria	1	0.906401336	5	Murrungower SF	Summer	1	1.7/1.5	75.93	5.00	75.00	0.00	18.33	1.67	692.73	3.27	56.00	25.67	65	44	Cabbage Tree Creek	26.60	28.78	15.40	13.38	0.7801618
23-V	Victoria	3	0.786391338	5	Murrungower SF	Summer	1	2.8/0	72.73	8.33	80.00	1.67	8.33	1.67	529.20	3.87	168.67	52.00	65	44	Cabbage Tree Creek	5.60	20.38	13.53	6.85	0.6005761
24-V	Victoria	1	0.874915679	5	Murrungower SF	Summer	1	0.66/0.66	66.53	0.00	80.00	0.00	6.67	13.33	512.33	3.80	165.00	76.33	65	44	Cabbage Tree Creek	32.20	20.19	15.89	4.29	0.7962136
25-V	Victoria	2	0.744283656	5	Murrungower SF	Summer	1	2.2/0.59	71.47	1.67	91.67	0.00	3.33	3.33	628.33	5.13	219.33	59.00	58	44	Club Terrace	25.13	25.36	15.27	10.09	0.7606750
26-V	Victoria	1	0.896931668	5	Murrungower SF	Summer	1	1.6/1.6	77.67	5.00	85.00	0.00	8.33	1.67	563.60	3.63	47.00	34.00	65	44	Cabbage Tree Creek	32.20	22.11	15.89	6.21	0.8049361
28-V	Victoria	3	0.377955665	5	Bemm SF	Summer	1	0.138/0.138	58.93	1.67	80.00	0.00	5.00	13.33	495.93	5.60	121.67	71.00	4	24	Cabbage Tree Creek	5.60	18.60	13.53	5.07	0.4079711

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- Pianka, E. R. (1978). *Evolutionary ecology*. 2nd edn. New York: Harper & Row.
- Whitear, M. (1992). Solitary chemosensory cells. In *Fish chemoreception*: 103-125. Hara, T. J. (Ed.). London: Chapman & Hall.

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