A predictive habitat model for Koalas *Phascolarctos cinereus* in north-east New South Wales: Assessment and field validation

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Cover image: Brad Law

Executive summary

Predictive models of habitat suitability have great potential to efficiently direct management actions for threatened species, especially for those that are rare or cryptic. We developed a model at a 250 m resolution for the Koala *Phascolarctos cinereus* in north-eastern New South Wales using 'presence only' records and MaxEnt modelling. We reduced substantial spatial clustering of records in coastal urban areas using a 2 km spatial filter and by modelling separately two sub-regions divided by the 500 m elevational contour. We used an average of 1086 occurrence records to develop our models. A bias file was prepared that accounted for variable survey effort, including the concentration of Koala records along sealed and unsealed roads. A reduced set of 14 variables was used in model building. The models were evaluated using a test set of 25 % of the records, with a resulting good fit for each model, as measured by AUC (0.74-0.80). Most importantly, there was good discrimination by different habitat suitability classes when compared with Koala records not used in modelling. Frequency of wildfire, Australian Soil Classification, floristic mapping and elevation had the highest relative contribution to the model, whilst a number of other variables made minor contributions.

The combined MaxEnt model was ground-truthed at 65 sites using SongMeters to acoustically record the presence of Koalas in the mating season and via quantitative sampling of browse tree size and availability. Records of Koala bellows (n=276 bellows) were analysed in an occupancy modelling framework, while a site habitat quality index was constructed based on browse tree basal area and diversity. Koala bellows were recorded on 29 % of ground-truth sites compared to Koala pellets that were recorded on 17 % of sites (13 of 2,600 trees searched). Field validation of the continuous model output demonstrated a linear increase in estimated Koala occupancy with higher model output values. Similarly, the site habitat quality index was correlated positively with the model output. However, the model output provided a better fit to estimated Koala occupancy than the site-based habitat quality index, probably because many variables were considered simultaneously by the model rather than just browse species. We suggest that this provides strong evidence for using the MaxEnt model to guide management decisions for Koalas in forested habitat.

Introduction

Predictive models of species distributions are a useful management tool for guiding and informing on-ground management, especially for threatened species (Liu *et al.* 2013). There has been much progress in recent years in developing habitat suitability models using ever more sophisticated statistical techniques and data layers with higher resolution (Latif *et al.* 2015). MaxEnt is a powerful machine learning technique that models 'presence only' records with a validation procedure that leaves a portion of records aside for testing model goodness of fit (Elith *et al.* 2011). 'Presence only' modelling is particularly important for species where false absences are likely to occur due to the species being cryptic, having a low probability of detection or where sampling effort is not recorded. Such environmental niche models, alternatively known as species distribution models or hereafter predictive habitat suitability models, are based on the process of using computer algorithms to predict the distribution of species in geographic space using relationships between species records and environmental variables. The result is a map of predicted habitat suitability that should also correlate with likelihood of occurrence given the MaxEnt relationship is developed from species records.

The Koala *Phascolarctos cinereus* is a vulnerable, iconic Australian species where a reliable, spatially explicit predictive model would benefit management (Sequeira *et al.* 2014). The species is listed as Vulnerable both federally and in NSW. It occurs in varying population densities across a broad range of forest types in NSW, Queensland, Victoria and South Australia. North-east NSW is considered to be a hot-spot for Koalas, but populations face a range of threats (Lunney *et al.* 2002; McAlpine *et al*. 2015). Being an obligate folivore, it is typically associated with particular forest types that provide primary browse species (Phillips *et al.* 2000; DECC 2008). However, certain tree species may be frequently browsed in one area and less so in another, probably because of differences in site productivity or because the availability of more desirable tree species varies (Phillips and Callaghan 2000; Crowther *et al.* 2009). Indeed, site productivity is well known to be an important driver of Koala habitat suitability (Moore *et al.* 2010). Mapping of Koala habitat based on relationships between Koala surveys and vegetation has proved successful at local scales (Callaghan *et al.* 2011). However, modelling of Koala habitat suitability over extensive areas by relying solely on vegetation mapping may provide unreliable predictions in areas where Koalas have not been surveyed, especially given the influence of site productivity on Koala occurrence. Other factors are also important, such as landscape context, patch size, fragmentation, connectivity and roads as well as the presence of individual preferred *Eucalyptus* species (McAlpine *et al*. 2006; McAlpine *et al*. 2008; Rhodes *et al*. 2008). Local landscape features are likely to be of most importance in rural areas where Koala habitat is now fragmented.

Recently, approaches that use a variety of data-layers have proved effective for regional modelling of Koala distribution, for example in South Australia (Sequeira *et al.* 2014).

Current management of Koalas in public state forests is guided by the presence of 'preferred forest types', but management is ultimately triggered by the presence of a pre-existing Koala record or surveys for pellets prior to compartments being harvested. In private native forests, 'Core Koala habitat' is the trigger for prescriptions and an existing Koala record increases the requirement for tree retention. A heavy reliance on scat surveys or past records to trigger management is limited by the fact that many areas are difficult to access or have been poorly surveyed for Koalas in the past and new pellet surveys, as specified under the Integrated Forestry Operations Approval (IFOA) (www.epa.nsw.gov.au/forestagreements/UNEagreement.htm), may not always be effective at detecting Koalas. For example, pellet surveys can be unsuccessful in detecting Koala high-use areas that require protection because dense understorey vegetation impedes detection of pellets, pellet deposition rates are not constant and a bias exists towards detection in dry habitats where pellets will persist for longer (Cristescu *et al.* 2012). Moreover, while pellet abundance is correlated with Koala density, pellet surveys are imprecise indicators of tree use (Ellis *et al*. 2013). A more effective approach could be to develop and use a high resolution spatially explicit model to identify areas of suitable habitat for Koalas across the landscape and use this to guide further habitat inspections and to trigger various management actions (Dickson *et al*. 2014; Latif *et al*. 2015).

Field validation of Koala habitat model

Implementation of predictive habitat suitability models for management purposes requires a high level of confidence in the model reliability. Field validation or ground-truthing to collect an independent data set is an essential part of that process. One of the difficulties of ground-truthing is identifying varying quality of habitat and establishing whether it is occupied, or if unoccupied, whether the habitat quality is still suitable and maybe be recolonised at a later time. In particular, species occupancy (presence) is influenced by imperfect detection which can also vary with time or habitat type (Wintle *et al*. 2005). To overcome this, occupancy modelling has been developed to adjust site occupancy by first calculating detectability of a species (MacKenzie *et al.* 2002). Detectability is estimated by using multiple visits to a site to create detection histories. For example, a site could be visited for seven consecutive nights and the species may be detected on any number of nights (e.g. just a single night). Probability of occupancy contrasts with naïve occupancy, which is purely a measure of presence/absence without accounting for detectability. For the purposes of field validation of a habitat model, probability of occupancy is estimated by incorporating covariates for both detectability and occupancy, such as the predictive habitat suitability model output at each ground truth site. Using model selection procedures, the fit of a range of potentially important site covariates can be compared against that of the model. Both the fit and relationship of predicted occupancy values against the model output provides the validation assessment of the ground-truthed data.

An alternative approach for validation makes no assumption about occupancy of the predicted habitat suitability. Instead, it relies on an independent assessment of habitat quality based on the known habitat or dietary preferences of the focal species. This approach is limited by available knowledge on the importance of different browse species and how this varies across a species range or in association with co-occurring browse species, soil type, moisture, disturbance, etc. However, for Koalas a reasonable knowledge base exists concerning tree preferences (e.g. Phillips *et al.* 2000), bearing in mind limitations of recording pellets beneath trees as discussed above, and a scarcity of dietary studies in NSW.

Project Aims

We collated existing records of Koalas and used MaxEnt to model the potential habitat of the species in north-east NSW. A major determinant of the project boundaries was the extent of available vegetation mapping of sufficient resolution that Koala browse preference could be inferred for different forest types. In this study, the Crafti vegetation layer, which is a classification driven by the presence of canopy species, extends from the Port Stephens area in the south, to the Queensland border in the north and includes tablelands areas at higher elevations to the west. We also confined our modelling to this area because regional variation in habitat occupancy thresholds has been demonstrated (Rhodes *et al.* 2008; Crowther *et al.* 2009). Our aim was to develop a cross-tenure predictive habitat suitability model that would be useful for managing the species in the context of forest management, especially timber harvesting. To achieve this, our objective was to ensure the model's resolution was fine enough to indicate habitat suitability for the species at a sub-compartment scale (250 m grid cell). This would allow triggering of appropriate management actions for Koalas. While management triggers should be based on the best available knowledge as to how the species responds to disturbance, it should be acknowledged that this is limited for Koalas with respect to timber harvesting (see Roberts 1998; Smith 2004; Kavanagh *et al.* 2007). There are abundant Koala records available for modelling, however, they represent a highly biased data-set because of clustering of records close to roads and near coastal urban centres (e.g. Port Stephens, Port Macquarie and Coffs Harbour), even though such areas may represent true Koala hotspots (Lunney *et al*. 2009). As a result, care needs to be taken to minimise the influence of this bias prior to modelling (Sequeira *et al.* 2014).

Field validation of the Koala MaxEnt models followed two different, though complementary, approaches. The first approach systematically recorded the presence of Koalas to calculate probability of occupancy at ground-truth sites. We then assessed whether the probability of occupancy was correlated with the MaxEnt model output. Probability of occupancy accounts for detectability of a species and it ranges from 0-1. When assessed across many sites we assume that the probability of occupancy is correlated with Koala habitat quality, although it is likely that occupied habitats could vary substantially in abundance (a much more difficult variable to quantify reliably at many sites than occupancy). The second approach produced an index of Koala habitat quality (e.g. browse species availability) at each ground-truth site. For model validation purposes we would expect an increase in habitat quality with model output scores across all ground-truth sites. Each of these approaches use a quantitative assessment of habitat quality or probability of occupancy to compare against the MaxEnt model output on a continuous scale for ground-truth sites.

Data and Methods

Study area and Koala occurrence records

The analysis focused on north-eastern New South Wales. The study area (~8.5 million ha) consisted of two subregions: subregion 1 (areas below 500 m ASL) and subregion 2 (areas above 500 m ASL) (Figure 1). This subdivision was chosen because it was considered likely that different drivers of Koala habitat operated in coastal areas compared to uplands (McAlpine *et al*. 2008) and it assisted in dealing with a coastal bias in records (see below). Subdivisions based on 300m and 400m elevations were also tested but they were discarded because they produced models more biased towards the coast, including areas where there were no previous Koala records and the habitat is unsuitable. Using a higher elevation contour (500 m) reduced the coastal influence and improved predictions at certain known high elevation Koala habitat (e.g. Nowendoc; Krockenberger 1993) by including a second peak in records between 400 and 500 m in subregion 1 and providing a more even spread of records in subregion 2.

We acquired a set of reliable locations (n=7997, < 100 m accuracy), ensuring duplicates were removed, where Koalas have been recorded in the last 25 years from the New South Wales National Parks and Wildlife Service Wildlife Atlas (accessed April 2015). All the records located within cleared areas (e.g., farmland, residential areas, freshwater wetlands, industrial areas, etc.) and agricultural lands were removed because our study focused on forested environments. That reduced the number of suitable records to 5558 (4238 in Subregion 1 and 1320 in Subregion 2).

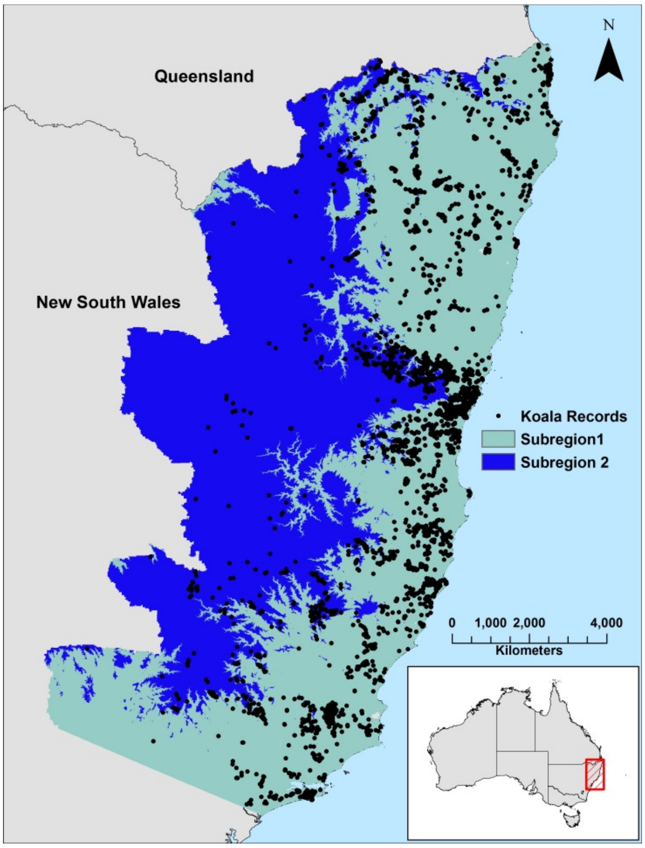


Figure 1. Map of north-east NSW indicating the locations of 5558 Koala records within the two sub-regions.

Koala records were strongly clustered at a number of urban centres (e.g. Coffs Harbour, Port Macquarie) (Figure 1). In order to reduce pseudoreplication and spatial aggregation in our records (e.g., Penman et al., 2010; Parolo et al., 2008; Kramer-Schadt et al., 2013; Fourcade et al., 2014), we randomly selected Koala occurrences that were separated by a minimum distance of 2 km. Other spatial filters were also tested, including 1 km, 5 km and 10 km; however 2 km was chosen as the best compromise between reducing spatial bias in records (in combination with splitting the study area and using a sample bias layer) and providing a large sample size for modelling. To ensure a larger variability in the records used in the analysis, we replicated the ‘thinning’ process five times and generated five random sets of records for each subregion (Figure 2). The number of records in the five sets ranged from 1078 to 1090 (mean = 1086). Records (n=3116) that were not included in the five random sets were retained and used for model evaluation (see section *Model evaluation*)

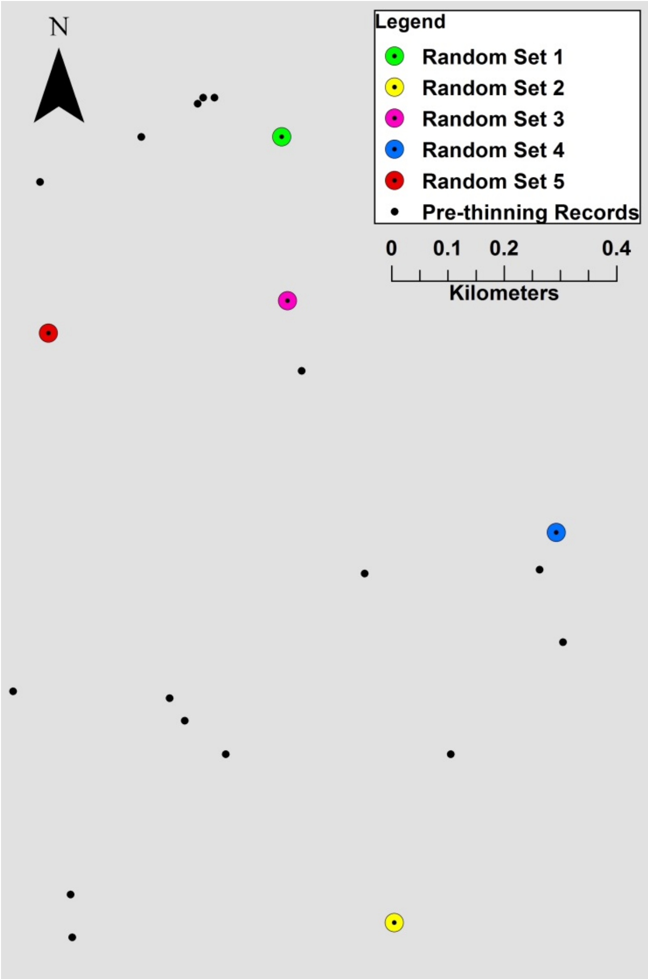


Figure 2. Example of a small area (~1km x ~1.5km) where each random set contains a different sample, capturing a larger portion of the pre-thinned record (n=21) variability.

Environmental variables

We selected 30 gridded environmental variables for their potential influence on Koala habitat suitability (Table 1). Variables included both biotic (e.g., floristic composition) and abiotic (e.g., slope) factors and were produced at 250 metre spatial resolution (i.e., pixel size = 250 metre) for both subregions.

Table 1. List of the 30 environmental variables used in the MaxEnt predictive modelling

Name	***Description***	***Type***
Asc	*Australian Soil Classification:*	*Categorical*
	Class1= Anthroposols; Class2= Calcarosols; Class3= Chromosols; Class4= Dermosols	
	Class5= Ferrosols; Class=6 Hydrosols; Class7= Kandosols; Class8= Kurosols	
	Class9= Organosols; Class10= Podosols; Class11= Rudosols; Class 12= Sodosols	
	Class13= Tenosols; Class14= Vertosols	
Awc	*Available water capacity (%)*	*Continuous*
Bio01	*Annual Mean temperature (°C)*	*Continuous*
Bio08	*Mean Temperature of Wettest Quarter (°C)*	*Continuous*
Bio09	*Mean Temperature of Driest Quarter (°C)*	*Continuous*
Bio10	*Mean Temperature of Warmest Quarter (°C)*	*Continuous*
Bio11	*Mean Temperature of Coldest Quarter (°C)*	*Continuous*
Bio12	*Annual Precipitation (mm)*	*Continuous*
Bio14	*Precipitation of Driest Period (mm)*	*Continuous*
Bio17	*Precipitation of Driest Quarter (mm)*	*Continuous*
Bio20	*Annual Mean Radiation (Mj/m^2/day)*	*Continuous*
Bio28	*Annual Mean Moisture Index*	*Continuous*
Biomass	*Above ground biomass (Mg Ha^{-1})*	*Continuous*
Cra	*Crafti floristic groups:*	*Categorical*
	Class 1: Primary browse species	
	Class 2: Secondary browse species	
	Class 3: Tertiary browse species	
	Class 4: Unsuitable habitat	
Cra%	*Percentage cover of primary and secondary Crafti-based browse species*	
DEM	*Digital elevation model (m)*	*Continuous*
Dep	*Soil depth (m)*	*Continuous*
Fire	*Wildfire frequency (1970 - 2015):*	*Categorical*
	Class 0: Areas that never burned and that are considered not flammable (e.g., rainforests)	
	Class 1: Areas that never burned	
	Class 2: Areas that burned 1 to 3 times	
	Class 3: Areas that burned more than 3 times	
Fpc	*Foliage projective cover (%)*	*Continuous*
NDVI_au	*Normalized Difference Vegetation Index in Autumn*	*Continuous*
NDVI_sp	*Normalized Difference Vegetation Index in Spring*	*Continuous*
NDVI_su	*Normalized Difference Vegetation Index in Summer*	*Continuous*
NDVI_wi	*Normalized Difference Vegetation Index in Winter*	*Continuous*
NPP	*Net primary productivity (kg C/m^2)*	*Continuous*
Oc	*Organic carbon (%)*	*Continuous*
Sea	*Density of sealed roads (m of road per Km^2)*	*Continuous*
Slo	*Slope (degree)*	*Continuous*
Top	*Topographic position index*	*Continuous*
Tor	*Topographic roughness (m)*	*Continuous*
Tp	*Total phosphorus (%)*	*Continuous*

Four topography-related variables were used (i.e., Digital elevation model, slope, topographic roughness and topographic position index) because terrain is expected to influence habitat suitability for Koalas (Van Dyck and Strahan, 2008). Digital elevation model (m) at 25 m resolution was resampled to 250 m by calculating the median elevation value within each 10 pixel-by-10 pixel neighbourhood. Slope (degree) was first generated at 25 m from the digital elevation model and then resampled to 250 m by calculating the median slope value within each 10 pixel-by-10 pixel neighbourhood. Topographic roughness (m) is an indicator of terrain complexity and was calculated as the standard deviation of slope within each 10 pixel-by-10 pixel neighbourhood. Finally, topographic position index (data provided by Allen McIllwee, OEH) classifies the landscape into slope position (i.e., ridge top, valley bottom, mid slope, etc.).

The density of sealed roads (m of road per km^2) was included in the analysis to account for anthropogenic disturbance. Vegetation and browse trees are known to affect the distribution of Koalas (Sequeira et al., 2014). Consequently, four broad floristic categories (i.e., Class 1= primary browse species, Class 2=secondary browse species, Class 3=tertiary browse species and Class 4=unsuitable habitat) were derived from available Crafti floristic maps for the north coast (NSW National Parks and Wildlife Service, 2001a; 2001b) based on the importance of tree species to Koalas as listed in the NSW Koala Recovery Plan (DECC 2008). A number of non-forest cover types (i.e., Cleared, Freshwater wetland, Saline wetland, etc.) were excluded from the analysis because they were considered unsuitable for Koalas. Additionally, we calculated the percentage cover of Class 1 and Class 2 combined within a 1 km radius of each 250 m pixel to account for the spatial distribution of primary and secondary browse species at a landscape scale.

Soil properties can have an indirect influence on habitat suitability by affecting site productivity and vegetation characteristics. Soil types were derived from the National soil data provided by the Australian Collaborative Land Evaluation Program ACLEP, endorsed through the National Committee on Soil and Terrain NCST (www.clw.csiro.au/aclep, accessed September 2014). This map was based on the Atlas of Australian Soils (Northcote et al, 1960-68) and available at 250 m spatial resolution (www.asris.csiro.au/themes/NationalGrids.html, accessed April 2016). Additionally, we used soil depth (m), organic carbon (%), total Phosphorus (%) and available water capacity (%) grids at 80 m resolution acquired from The Soil and Landscape Grid of Australia (www.clw.csiro.au/aclep/soilandlandscapegrid/ProductDetails-SoilAttributes.html, accessed April 2016) to account for soil characteristics (Williams et al., 2010). All grids were resampled from 80 m to 250 m.

We used the Normalized Difference Vegetation Index (NDVI, Rouse et al., 1974) because it has been found to relate to a range of vegetation properties such as leaf area index, biomass and net primary productivity (e.g., Coops et al., 1997, Chafer et al., 2004) that could influence habitat suitability for Koalas (Van Dyck and Strahan, 2008). We used 250 m resolution 16-day composite surface reflectance MODIS data (MOD13Q1, collection 5) acquired in January, April, July and October from 2000 to 2015. Those months were selected to provide average NDVI values in the middle of summer, autumn, winter and spring. Data anomalies (e.g., cloud, cloud shadow, fire and cirrus) were masked using

MODIS quality assurance (QA) metadata (after Caccamo *et al.*2011). For each year, time-series of NDVI were calculated from MODIS Band1 (620-670 nm) and Band2 (841-876 nm), using the following formula:

$$\mathbf{NDVI = (Band2 - Band1) / (Band2 + Band1)}$$

Finally, all NDVI data (2000-2015) in January, April, July and October were averaged to produce long-term means.

Three additional vegetation-related variables were included in the analysis. An estimation of above ground biomass (Mg Ha^{-1}) at 50 m resolution was acquired from NSW Office of Environment and Heritage (ALOS Woody biomass, Lucas et al., 2010) and resampled to 250 m. Foliage projective cover (%), providing an estimation of the fraction of the ground covered by vegetation, was acquired at 5 m resolution from NSW Office of Environment and Heritage (www.environment.nsw.gov.au/research/AncillaryVegetationProductsDataInventory.htm, last accessed April 2016) and resampled to 250 m. Net primary productivity (NPP, kg C/m^2) grids were extracted from MODIS data (MOD17A3). MOD17A3 provides total annual NPP at 1km resolution. Annual data from 2000 to 2015 were averaged and resampled to 250 m to calculate the mean annual NPP per pixel within the study area.

A number of bioclimatic factors were investigated for their potential influence on the distribution of Koalas. Bioclim (Houlder et al., 2009) was used to produce 10 bioclimatic parameters at 250 m resolution based on long-term meteorological data and DEM. Bioclim has been extensively discussed in the literature (e.g., Busby, 1991) and full details of the model are given in Houlder *et al.* (2009).

We used wildfire history data (1970-2015) acquired from NSW Rural Fire Service for the potential influence of this disturbance on Koala habitat suitability. Fire data were rasterized at 250 m resolution and, for each cell, the total number of fires recorded from 1970 to 2015 was calculated. A fire frequency map was then calculated by classifying the data into four categories: Class 0: Areas with zero records of burning and that are considered not flammable (e.g., rainforests); Class 1 – Areas with zero records of burning; Class 2 – Areas recorded to have burned 1 to 3 times; Class 3: Areas recorded to have burned more than 3 times. We included Class 0 because many rainforest areas are shown by the layer as having been burnt. However, we consider this to be a limitation of the fire history layer where often the broad extent of wildfires were mapped, ignoring smaller internal areas such as gullies and rainforest that were likely to be unburnt. It should also be noted that our approach does not map number of wildfires prior to a Koala being recorded at a site. Rather it is an index of wildfire frequency estimated over a longer period of time, which we considered to be more reliable given the interval between fires was often > 10 years.

Finally, we explored the use of forest successional stage mapping as an input variable, but concluded an adequate and current data layer was not available for reliable modelling (see Appendix A for test results).

Bias file

Koala records were biased toward roads (Figure 3). MaxEnt assumes that occurrence records are unbiased, therefore a *bias* file was created to account for sampling effort. Ideally, bias files should be based on actual sampling intensity (Fourcade *et al*. 2014) to distinguish between areas that are unsuitable and areas that are subject to low sampling effort. Following Predavec *et al.* (2015), we created a bias file (pixel size = 250 m) by estimating sampling intensity using the aggregation of occurrences for arboreal mammal species (taxonomic groups: Petauridae, Phalangeridae, Phascolarctidae and Pseudocheiridae) that are likely to reflect detectability of the Koala (Phillips *et al*. 2009). A Gaussian Kernel Density map of Koala and arboreal mammals' occurrences was generated and rescaled to 1 – 30 (similar to Elith *et al.* (2010) and Fourcade *et al.* (2014)). Values in the resulting map were higher in densely sampled areas indicating higher sampling effort (Figure 4). Koala distribution in north east NSW is not closely correlated to other arboreal mammal species (Kavanagh *et al.* 1995).

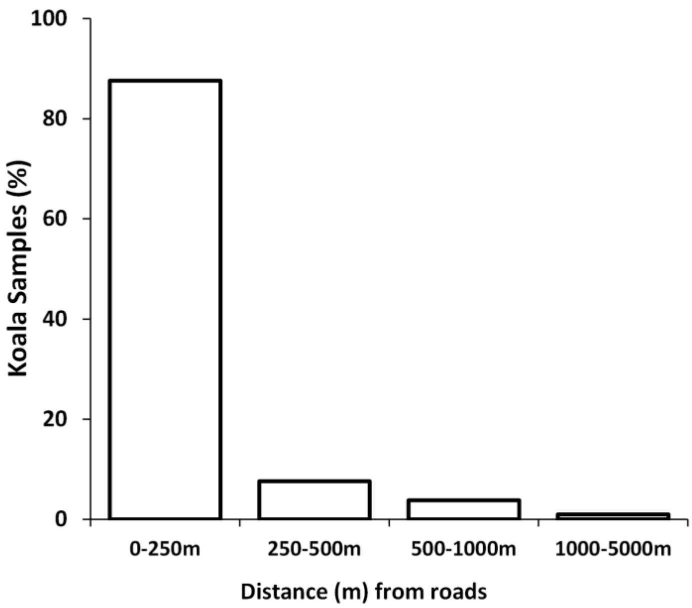


Figure 3. The majority (~90%) of Koala records were within 250 m of roads.

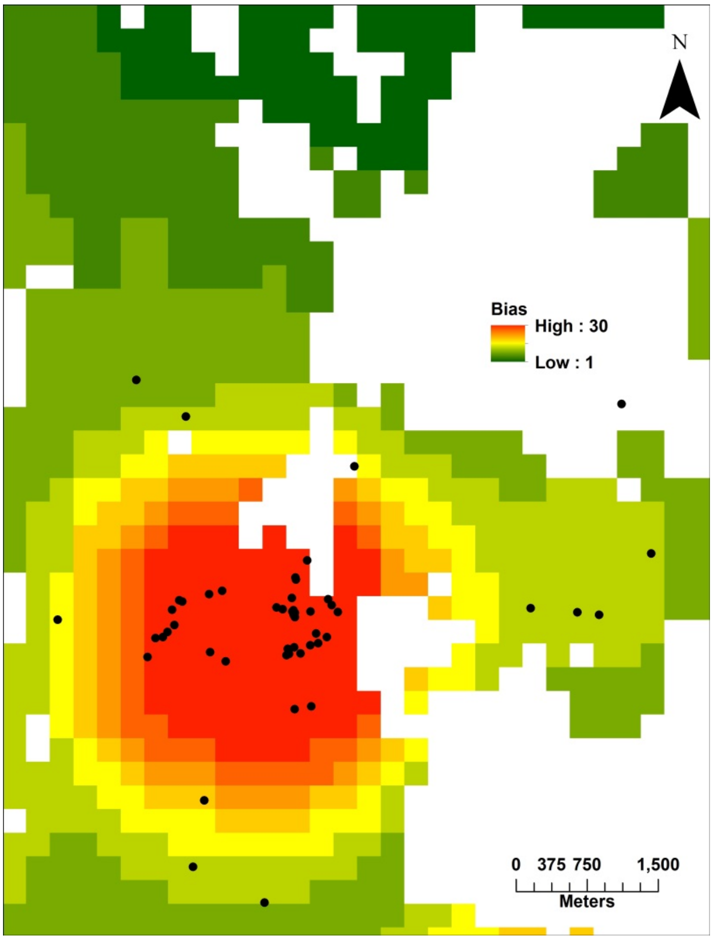


Figure 4. In the bias file, densely sampled areas indicate higher sampling effort.

MaxEnt modelling

Koala habitat suitability in subregion 1 and subregion 2 were modelled separately using Maximum Entropy Species Distribution Modelling Software (MaxEnt version 3.3.3k; www.cs.princeton.edu/~schapire/maxent, last accessed April 2016, Phillips *et al*., 2006). MaxEnt is a widely used machine learning model that uses the principle of maximum entropy to predict the spatial distribution of suitable conditions for species based on presence only data (e.g., Elith et al., 2006). For each run, hinge feature type was used (after Phillips and Dudik, 2008), and maximum number of iteration, convergence threshold, regularization multiplier, maximum number of background points were set to 1 000, 10^{-5}, 2 and 10 000, respectively.

To minimize multicollinearity, the number of continuous variables was reduced by eliminating highly correlated (Pearsons' R > 0.75) predictors and retaining the variable with the most interpretable biological response (Kramer-Schadt et al., 2013). For each of the five random sets (Figure 2), models were built on 75 % of the occurrences, whilst the remaining 25 % was used as test sample. For each of the sets, we ran 20 replicates (i.e., random partitions of training and testing data) and retained the mean habitat suitability predicted. Finally, we averaged the mean habitat suitability predicted for each of the five sets to generate the final Koala habitat suitability map.

Model evaluation

We used the Receiver Operating Characteristics (ROC) curve on test data to evaluate the models performance. ROC curves indicate the relationship between the percentage of presences correctly predicted and 1 minus the percentage of absences correctly predicted (e.g., Parolo et al., 2008). The area under the ROC curve (AUC) provides a single indicator of model performance (Philips et al., 2006). Models with AUC > 0.7 have good discriminatory power (Hosmer and Lemeshow, 1989). AUC on test data was calculated for each of the five sets of Koala records in both subregions.

MaxEnt allows users to produce three different spatially-explicit habitat suitability maps (i.e., raw, cumulative and logistic). The logistic output was selected because it is the easiest to interpret. Each pixel (250m) is assigned with a value ranging from 0 to 1 which represents the probability of presence of suitable environmental conditions for the target species (i.e., higher values indicate higher suitability).

As a model evaluation step, we analysed the relationship between the Koala records (n=3116) that were not used in the MaxEnt analysis (see section "*Study area and species occurrence records*") and the predictive habitat suitability model output. These records were neither filtered nor adjusted based on survey effort.

Finally, we analysed the response curves of the predictor variables to assess their influence on the prediction. Response curves show how the predicted suitability of a model built using only one variable changes as the variable is varied.

Model validation

Site Selection

To ground-truth the Koala MaxEnt Model, we established 65 sites on the north coast of NSW between Port Stephens in the south, and the border with Queensland in the north (Appendix B). Sites extended from the coast to over 1000 m in altitude to account for our high and low elevation subregions (Figure 5). Sites were equally distributed between three broad regions: 1. at the southern end of the north coast region (Port Stephens to Wauchope), 2. Coffs Harbour region (Wauchope to Grafton) and, 3. Inland of far north coast (Grafton to border).

In each of these regions, sites were located at both higher and lower elevations. The target areas for validation were forested and subject to timber harvesting, especially State forests, as the primary purpose for implementation of the model was for improved identification of Koala habitat in areas planned for logging. As such, key coastal sites for Koalas (e.g. far north coastal strip) were not sampled. Sites with a recent history of logging or fire (< five years) were avoided.

Allocation of sites was stratified using four habitat quality classes (very high, high, moderate, low) derived from a preliminary version of the Koala habitat suitability model (Law *et al.* 2014). Where possible, a cluster of sites was allocated in a local area (~10 km radius) with one site in each habitat class (minimum distance between sites = 1 km; average distance = 166 km). In practice, this was often not possible due to local absence of a particular class. In these circumstances, the missing class was replaced by a locally available class.

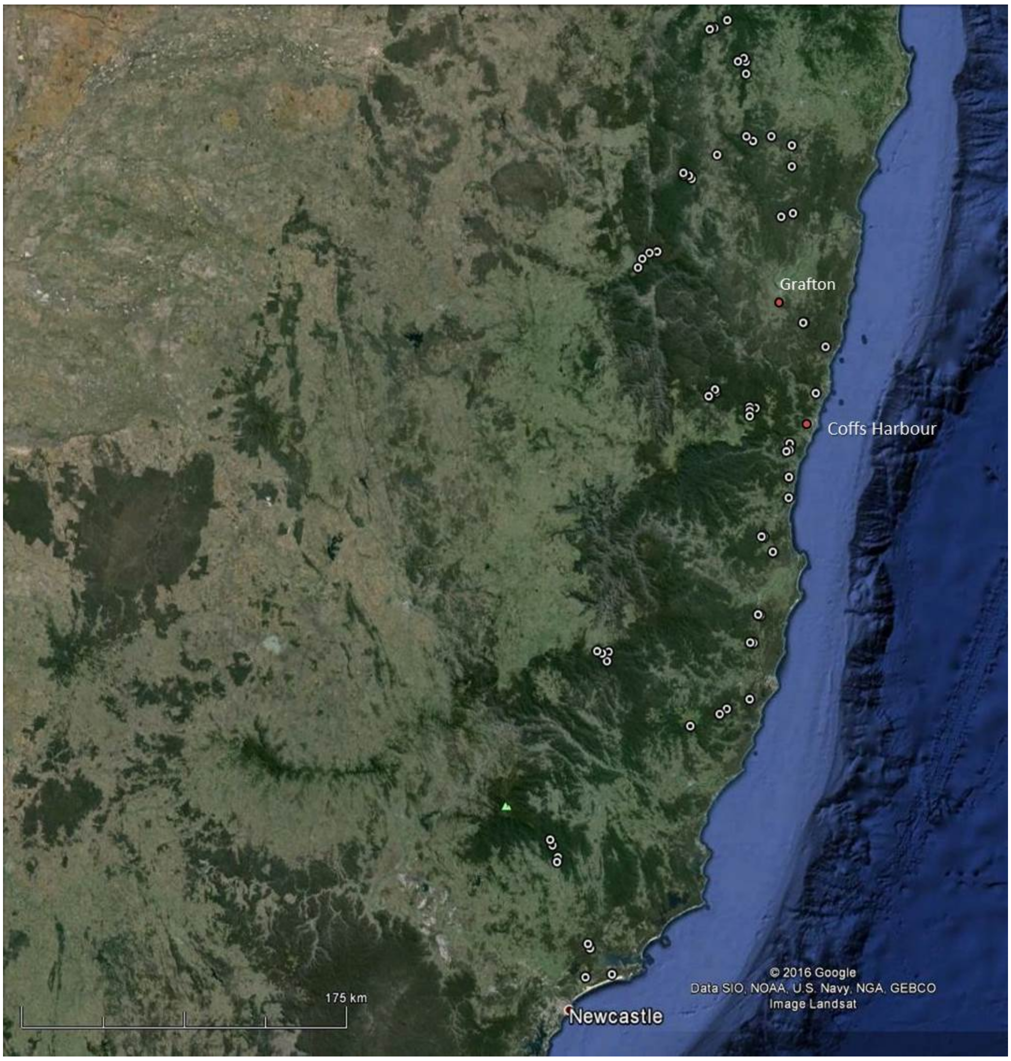


Figure 5. Distribution of 65 Koala ground truth sites in northern New South Wales*.*

Koala Occupancy

Koala males emit loud bellows during the breeding season. This behaviour has great potential for estimating occupancy across a variety of landscapes now that sophisticated acoustic recorders are widely available and sound analysis software has been developed to process recorded calls. For example, a novel remote sound detection network has been used to monitor Koala bellowing while simultaneously collecting Koala behavioural data using collar-mounted GPS units (Bercovitch *et al.* 2011). This study found that the number of bellow vocalizations recorded during an annual period mirrored breeding activity, with nearly all male bellows recorded during peak mating season (September-December). The distance travelled by Koalas and the occurrence of Koala bellows both peaked around midnight. The study concluded that male bellows function to attract females rather than to repel males.

At each site we deployed one SongMeter (SM2 – Wildlife Acoustics) to record Koala bellows. SongMeters were programmed to record from one hour before sunset until sunrise for seven consecutive nights. This equates to 455 nights of sampling. The recordings were processed by newly developed software (Towsey *et al.* 2012), which has been used to develop reliable recognisers for a select group of fauna, including Koalas. The distance at which Koala calls can be detected is likely to vary with environmental conditions, but bellows are considered to be detectable by SongMeters up to at least 100 m (W. Ellis pers. comm.). All SongMeter sampling was undertaken in the Koala mating season across three trips; one trip in October/November, one in late November and one in December 2015.

Koala pellet searches were also undertaken to compare with occupancy recorded by SongMeters, given that pellet searches are a standard survey technique for recording Koala presence (e.g. Phillips and Callaghan 2011) while use of SongMeters is relatively novel. Scat searches were undertaken for 1 minute within a 1 m radius of each tree measured in the browse tree availability searches outlined below (see '*Habitat Availability*'). This resulted in 40 trees being surveyed per site. This method represents a slight departure from the SAT method of Phillips and Callaghan (2011) in that 40 not 30 trees are measured, and the location of these trees is not determined from a focal tree. Our method is consistent with the Koala Rapid Assessment Method of Woosnem-Merchez *et al.* (2012). The method yields data on the proportion of trees per site at which a Koala scat has been recorded. Browse trees are not targeted to ensure sampling effort is even across sites where browse tree density varies; as was the case with field validation across a range of model qualities. Scats searches and identification was carried out by Matthew Stanton and Larissa Potter (Niche Environment and Heritage) for NSW DPI as part of tree transects at each site.

Analysis of Koala Calls

Recordings were sent to Queensland University of Technology (QUT) for processing by acoustic software and a Koala recogniser previously developed and tested by QUT. Various indices were output by the QUT acoustic software and were available for manually reviewing matches by the Koala recogniser, including visualising spectrograms of the audio (Figure 6) and the capability of listening to the recordings. Manual checking of Koala calls and data collation was carried out by Anna McConville (Echo Ecology).

Each event trigger was visually checked. The checking process was as follows for each site:

1. Visually inspect the spectrogram (Figure 6) for activity at the Koala frequency (0–3 kHz) and listen to any potential Koala calls using quality headphones and adjusting volume as required.
2. Visually scan the spectrogram to any sequential events and repeat as required.
3. Enter ‘yes’ or ‘no’ in the “Validation Koala?” column of a spreadsheet and make any notes about the recording.

Once all events had been inspected, we then summarised the results. A single Koala call was made up of multiple event triggers. We defined a Koala call as sequential event triggers that were < 60 s apart. We visually inspected the spectrogram for any event triggers that were close to the 60 s cut-off to identify any calls that extended past the last event trigger and may be within the 60 s cut-off.

Some sites had no event triggers recognised by the QUT acoustic software. We checked the original recording files to determine which sites were sampled and for how long. We checked whether the last night of recording was incomplete due to battery failure etc. The number of Koala calls was then manually tallied to give the total Koala calls per site per night.

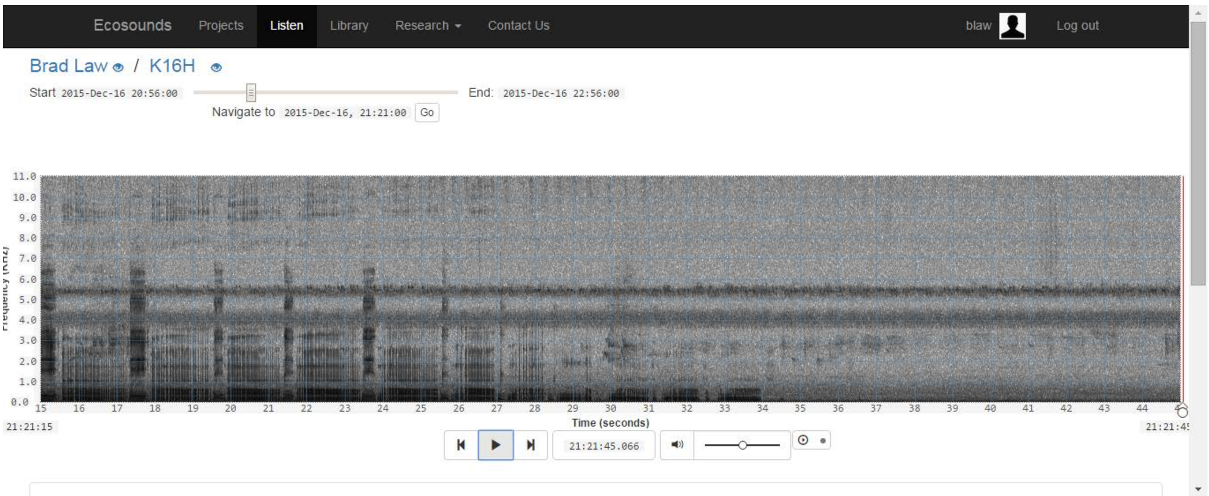


Figure 6. Spectrogram of Koala bellow repeated multiple times

Site Habitat Quality

The second approach for field validation was a site based assessment of habitat potential for Koalas. To quantitatively assess browse tree availability at each site a 200 m transect was established to correspond with the 250 m pixel resolution of the MaxEnt model. The transect followed the contour and at every 20 m interval the Point-Quarter technique (Pollard 1971) was employed to measure the distance to the nearest tree (>20 cm diameter at breast height, dbh) in each quadrant. Although Koalas also use trees < 20 cm dbh, there is some evidence that larger trees are preferred (Callaghan *et al.* 2011). Each tree was identified where possible and its diameter was measured and height estimated. This resulted in data on 40 trees from 10 points along the transect. The Point Quarter technique was then used to estimate stem density and when multiplied by the % occurrence of different species and their mean diameter, we were able to calculate the basal area for the different species measured (i.e. account for tree size of different species). Transects and tree identification were carried out by Matthew Stanton and Larissa Potter (Niche Environment and Heritage) for NSW DPI.

An index of habitat quality for Koalas at each ground-truth site was calculated based on browse tree basal area and diversity. First, species of Koala browse trees were classified into four classes of varying quality, based on literature reporting primary, secondary and supplementary browse species, and expert opinion (Table 2). Class 1 and Class 2 species generally refer to those browse species that represent high food quality for Koalas and would represent high quality breeding habitat. Class 3 represents species of lower quality, although they are still likely to support some Koala breeding habitat and low density populations. Class 4 species are likely to represent marginal habitat, but may be important for Koala movement and dispersal (McAlpine *et al.* 2006). Species rarely used by Koalas are those not classed as browse species in our classification.

Allocation of tree species to quality class was often difficult given incomplete knowledge of Koala diet and uncertainty related to assessing the importance of tree species when based on scat deposits beneath trees as scats can accumulate under both shelter and diet species (Ellis *et al*. 2013). One example of uncertainty is the Sydney Blue Gum *Eucalyptus saligna*, which was categorised as Class 3, whereas an alternative could have been Class 2.

In addition to browse tree basal area, browse tree diversity is also likely to contribute to habitat quality at a site, because different browse species could provide different nutrients and a more diverse stand of browse trees is likely to provide a more resilient food base at times of habitat disturbance or stress (e.g. drought) (Smith 2004). Browse tree diversity was calculated using the Shannon-Wiener Index for counts of tree species in Class 1, 2 and 3. Class 4 was omitted from diversity calculations as they were considered to have lower value.

Other aspects of the local landscape can influence habitat suitability for Koalas, such as patch size, fragmentation, connectivity and roads (McAlpine *et al.* 2006). However, these were generally considered to be of lesser importance for the more extensive forest landscapes that we sampled.

Browse tree basal area and diversity were combined into a site scale index of habitat quality using the following formula:

> **Site Habitat Quality** = *[(0.8*basal area of Class 1 trees) + (0.6*basal area of Class 2 trees) + (0.25*basal area of Class 3 trees) + (0.1*basal area of Class 4 species) + (0*basal area of all other trees)]* $^{0.6}$ ** [site Class 1, 2 & 3 browse tree diversity]* $^{0.4}$

We used strike rates of use for different browse trees derived from pellet counts beneath trees across a range of local studies as a guide to select weights for browse tree classes. For example, *E. tereticornis* is a Class 1 species and it has strike rates of 0.7 at Noosa (Callaghan *et al.* 2011). We weighted browse tree availability higher than browse tree diversity because Koala habitat quality can still be high when browse diversity is low. We also experimented with alternative weightings and settled on values that yielded a higher r^2 to optimise the relationship prior to comparing against the MaxEnt model output.

Table 2. Classification of tree species into 5 different browse qualities for Koalas based on literature and expert opinion (as an example see NSW Koala Recovery Plan 2007)

Class 1	Class 2	Class 3	Class 4	Class 5
E. acaciiformis	*E. biturbinata*	*E. globoidea*	*C. gummifera*	all other
E. microcorys	*E. canaliculata*	*A. torulosa*	*C. intermedia*	
E. robusta	*E. glaucina*	*E. agglomerata*	*E. acmenoides*	
E. tereticornis	*E. largeana*	*E. cameronii*	*E. pilularis*	
E. viminalis	*E. moluccana*	*E. eugeniodes*	Ironbark spp.	
E. amplifolia	*E. propinqua*	*E. grandis*	*M. quinquenervia*	
Red Gum	*E. punctata*	*E. laevopinea*	Stringybark spp.	
	E. radiata	*E. nobilis*	*E. williamsiana*	
	E. seeana	*E. obliqua*		
		E. quadrangulata		
		E. resinifera		
		E. rummeryi		
		E. saligna		
		E. siderophloia		
		E. signata		
		E. tindaliae		
		E. caliginosa		

Site Field Assessment

A field assessment of site attributes included topographic position (1 – summit to 12 – swamp), logging history and fire history. Site elevation was extracted from GIS. Logging history was assessed in the field and recorded as extensive (even age regrowth, with few large (>80 cm dbh, hollow-bearing trees remaining), moderate (even-aged regrowth with a scattering of hollow trees), light (uneven age regrowth with plentiful hollow trees) and unlogged (uneven aged forest with abundant large hollow trees). Note that logging history does not necessarily equate to logging intensity if multiple rotations of light intensity have reduced large, tree density over time. However, dominance of even age regrowth in the "extensive" category suggests that high intensity operations were likely. Time since logging was based on an assessment of regenerating tree height and diameter as well as stump characteristics and was classified into decades: 1 (0-10 years), 2 (11-20 years), 3 (21-30 years) and 4 (> 30 years or unlogged). Fire severity was classified based on charcoal height on rough barked trees while time since fire was based on the distribution of charcoal (including presence on smooth barked trees) and signs of post-fire regeneration. Fire classifications, especially the effects of low severity fires, were difficult to assign beyond about five years and were not suitable for comparing to the wildfire history layer. All field assessments were completed by B. Law (NSW DPI).

Occupancy Analysis and Validation Method

We used an occupancy modelling framework to account for imperfect detection of Koala bellows at sites and used this to estimate the probability of site occupancy (MacKenzie *et al.* 2002). We used seven consecutive nights of sampling to estimate the probability of detection and used this to calculate probability of occupancy in PRESENCE version 10.5 (Hines 2006). For the validation of the MaxEnt model, probability of occupancy per site was estimated by incorporating the MaxEnt model output for each ground truth site as a covariate (predictor) in a regression relationship. The fit of this relationship against Koala occupancy was compared, via model selection procedures, with other potentially important site covariates. Competing models were ranked using Akaike Information Criterion (AIC), which measures the trade-off between model complexity (number of parameters) and precision (fit) of the models. The difference between each model's AIC value and the best-fitting model were calculated, with models of delta AIC < 2 considered to have substantial support.

Modelling followed a multi-staged process.

1. We identified the importance of possible covariates for Koala detectability to improve the accuracy of occupancy estimates. Daily rainfall (p(rainfall)), month of sampling trip (p(trip)) and topographic position (p(topo)) were compared against a null model with constant detectability (p(.)).
2. Using results for detectability from Step 1, MaxEnt model scores for each ground-truth site were validated against Koala occupancy for that site. We compared MaxEnt model outputs with different spatial scales to identify the best scale for predicting occupancy. For instance, more extensive areas of higher habitat suitability than a 250 m pixel may be better predictors of Koala occupancy. Spatial scales varied from 250 m (pixel), to surrounding buffers of 500 m, 1000 m and 2000 m. All models were compared to a null model where occupancy was held constant across sites (Psi(.)).
3. From Step 2, the MaxEnt model using the best spatial scale was compared against our habitat quality index derived from browse tree availability at each site and a null model with occupancy held constant across sites (Psi(.)). This allowed us to compare the performance of the MaxEnt model against tree availability data (habitat quality index).
4. Finally, we compared the strength of the relationship between Koala occupancy, the MaxEnt model output and the site habitat quality index with a small selection of other potential predictors of Koala habitat, including those that were used in the MaxEnt model (NPP, topographic position, elevation and wildfire frequency). These were extracted for the 250 m pixel for each of the ground-truthed sites.

Simple validation of the MaxEnt model using the site habitat quality index was undertaken using a scatterplot of Index scores against model output scores (0-1) for each ground-truth site. An r^2 value was calculated for this relationship.

Results

MaxEnt analysis

Pearson's correlation analysis showed that a large number of continuous variables were highly correlated (R>0.75) and were therefore excluded from this study (Appendix C). For example, NDVI_su, NDVI_au, NDVI_wi and NDVI_sp were strongly correlated with each other (R values ranging from 0.83 to 0.93) and with Fpc (R values ranging from 0.75 to 0.80). The continuous variables initially retained were: **Awc**, **Bio14**, **Bio28**, **Biomass**, **Cra%**, **DEM**, **Dep**, **Fpc**, **NPP**, **Oc**, **Sea**, **Slo**, **Top**, **Tp** and **Tor** (Table 1). However, **Awc**, **Oc**, **Sea** and **Tp** were also discarded after exploratory analysis showed their response curves lacked realism and ecological sense. For example, Koalas showed a positive correlation with the density of sealed roads in coastal regions due to the high concentration around urban centres. Therefore, the models for subregion 1 and subregion 2 were built on a total of 14 predictors: three categorical variables (**Asc**, **Cra** and **Fire**) and 11 continuous variables (**Bio14**, **Bio28**, **Biomass**, **Cra%**, **DEM**, **Dep**, **Fpc**, **NPP**, **Slo**, **Top** and **Tor**). We also checked for an association between two categorical variables: wildfire frequency and Crafti. We found that the two were not closely associated as % cover of the four fire frequency classes had a similar distribution within each Crafti floristic group, except for fire frequency class 0, which was only present in Crafti floristic group 4 because it is represented by rainforest types. The lack of association between these two variables was supported by a Cramer's V = 0.45, and accordingly, we included both variables into the model.

AUC on training data ranged from 0.736 to 0.752 (n=5, average=0.741±0.006) for subregion 1 and from 0.786 to 0.801 (n=5, average=0.796±0.006) for subregion 2. For both subregions, **Asc, Cra, DEM** and **Fire** provided the greatest contribution to the model (Figure 7).

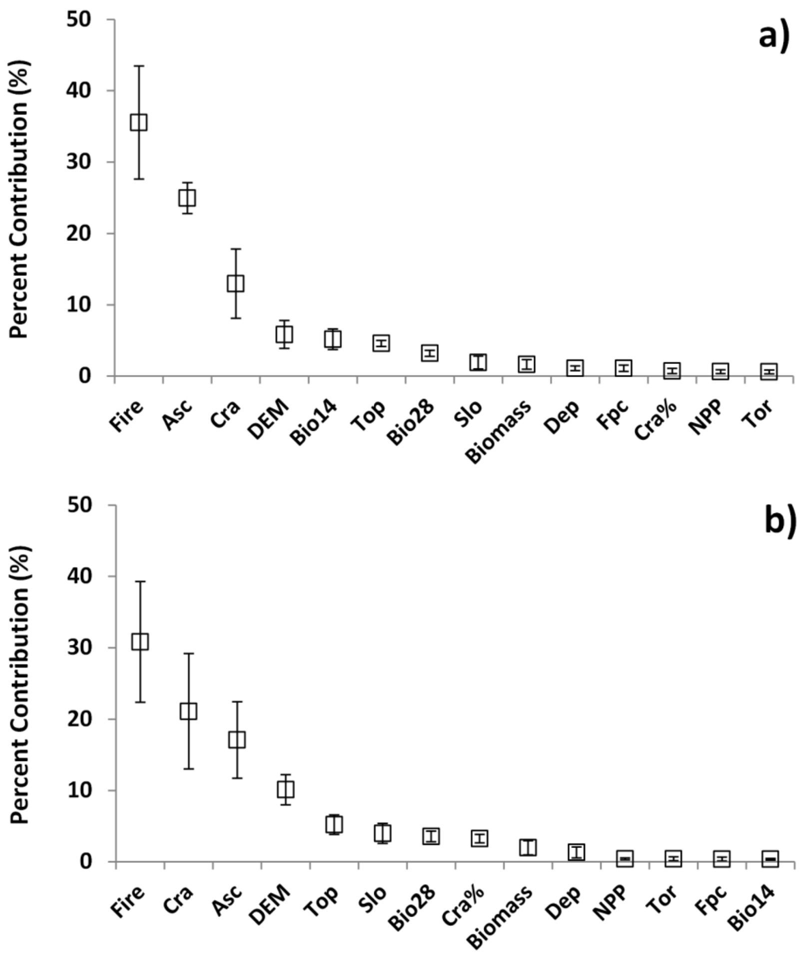
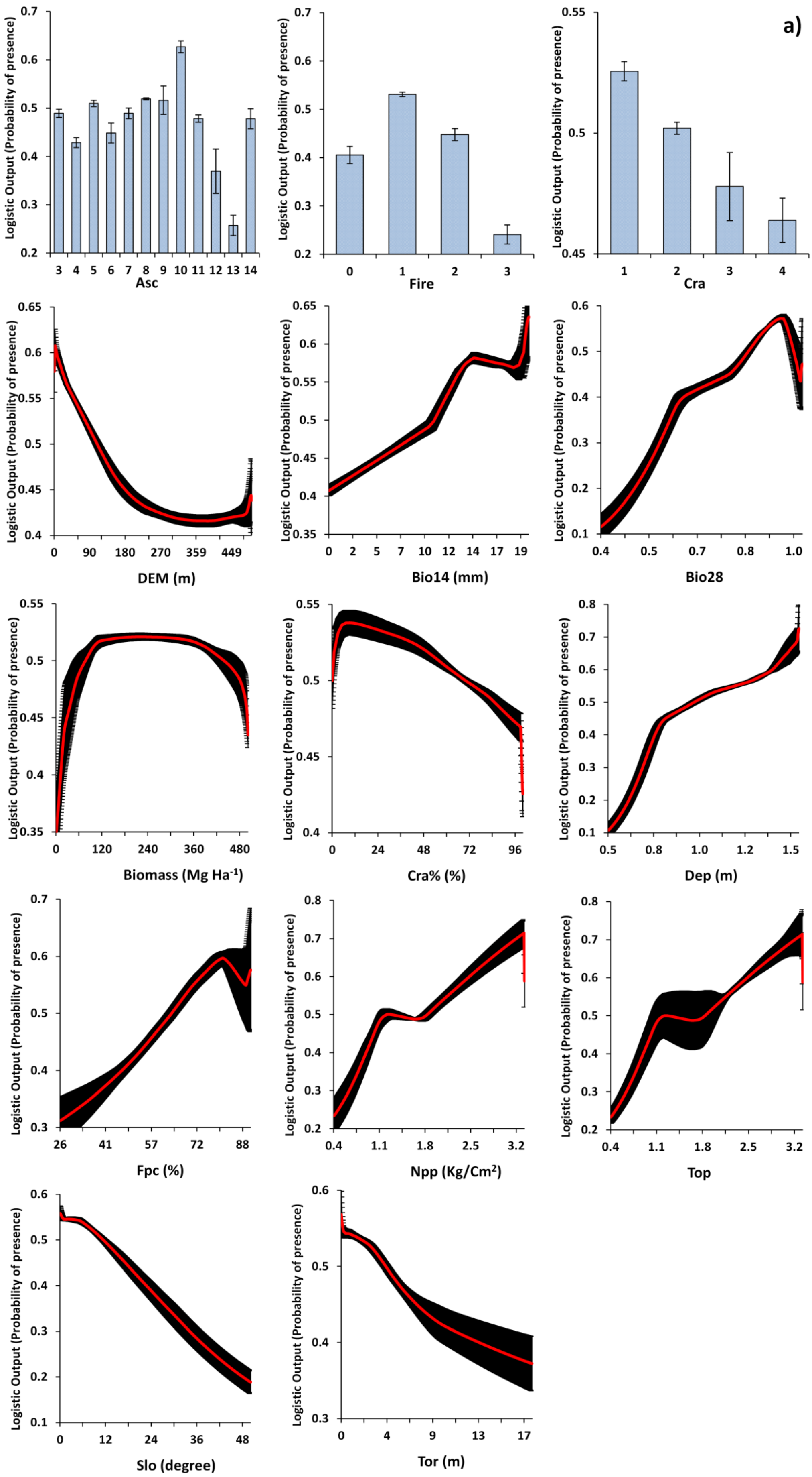


Figure 7. Percent contribution of the 14 predictor variables in (a) subregion 1 and (b) subregion 2. Fire= Wildfire Fire frequency (1970-2015); Cra = Classification of browse species based on Crafti floristic groups; Asc = Australian Soil Classification; DEM = Digital elevation model (m); Top = Topographic position index; Slo = Slope (degree); Bio28 = Annual Mean Moisture Index; Cra% = Percentage cover of primary and secondary Crafti-based browse species; Biomass = Above ground biomass (Mg Ha^{-1}); Dep = Soil depth (m); NPP = Net primary productivity (kg C/m^2); Tor = Topographic roughness (m); Fpc = Foliage projective cover (%); Bio14 = Precipitation of Driest Period (mm).

The response curves of **Asc, Cra, Fire** and **DEM** (Figure 8a-b) showed some differences between the two subregions. Predicted suitability of **Asc** was higher for Class 10 (Podosols) in subregion 1 and Class 12 (Sodosols) in subregion 2, whilst Class 13 (Tenosols) and Class 11 (Rudosols) showed the lowest probability values for subregion 1 and subregion 2, respectively. Predicted suitability of **Cra** was higher for Class 1 and decreased gradually from Class 2 to Class 4 in both subregions. Predicted suitability of **Fire** showed similar values for Class 0, Class 1 and Class 2 (~36%, ~53% and ~44%, respectively) in both subregions. However, Class 3 showed a markedly higher predicted suitability (~49%) when compared to subregion 1 (~24%). Frequency of wildfire was similar across the four major Crafti floristic groups that were classified for Koala prevalence, except that Class 4 (unsuitable Koala habitat) had a much small area of forest types that had never burned and

Class 3 had slightly more area that had experienced high wildfire frequency (Appendix D). In addition, Class 4 was the only group where there was an extensive area of Crafti types that were not expected to burn (rainforest). The response curve of **DEM** showed a similar pattern in both subregions as predicted suitability decreased for higher values. High predicted suitability <100 m and between 500-600m elevation, reflect a concentration of Koala records at those elevations.

Habitat suitability values ranged from 0 to 0.88 (average=0.39±0.15) and were classified into nine categories corresponding to 0.1 increments (Figure 9). Most of the areas characterised by high frequency of Koala records (Figure 10) were correctly modelled and assigned with High or Very High Suitability class. Koala records less frequently fell in areas modelled as Moderate Suitability and rarely in Low Suitability habitat.



a)
Logistic Output (Probability of presence)
Asc
Fire
Cra
DEM (m)
Bio14 (mm)
Bio28
Biomass (Mg Ha^{-1})
Cra% (%)
Dep (m)
Fpc (%)
Npp (Kg/Cm^2)
Top
Slo (degree)
Tor (m)

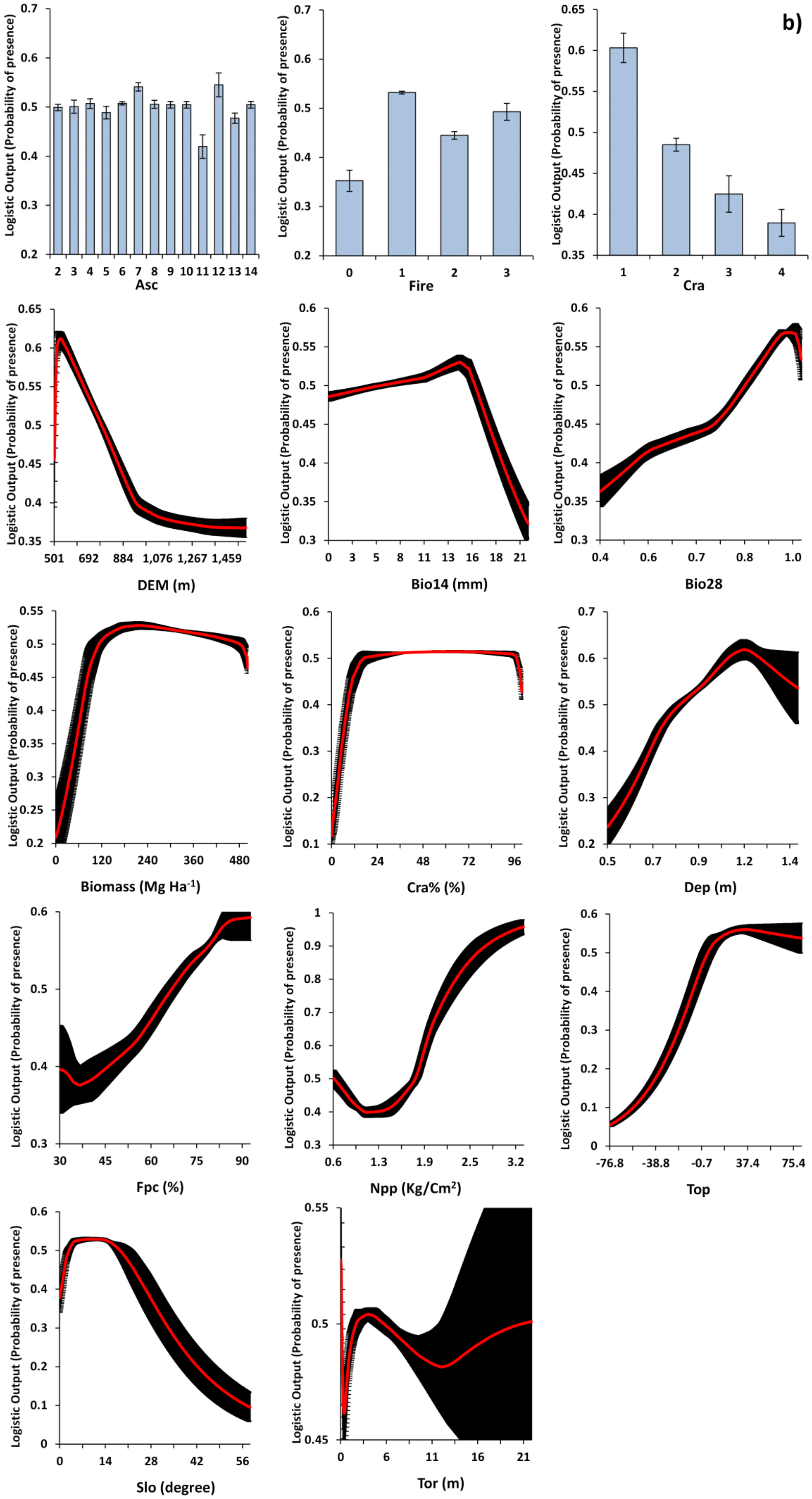

b)
Logistic Output (Probability of presence)
Asc
Fire
Cra
DEM (m)
Bio14 (mm)
Bio28
Biomass (Mg Ha^{-1})
Cra% (%)
Dep (m)
Fpc (%)
Npp (Kg/Cm^2)
Top
Slo (degree)
Tor (m)

Figure 8 (on the previous two pages). Response curves for (a) subregion 1 and (b) subregion 2: Asc (*Australian Soil Classification; Class1=Anthroposols; Class2=Calcarosols; Class3=Chromosols; Class4=Dermosols; Class5=Ferrosols; Class6=Hydrosols; Class7=Kandosols; Class8=Kurosols Class9=Organosols; Class10=Podosols; Class11=Rudosols; Class 12=Sodosols; Class13=Tenosols; Class14=Vertosols*); Fire (*Fire frequency 1970-2015; Class 0=Areas that never burned and that are considered not flammable; Class 1= Areas that never burned; Class 2= Areas that burned 1 to 3 times; Class 3=Areas that burned more than 3 times)*; Cra (*Classification of browse species based on Crafti floristic groups; Class 1=primary browse species, Class 2=secondary browse species, Class 3=tertiary browse species; Class 4=unsuitable habitat*); DEM (*Digital elevation model); Bio 14 (Precipitation of driest period); Bio28 (Annual mean moisture index); Biomass (Above ground biomass); Cra% (Percentage cover of primary and secondary Crafti-based browse species); Dep (Soil depth); Fpc (Foliage projective cover); NPP (Net primary productivity); Top (Topographic position index); Slo (Slope); Tor (Topographic roughness).*

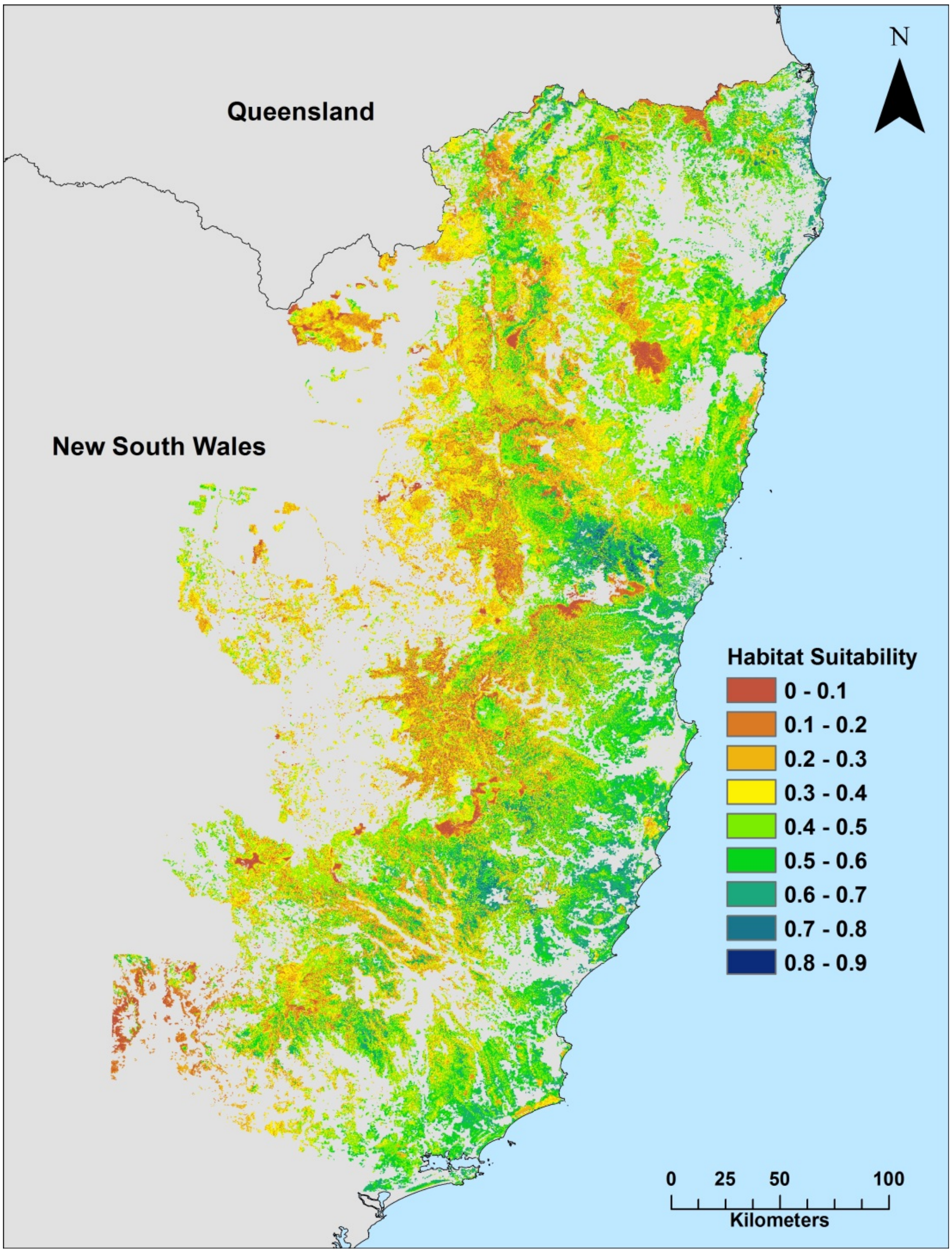


Figure 9. Koala habitat suitability map.

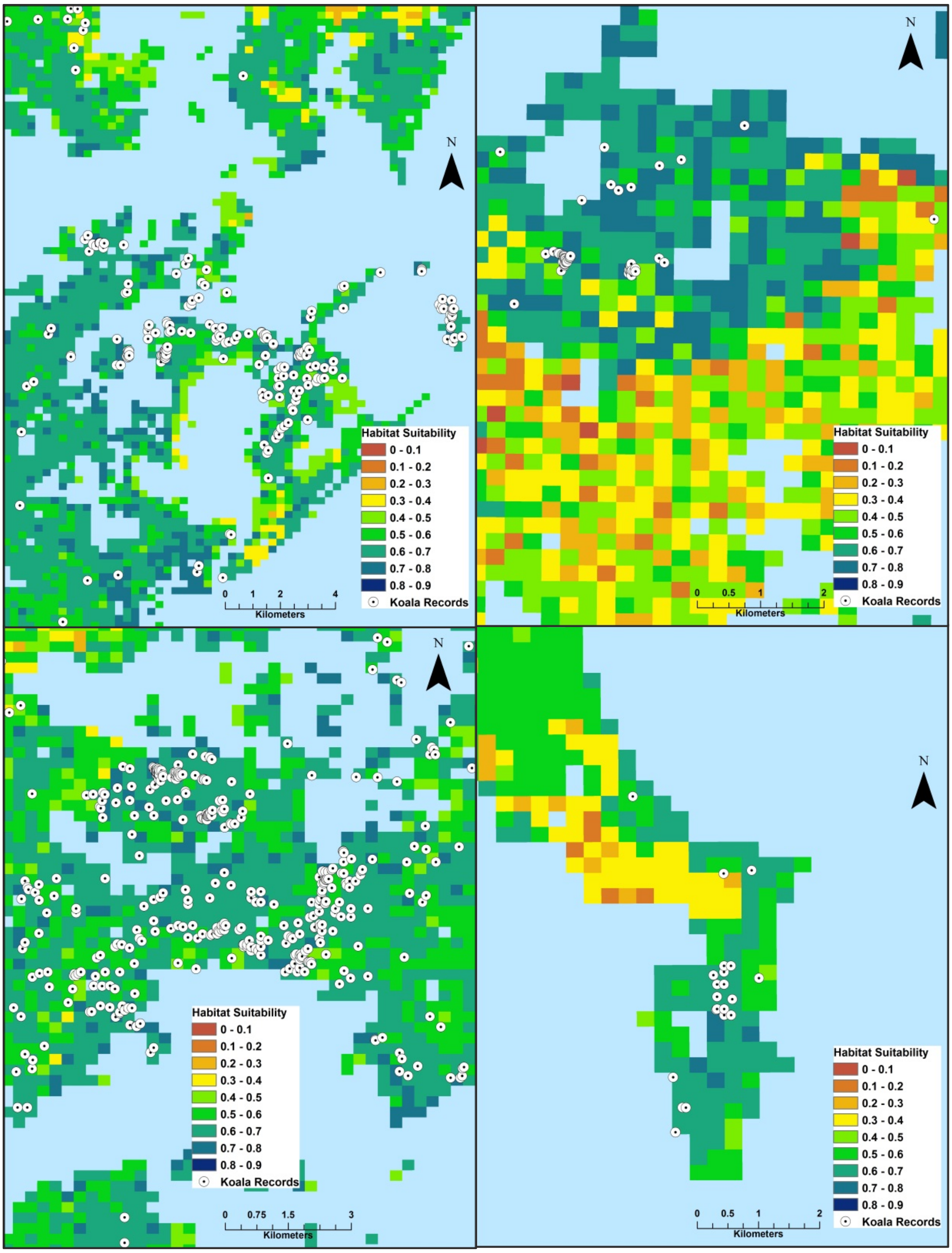


Figure 10. Koala habitat suitability map in four areas characterized by high record density

We analysed the frequency of the 3116 Koala records that were excluded from MaxEnt analysis (see section *Study area and* Koala *occurrence records* and *Model evaluation*) within the nine suitability classes. The frequency of the nine classes was unimodal with over 75% of the study area recording habitat suitability values lower than 0.5 (Figure 11). The distribution was unequal across the classes and ~50% of the records were located in areas with habitat suitability > 0.6, representing ~8 % of the study area. The highest frequency of records (~34%) was recorded between 0.6 and 0.7. Only ~7% of the records were located in areas with suitability <0.4, yet this constituted ~51 % of the study area.

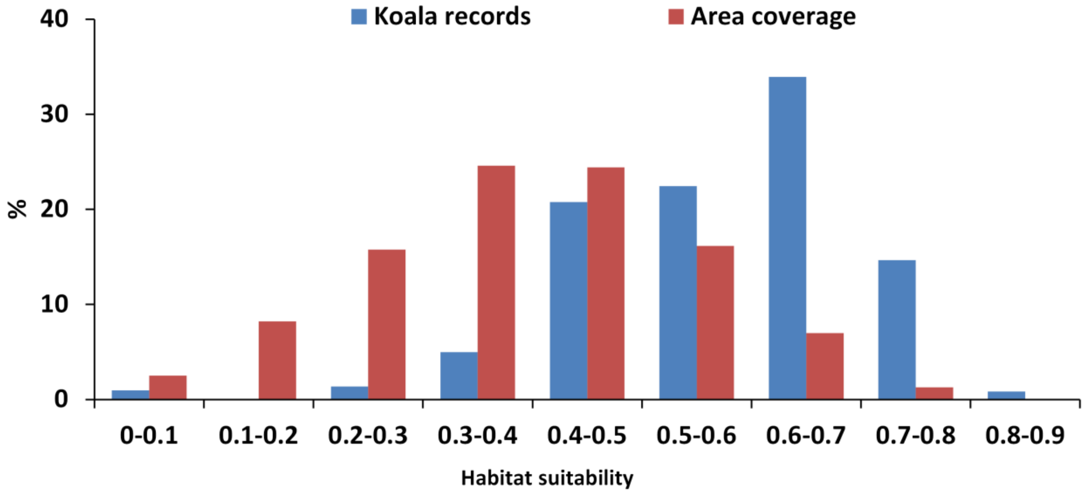


Figure 11. Distribution of area coverage (percentage) and Koala records (percentage) within nine habitat suitability classes.

When the number of Koala records was displayed separately for each subregion (Figure 12a,b), a different distribution is apparent. It is evident that the model for subregion1has a pattern where there are proportionally more records than expected for the area available for model output values >0.5. While this is also the case for subregion2, the discrimination ability of this model, based on the ratio of records to area, is better than in subregion1 for output values >0.6. The models for both subregions have few Koala records below model values <0.4.

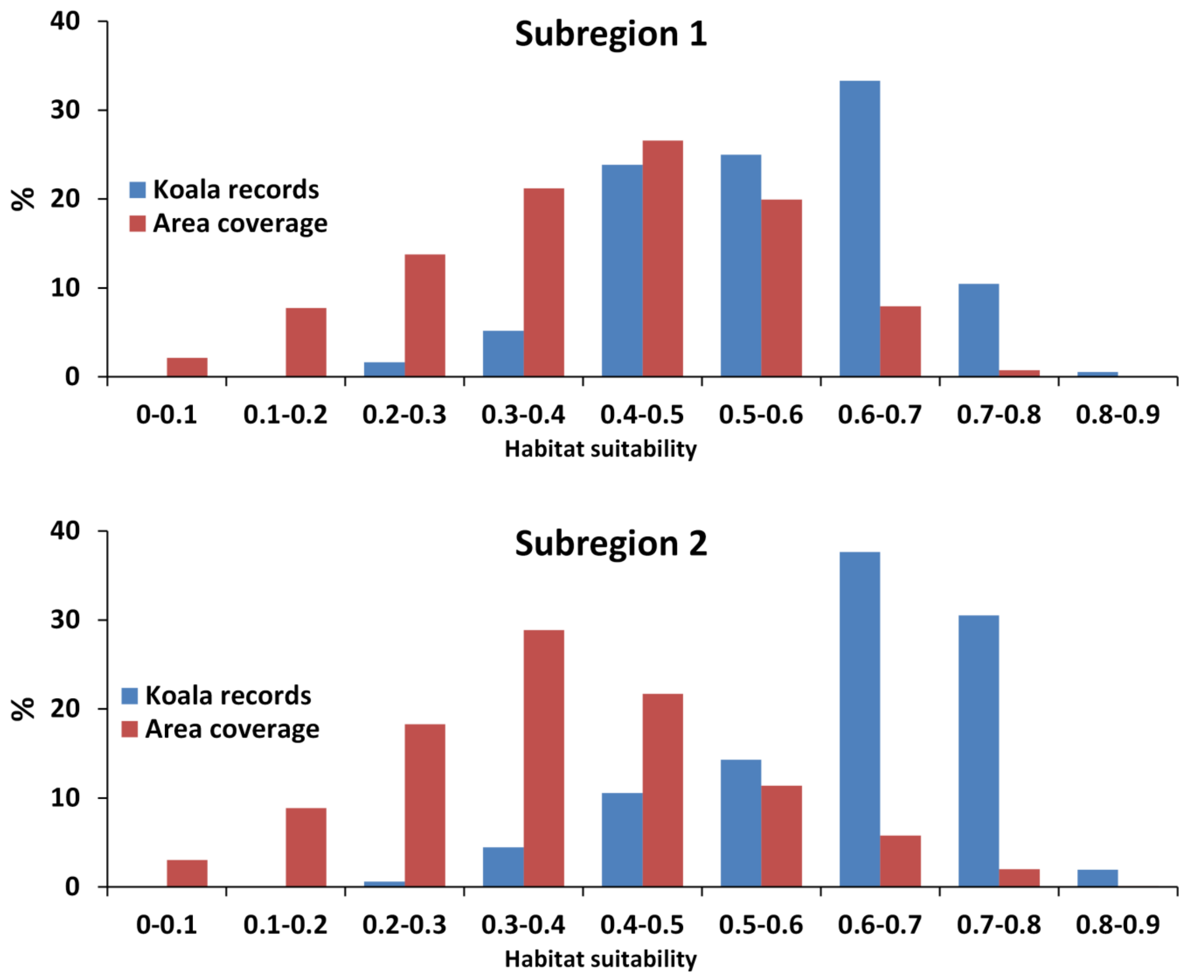


Figure 12. Distribution of area coverage (percentage) and Koala records (percentage) within nine habitat suitability classes for (a) subregion1 and (b) subregion2.

Field Validation of Habitat Model

Ground-truth sites were evenly spread between lower slopes (n=28) and upper slopes (n=32) with a small sample from mid-slopes (n=5). Most sites were located in regrowth aged 11-30 years (noting we avoided sites recently logged < 5 years ago) (Figure 13). Two of the 65 SongMeters failed to record data, leaving us with occupancy data for 63 sites.

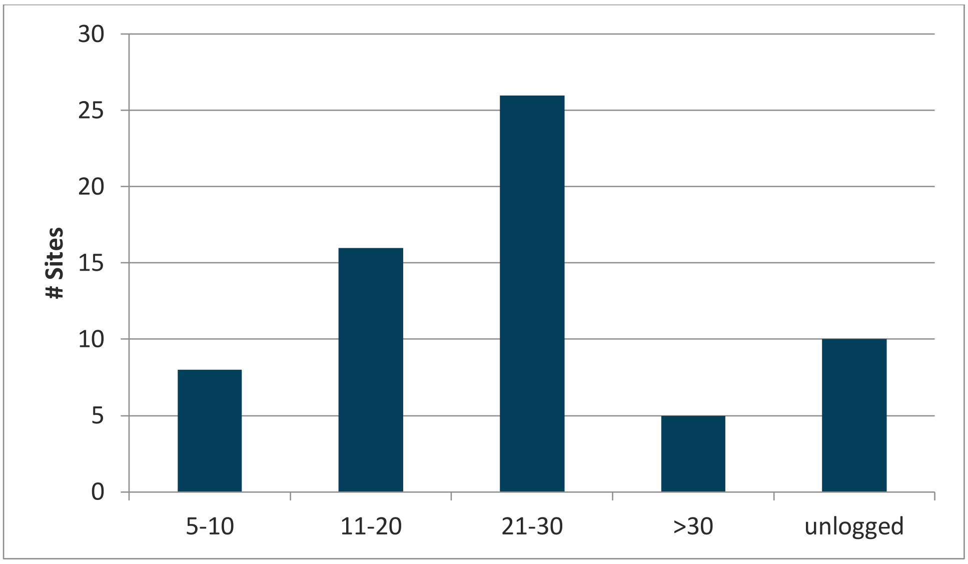


Figure 13. Distribution of sites across different logging histories. Years since logging were estimated in the field.

Model Validation Using Koala Occupancy

A total of 276 Koala bellows were recorded on 46 out of 441 nights of sampling at 29 % of sites. In comparison, Koala pellets were recorded at just 13 of 2,600 trees searched, representing 17 % of sites. No accumulations of pellets were found, with just a one or two being recorded beneath a tree. Moreover, 22 % of sites recorded a bellow, but no pellet and just 12 % of sites recorded a pellet, but no bellow. One individual Koala was observed at each of two sites (Maria River State Forest and Braemar State Forest). Interestingly, no Koala calls were recorded at Maria River State Forest, but Braemar State Forest yielded the highest number of calls of any site (Appendix B). No pellets were visible directly beneath the Koalas observed. Just a single pellet was found at Braemar State forest and none were found at Maria River State Forest (Appendix B). A high number (>20) of Koala calls were recorded at the following sites: Braemar State Forest, Wild Cattle Creek State Forest, Chichester State Forest, Pine Creek State Forest and Yabbra State Forest. These sites have a long history of logging, while just a single pellet and zero calls were recorded from unlogged sites (n=10, Appendix B).

Validation of the MaxEnt model using occupancy data followed a number of steps. Modelling of detection probability indicated that constant detection was the best supported model (Table 3), with a low probability of detection per night of 0.32. However, varying detectability by trip fell within 2 AIC points of the top model and so was also supported (though with half the AIC weight). Koala detectability declined slightly from 0.43 in October/November to 0.36 in late November to 0.30 in December. While different sites were sampled in each trip, a similar distribution of modelled habitat quality was sampled as per the sampling stratification for ground-truthing. There was no indication that daily rainfall influenced bellow detectability, though it is possible that using rainfall just for the nocturnal recording period may have altered this result. The site-based, topographic position index had the least support for influencing detectability.

Table 3: Model selection results for comparing Koala bellow detectability with rainfall, trip and topographic position in comparison to the null model with constant detection.

Model	AIC	Delta AIC	AIC weight	Model Likelihood	No. parameters	-2*Log Likelihood
psi(.),p(.)	238.74	0.00	0.6657	1.0000	2	234.74
psi(.),p(trip)	240.22	1.48	0.3176	0.4771	2	236.22
psi(.),p(rainfall)	246.12	7.38	0.0166	0.0250	2	242.12
psi(.),p(topo)	253.2	14.46	0.005	0.0007	2	249.2

Modelling of occupancy per site against the MaxEnt model values calculated at different spatial scales surrounding each ground-truthed site revealed most support for the 250 m pixel scale, with detectability either held constant or allowed to vary by trip (Table 4). All other models, including constant occupancy, were not supported. The plot of fitted values of occupancy per site demonstrates a near linear relationship with the MaxEnt model output (Figuer 14). In other words, an increase in model output was correlated positively with Koala occupancy (df=62, r=0.681, P<0.001). The data were considered to be a good fit to this model as assessed by the Pearson Chi-squared statistic (Chi-square=338.349, *P*=0.10, c-hat = 1.5781). The probability of Koala occupancy ranged from <0.1 to just over 0.5. Low detectability of Koalas meant that occupancy could still be estimated for many sites where Koalas were not detected, albeit this ‘probability of occupancy’ was typically low. A similar positive relationship was evident when Koala occupancy and modelled output from each subregion were treated separately in the occupancy modelling framework (Sub-region 1 (<500m ASL): df=36, r=0.622, P<0.001; Sub-region 2 (>/=500m ASL): df=25, r=0.704, P<0.001; Figure 15 a, b). Wider confidence intervals were especially evident for subregion 1 at low MaxEnt model values and these are indicative of few ground-truthed sites sampled at low model values of < 0.29. For example, a red bloodwood and blackbutt dominated site on sandy soil at Banyabba SCA had the lowest model output score for subregion 1 (0.11) and it also had the lowest predicted Koala occupancy value (0.06). Yet confidence intervals were high because no other sites were sampled with such low model output scores. The outcome of few sites sampled at very low model output scores partly resulted from rainforest sites having higher than expected MaxEnt model values and some occupancy by Koalas (see

Model Validation Using the Site Habitat Quality Index). In addition, clearly unsuitable habitat such as heath or swamp was not ground-truthed.

Table 4. Model selection results for comparing Koala occupancy with MaxEnt model output calculated for each ground-truth site at four different spatial scales. Detectability was held either constant (p(.)) or allowed to vary by trip (p(trip).

Model	AIC	Delta AIC	AIC weight	Model Likelihood	No. parameters	-2*Log Likelihood
psi(250m),p(.)	236.25	0	0.3928	1	3	230.25
psi(250m),p(trip)	237.84	1.59	0.1774	0.4516	3	231.84
psi(.),p(.)	238.74	2.49	0.1131	0.2879	2	234.74
psi(500m),p(.)	239.04	2.79	0.0973	0.2478	3	233.04
psi(1000m),p(.)	239.62	3.37	0.0728	0.1854	3	233.62
psi(2000m),p(.)	240.5	4.25	0.0469	0.1194	3	234.5
psi(500m),p(trip)	240.61	4.36	0.0444	0.113	3	234.61
psi(1000m),p(trip)	241.18	4.93	0.0334	0.085	3	235.18
psi(2000m),p(trip)	242.03	5.78	0.0218	0.0556	3	236.03

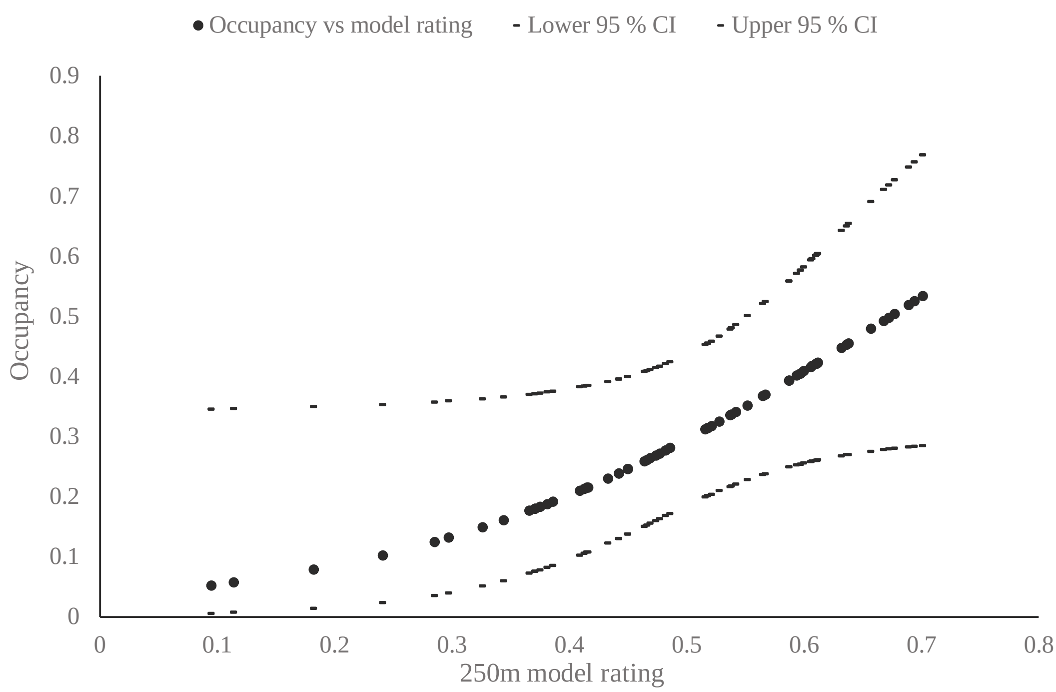
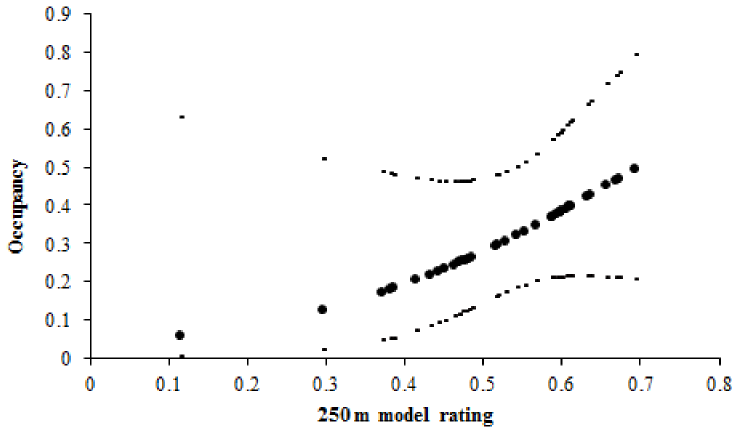


Figure 14: Validation results from 63 ground-truth sites. The graph shows the relationship between the fitted probability of Koala occupancy (after accounting for detectability) against the MaxEnt model output at a 250 m pixel scale. Values are the mean fitted values ± 95 % confidence intervals (i.e. predicted from the MaxEnt model). Model Fit: Chi-square=338.349, P=0.10, c-hat = 1.5781.

a. Subregion 1 (< 500 m elevation)



b. Subregion 2 (> 500 m elevation)

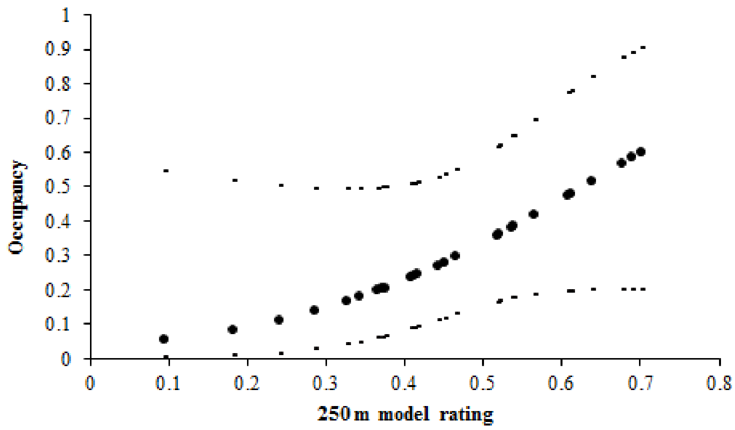


Figure 15. Validation results calculated separately for two subregions (subregion 1 (a), n = 38 ground-truth sites; subregion 2 (b), n = 27 ground-truth sites). The graphs show the relationship between the fitted probability of Koala occupancy (after accounting for detectability) against the MaxEnt model output (250 m pixel scale). Values are the mean fitted values ± 95 % confidence intervals (i.e. predicted from the MaxEnt model).

Model Validation Using the Site Habitat Quality Index

We used a site habitat quality index for model validation in addition to Koala occupancy to consider the possibility that the MaxEnt model was predicting habitat potential rather than occupancy. The site habitat quality index increased positively with the 250 m pixel MaxEnt output in both subregions (Subregion 1: r=0.537; P=0.0039; Subregion 2: r=0.384, P=0.017) (Figure 16). The relationship was weaker, though still significant, for the high elevation subregion 2, where there was more scatter and fewer ground-truth sites. On average, for a given model output, habitat quality was slightly higher in subregion2 than subregion1. Some of the scatter can be attributed to a group of rainforest sites that are potentially over-predicted by the model (Figure 16). These were typically small patches in close proximity to eucalypt forest. We also assessed the fit of alternative weightings for browse quality class, but these performed more poorly.

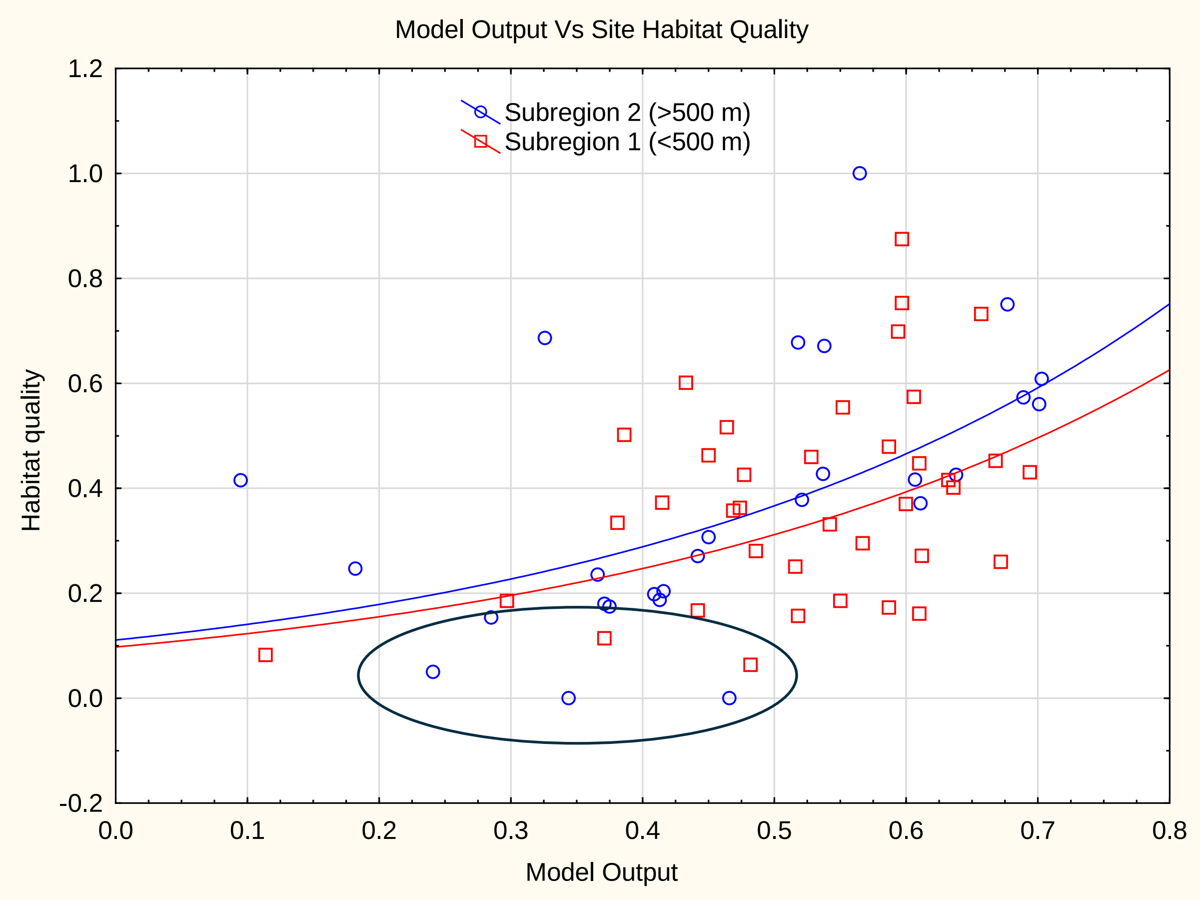


Figure 16. The relationships between a habitat quality index based on browse tree availability and diversity with each MaxEnt model output for two subregions across 65 ground-truth sites. The blue oval highlights a group of rainforest sites that may be over-predicted by the model.

How does the habitat quality index and other site attributes compare with the MaxEnt model for predicting Koala occupancy? We assessed this in the occupancy modelling framework and found that the MaxEnt model was strongly supported over the site habitat quality index, indicating that the MaxEnt model, which incorporates a range of explanatory variables, is a better predictor of Koala occupancy than a site based index based on browse tree availability and diversity (Table 6). When assessed individually, other site attributes including NPP, topographic position, elevation and the frequency of wildfires were also poorer predictors of Koala occupancy compared to the MaxEnt model,. To illustrate this, occupancy was not related to site elevation, although it was most variable at high elevations (Figure 17).

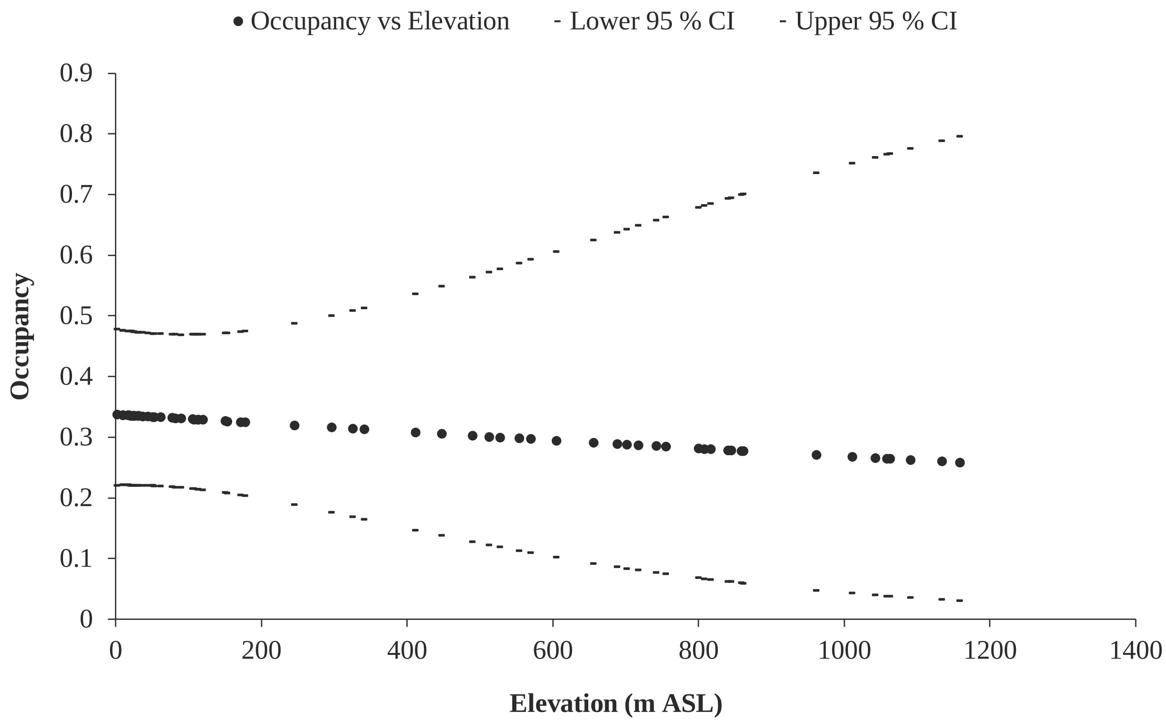


Figure 17. The relationship between fitted probability of Koala occupancy (after accounting for detectability) against elevation at 63 ground-truthed sites.

Table 6. Model selection results comparing Koala occupancy with the 250 m scale MaxEnt model output, the habitat quality index and other site attributes calculated for each ground-truth site, plus a null model with constant occupancy. Detectability was held constant.

Model	AIC	Delta AIC	AIC weight	Model Likelihood	No. parameters	-2*Log Likelihood
psi(250m),p(.)	236.25	0.00	0.5152	1.0000	3	230.25
psi(.),p(.)	238.74	2.49	0.1483	0.2879	2	234.74
psi(npp),p(.)	239.76	3.51	0.0891	0.1729	3	233.76
psi(topo),p(.)	240.07	3.82	0.0763	0.1481	3	234.07
psi(elevation),p(.)	240.55	4.3	0.06	0.1165	3	234.55
psi(fire),p(.)	240.69	4.44	0.056	0.1086	3	234.69
psi(habitat quality),p(.)	240.07	3.82	0.0551	0.1481	3	234.07

Finally, we also examined the accuracy of the Crafti layer to predict browse species present at ground-truth sites to assess the reliability of this predictor as an input variable for modelling. We found a good match between the dominant trees species present at ground truth sites and mapped Crafti type, with only 15 % of sites (n=10) being incorrectly typed. These were most frequently typed as New England Blackbutt (n=4), but often a mix of Messmate, Brown Barrel, Ribbon Gum or Sydney Blue Gum was present with no dominant

New England Blackbutt. Or alternatively, a site was incorrectly mapped as rainforest (n=3) where Brushbox and Sydney Blue Gum dominated. Seventy-one per cent of sites were classified correctly and a further 14 % contained species consistent with the Crafti forest type, but with one or more typical species absent.

Discussion

Koala Habitat Suitability Model

Predictive models of habitat suitability have great potential to efficiently direct management actions for threatened species, especially for those that are rare or cryptic. The aim of our modelling approach was to produce a spatially explicit map of predicted Koala habitat suitability at a resolution suitable for management implementation. It corrected for the high spatial bias in the distribution of Koala records and was evaluated statistically as a good fit to existing Koala records, both for independent test sets (AUC) and the suite of records extracted from the National Parks Wildlife Atlas, but not used in modelling. Most importantly, there was good discrimination by each of the habitat suitability classes when compared with the Koala records not used by MaxEnt as well as its relative area of extent; i.e. proportionately more records per area with increasing suitability.

The model used a suite of predictor variables that reflect vegetation productivity, soils, forest type, topography, climate and disturbance from wildfire. Other regional maps of Koala distribution in NSW focus on hot-spots of records and do not predict Koala occurrence in areas that have not been surveyed (Predavec *et al.* 2015). These maps are also produced at a much coarser resolution of 5 km^2 or 10 km^2. In comparison, fine-scale maps of Koala distribution have been produced at local scales and are based on associations between pellet counts and floristic associations (e.g. Lunney *et al.* 1998). Our modelling extends these approaches to the whole of forested north-east NSW at a fine resolution (250 m grid cell) and predicts habitat suitability in areas not surveyed. Another important advantage of the predictive regional model is that it contextualises the importance of particular areas for Koalas in a local-regional context or LGA scale such as for individual forests used for timber harvesting. This could be useful when considering cross-tenure protection or major projects such as urban development or highway upgrades.

The predictive map derived for Koalas identifies areas of high habitat suitability (and likelihood of occurrence) as those with a low wildfire frequency over the past 45 years. There was weak support for a correlation between wildfire frequency and preferred Koala forest types, suggesting that a small part of the fire effect could be due to a contribution from preferred Koala forest types being less prone to wildfires. High-intensity fires burn the canopy and can cause death or injury to Koalas and a reduction in the availability of foraging habitat (Lunney *et al.* 2004; Lunney *et al.* 2007). Existing studies on the impacts of wildfire on Koalas have mostly investigated small scale burns < 10,000 ha, suggesting that the scale of wildfires warrants further investigation. The model response curves showed that wildfire frequency had a more extreme response in sub-region 1 (elevation < 500 m). This is consistent with the north coast region recording the second highest number of fires of any region in the state (behind Sydney) (Bryant 2008), though it is unknown whether fire severity is higher in that region. Fire severity is likely to be a key factor threatening Koalas as the response of arboreal mammals to fire in Victorian forests was most strongly influenced by fire severity, with gullies and unburnt forest serving as key refuges (Chia *et al*. 2015). One implication of the importance of wildfires is that while an area may support a suitable suite of conditions for Koalas (e.g. browse species), such habitat may be unoccupied due to mortality from fire. Other historical factors or current threats including fragmentation by urbanisation, predation pressure (e.g. dogs) or extreme climatic events (e.g. drought and heat waves- Lunney *et al.* 2014; Briscoe *et al*. 2016) may similarly reduce Koala occupation levels. In addition, other forms of disturbance could also affect occupancy. The effect of logging disturbance on habitat suitability for Koalas warrants further investigation (e.g. Kavanagh *et al*. 1995; Smith 2004; Roberts 2008), though including logging history as an additional disturbance layer in future modelling of Koala habitat is not straightforward (Appendix A).

Koalas also had a lower likelihood of occurrence on Tenosol and Rudosol soils. Tenosols are generally sandy with very low productivity and chemical fertility, poor structure and low water-holding capacity (Northcote *et al*., 1960-68). Rudosols tend to be shallow with little soil development and are often gravely or rocky. Podosols and Sodosols were predicted to have higher suitability for Koalas and these soils have high organic matter and occur either in coastal areas (Podosols) or areas with poor drainage (Sodosols), yet both are considered to be relatively infertile. As an example, many Koala records in the Port Stephens area occur on Podosol soils, which are likely to be associated with Swamp Mahogany *Eucalyptus robusta*, a preferred browse species in this and other coastal areas (Phillips *et al.* 2000). A direct measure of soil fertility was not supported during model building, possibly because much of the better quality soils have been cleared for agriculture and these were masked from our modelling process.

Floristic composition was the third important variable contributing to the Koala model. Occurrence was more likely on areas mapped with primary browse species, including red gum species (e.g. *Eucalyptus tereticornis*), Tallowwood (*E. microcorys*) and Swamp Mahogany (*E. robusta*) and least likely in areas mapped as unsuitable habitat (e.g. banksia heath, rainforest with no eucalypt emergents). The two intermediate floristic classes for Koala suitability had less discriminating ability, probably because many of these types are broad classifications of forest that support varying frequencies of browse species. For example, Blackbutt *Eucalyptus pilularis* and Spotted Gum *Corymbia variegata* types are widespread and not considered highly suitable for Koalas (e.g. Phillips *et al*. 2000), although the frequency of Tallowwood and Grey Gum *E. punctata*, two primary browse species, are highly variable in these types.

Elevation was the fourth important variable in the Koala model. Habitat suitability was predicted to be higher at low elevations in sub-region one, but it was also predicted to be high at 500-600 m in sub-region 2. Elevations of 200-500 m and > 800 m were predicted to have lower suitability, though with other factors modifying this effect. This pattern of a low and mid-elevation peak for Koalas is probably driven to a large extent by the extensive number of records in coastal areas and in the Dorrigo plateau (e.g. Wild Cattle Creek State Forest) and adjacent to Comboyne plateau (Bulga State Forest). An association with low elevations has long been known (e.g. Kavanagh *et al.* 1995; Phillips *et al.* 2000; Smith 2004), however, high habitat suitability at mid-elevation and even some high elevations such as Nowendoc appears to be less widely appreciated (but see Krockenberger 1993; Kavanagh and Stanton 1995; Braithwaite 1996; Roberts 1998). Interestingly, Koala occupancy at ground-truth sites was not related to elevation. It is also important to note that the New England Tablelands (and the north coast NSW) are predicted to provide climate refugia under climate change scenarios (Briscoe *et al*. 2016). One outcome of splitting our study region into two subregions based on the 500 m contour was a discontinuity between the subregions at this elevation, rather than a seamless transition. This could represent a limitation for management implementation of the model that could be addressed via setting different thresholds for classes of habitat suitability in the two subregions to a better transition between the subregions.

Other variables made minor contributions to the Koala model, such as a greater likelihood of Koalas on flatter terrain and where soil depth, primary productivity, biomass and Fpc were higher. The contributions of variables differed somewhat between regions, such as a greater importance in sub-region1 than sub-region2 for precipitation in the driest quarter. A landscape effect of the surrounding area of preferred forest types had less influence in sub-region1 where there were many Koala records in fragmented forest and a negative response to the surrounding area of preferred forest types was observed.

The major challenge in developing the MaxEnt model for Koalas was the highly biased dataset of records. There were two sources of bias that we corrected for. The first was major clusters of records at urban centres along the coast. Spatial aggregation was minimised (e.g., Parolo *et al*., 2008; Kramer-Schadt *et al*., 2013) by only using records that were 2 km apart and by splitting regional records into two sub-regions using the 500 m elevation contour. The second source of bias was the concentration of records along roads where people are most likely to encounter Koalas. We minimised the influence of roads and surveying bias by producing a bias file that increased weighting away from areas with more records of arboreal mammals. There were also many records that we excluded from our model-building in semi-cleared/urban areas, which (based on records) can provide important habitat for Koalas. Thus it is important to remember that the model output only covers forested areas, albeit with minimum vegetation patch sizes of ~6.5 ha.

Further improvements to the model should be possible in the future. Perhaps the most significant would be more systematic surveys of Koalas in areas remote from major population centres to reduce the effect of record bias. An updated vegetation map for northeastern NSW with accurate data on canopy tree species, especially in farmland with scattered tree cover, would allow extension of the model into additional important Koala habitat. Theoretically, it could be possible to model to a finer resolution of 25 m with the data-layers used. However, use of such fine resolution needs to be balanced with an appreciation of the species ecology. For example, Koalas move over large areas and sightings recorded in a data-base are likely to include transient individuals making little use of that point in space. This suggests that there is value in maintaining a larger grid size that incorporates environmental conditions surrounding point records (see also Ream 2013). However, pixels larger than 250 m have the disadvantage of requiring excessive averaging over the fine scale variation in forest types and complex topography that occurs on the north coast of NSW. The current pixel size is considerably less than Koala home range size, which can vary from 59 ha for males to 26 ha for females, with considerable dispersal distances (> 20km) (Matthews *et al*. 2016).

Field validation

Ground-truthing of MaxEnt predicted Koala habitat suitability provided strong support for the reliability of the model. Koala occupancy was found to increase in a near linear pattern as model output values increased. The same relationship was evident for each subregion when analysed separately, though the consequent reduction in the sample size of ground truth sites yielded wider confidence intervals for these relationships. The model output at a 250 m scale was the strongest performer when a number of spatial scales was considered, indicating more extensive areas of higher habitat suitability than a 250 m pixel were not better predictors of Koala occupancy. This is consistent with the fact that the landscape variable, percentage cover of primary and secondary Crafti forest types, was a minor contributor to the Koala habitat suitability model. Such a result contrasts with local studies in fragmented rural areas that have identified the importance of landscape context, patch size, fragmentation and connectivity (McAlpine *et al*. 2006), though variations in threshold values for landscape variables vary with region (Rhodes *et al*. 2008).

The MaxEnt model clearly outperformed a site based habitat quality index calculated from browse tree availability and diversity when predicting Koala occupancy that had been adjusted for detectability. This is not surprising, given that the determinants of Koala habitat are likely to include a range of features including tree species, soil fertility, moisture, topography, elevation and especially disturbance variables like wildfire frequency, all of which are accounted for by the model. In addition, there was considerable uncertainty in how to allocate tree species into different classes of browse quality. More quantitative data on Koala diet would be required to more reliably allocate tree species to different classes and to set appropriate weights in developing such a habitat quality index. This has implications for directing conservation actions or management mitigations for Koalas. Identification of sites based solely on browse tree species is likely to be relatively inaccurate, whereas habitat models that consider a suite of potential important variables should be more successful. MaxEnt models have not only been used to predict Koala habitat suitable at large scales (Briscoe *et al*. 2016), they been recommended for general use to guide habitat conservation and restoration efforts (Latif *et al.* 2015).

It is important to note that models are not a perfect representation of the real world and, despite strong support, our MaxEnt model has limitations. In particular, the process of ground-truthing identified that patches of rainforest (especially at low elevation) are likely to be over-predicted by the model. Poor classification of rainforest is most apparent for smaller patches surrounded by otherwise suitable eucalypt forest. As an example, site 7L was a patch of rainforest in Cascade National Park, which in some areas contained emergent *E. saligna* and the patch itself was also in close proximity to eucalypt forest. Koalas were recorded calling at this site (Appendix B). It is possible that small rainforest patches are used for shelter by Koalas, especially during hot weather. This potential limitation of the model could be addressed by overlaying mapped rainforest over the model to highlight their low suitability. However, such a limitation is not likely to influence the implementation of the model given that rainforests are protected in NSW and cannot be harvested. Nevertheless, we recommend that model implementation for management purposes should be accompanied by field inspections, especially to identify the local presence of browse trees, in combination with using the model output.

Another key result of our ground-truthing was confirmation of the effectiveness of acoustic recorders, in conjunction with occupancy modelling, for quantitatively surveying Koalas based on detecting male mating bellows. SongMeters clearly outperformed pellet searches in detecting Koalas. Koala calls are considered to be detectable by SongMeters up to at least a 100 m radius (W. Ellis pers. comm.). More distant, faint calls may sometimes be recorded suggesting that acoustic recorders could have a larger sampling area than the 250 m transect pellet search area in our study. However, topographic position was not related to Koala bellow detectability, indicating Koala detection did not vary greatly between ridges and gullies as would be expected if bellows are detectable over large distances. The Koala pellet survey not only yielded limited returns, it was not possible to account for pellet detectability based on a single visit and this prevented its use for model validation. Difficulty in identifying Koala habitat from pellet searches in some forest types (e.g. moist forests or where a dense understorey and litter is present) was one of the drivers for developing a model of Koala habitat. It is well known that Koala pellet detectability depends on ground layer complexity and that pellet decay rates vary within and among vegetation communities, being notably faster in moist types (Cristescu *et al*. 2012).

Koalas were recorded acoustically on 29 % of ground-truth sites (42 % using all methods – acoustics, scats and sightings). However, it should be noted that a number of these sites were selected to test model performance in areas of low habitat quality, indicating true occupancy in better quality habitat would be higher. At areas of higher predicted quality, the estimated probability of occupancy is just over 0.5 (95 %CI: 0.28-0.77), suggesting that about half of the better quality forested habitat for Koalas in northern NSW is occupied. Further comparisons of occupancy would be valuable, such as against additional known and unknown populations or those predicted to be of very high quality by the latest version of the MaxEnt model. Some of these could be in coastal areas (e.g. far north coast), which were not a focus for ground-truthing. Previous surveys for Koalas in northern NSW have recorded them at much lower levels than our survey, including a regional survey of northern NSW (12 % of sites – playback and spot-lighting; Kavanagh *et al.*1995), Grafton/Casino forests (4 % of sites - spotlighting and scat searches; Smith *et al.*1994), Urunga-Coffs Harbour forests (13 % of sites- spotlighting and scat searches; Smith *et al.*1995) and Dorrigo forests (24 % of sites - playback and spotlighting; Kavanagh and Stanton 1995). More localised surveys have had more success. For example, Koala pellet searches detected Koalas at 79 % of a small number of random sites (n=14 sites) in the Dorrigo forests (Roberts 1998) and 49 % of survey sites in Pine Creek State Forest (Smith 2004).

Conclusions

A predictive habitat model for northeastern NSW was developed for Koalas at a 250 m resolution based on spatially filtered and bias-corrected records. The model provided good discrimination ability for Koala records not used in model building. Field validation of the continuous model output using acoustic detectors to record male bellows demonstrated a linear increase in estimated Koala occupancy with higher model output values. The model output provided a better fit to Koala occupancy than site-derived estimates of habitat quality based on browse tree availability, though the latter was also correlated positively with the model output. We suggest that this provides strong evidence for using this model to guide management decisions for Koalas in forested habitat. One approach for doing this would be to derive thresholds for Koala habitat suitability that trigger different management actions, such as different degrees of browse tree retention. For example, one approach might be to set a small total area as 'High Suitability' (e.g. probability of occupancy >0.7) and allow this to trigger either exclusion areas or strict browse tree retention and to have reduced browse tree retention for a 'moderate suitability' class. Another approach would be to set the area of 'High Suitability' more broadly and allow this to trigger a less rigid protection for browse trees. This approach would have the advantage of being less sensitive to prediction errors and in effect would spread the risk of failing to predict High Suitability habitat. A further alternative could combine both approaches.

Finally, acoustic recorders represent an innovative opportunity to develop a robust and efficient method for monitoring trends in Koalas over time. This has traditionally been a difficult task that has led to an absence of reliable estimates of Koala trends. Combining acoustic recorders with an occupancy modelling framework would be a powerful method for monitoring Koalas across many sites at a landscape scale (MacKenzie *et al.* 2002).

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Appendix A

Forest successional stage data-layers were explored for use as input variables to MaxEnt modelling of Koala habitat suitability. We followed two approaches to assess the usefulness of such layers.

High Conservation Value Old Growth layer

High Conservation Value Old growth was mapped in the 1990s for the North East CRAFTI Structural and Floristic Layers project as part of the CRA process. We assumed old growth had not dramatically changed in extent since that time because old growth is not harvested in northern NSW. This allowed us to model with the entire sample of Koala records from 1990 to 2016. This layer was used in conjunction with the same predictors, Koala samples, bias layer and parameters as those used for our previous best model. Five random sets of Koala records were run to produce five separate models. All pixels within Old Growth were classified as 1 and all other pixels 0.

The model predicted that Koala habitat suitability was lower in old growth than non-old growth (Figure A1), with similar patterns observed in both sub-regions. However, this data layer made only a minor contribution to the model compared to other variables, ranging from 0.1-0.5 % contribution in sub-region 1 and 0.6-3.7 % in sub-region 2 (range in contribution reflects variability in the five random sub-sets of Koala records modelled). Inspection of the map output from this model indicated little difference between our previous best model and the model including old growth as an input. Given the minor contribution to the model and the need to minimise the total number of variables for parsimony in modelling, we excluded this layer from the final model.

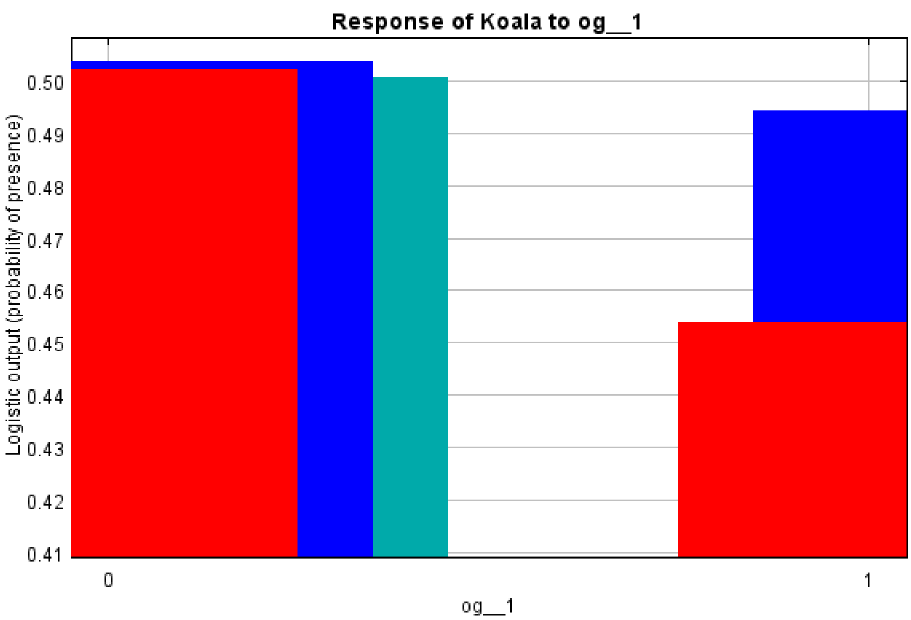

Figure A1. Example response curve for predicted Koala habitat and the old growth layer from one random data set from sub-region 1. The red bar represents the mean response whilst the two shades of blue represents the mean +/- one standard deviation. 1= old growth and 0=non-old-growth.

Forest Successional Stage Layer

This layer was mapped in conjunction with the old growth layer in the 1990s for the North East CRAFTI Structural and Floristic Layers project (CRA process) using aerial photography between 1991 and 1997 and various other disturbance information inputs. It is an update of the original Successional Stages layer produced during the U/LNE Comprehensive Regional Assessment (CRA) process in 1998, being completed in 2001. Although the mapping extended across all land tenures, a major issue with including it in Koala modelling is that the layer provides a snapshot of successional changes in the 1990s, which is likely to have dramatically changed since then. For example, a considerable proportion of the 'mature forest' is likely to have been harvested since then and much of the 'recently disturbed forest' could have transitioned to 'young forest'. Rather than include Koala records from our entire data-set (1990-2015) we explored the usefulness of this layer with Koala records extracted from the same time period as the successional mapping(1990-2000).

The successional stage layer was acquired from:

data.environment.nsw.gov.au/dataset/successional-stages-for-cra-lower-north-east-vis_id-3892bbee9

data.environment.nsw.gov.au/dataset/successional-stages-for-cra-upper-north-east-vis_id-389302b97

The layer was used in conjunction with the same predictors, bias layer and parameters as those used for our previous best model, though Koala samples were restricted to 1990-2000. Five random sets of Koala records were run to produce five separate models. The layer was reclassified as follows: Non forest = 0, Candidate old growth = 1, Disturbed Mature Forest = 2, Disturbed Old Growth = 3, Mature forest = 4, Rainforest = 5, Recently Disturbed = 6, Young = 7.

The model predicted that Koala habitat suitability was lowest in old growth and rainforest and highest in recently disturbed, young and disturbed mature forest (Figure A2), with similar patterns observed in both sub-regions. This data layer made a moderate contribution to the model, ranging from 7.6-13.1 % contribution in sub-region 1 and 8.8-15.1 % in sub-region 2 (range in contribution reflects variability in the five random sub-sets of Koala records modelled). Inspection of the map output from this model indicated some important differences from our previous best model. Notably, the coastal strip of the far north coast was no longer modelled as very high quality, while new areas were modelled as very high quality such as forests immediately south of the Bellinger River. Much of the Tablelands were predicted to be of lower quality than indicated by the previous best model. Other areas such as the broader Dorrigo plateau continued to be modelled as very high quality habitat.

While the results from modelling this input layer suggest there is some merit in considering forest successional stage in modelling Koala habitat, there are a number of reasons why we considered that this layer was inappropriate for inclusion in our best model. First, a previous preliminary field validation of its accuracy for the Upper North East assessment found 41% of 56 sites indicated agreement with the API growth stage, while 59 % showed disagreement[1]. Such uncertainty was considered problematic. Second, because the layer described forest succession in the 1990s, we were limited to using Koala records only from that decade. Finally, and most importantly, any model produced from this snap shot of forest succession in the 1990s necessarily provides a snap-shot of Koala habitat, as influenced by this layer, for that time period. These successional stages have now changed in many areas (as described above), so there is little value in using this layer to predict Koala habitat suitability in 2016.

Derivation of an up to date successional stage layer that spans across tenure has the potential to improve modelling of Koala habitat suitability, but this was beyond the scope of this project. It would also always have the limitation of applying to a narrow window of time given dynamic changes to forest successional ages. Derivation of a new layer quantifying the frequency of logging events also could be of potential value for modelling logging disturbance history and Koalas. However, given the rotation lengths of logging, this would need to be derived over a considerable time period and on public and private tenure. The extended window needed for classifying number of logging events is an important distinction from wildfires, which can burn in relatively close succession if conditions are suitable, and it was this characteristic that allowed us to classify frequency of wildfires within the last 45 years from an existing fire layer.

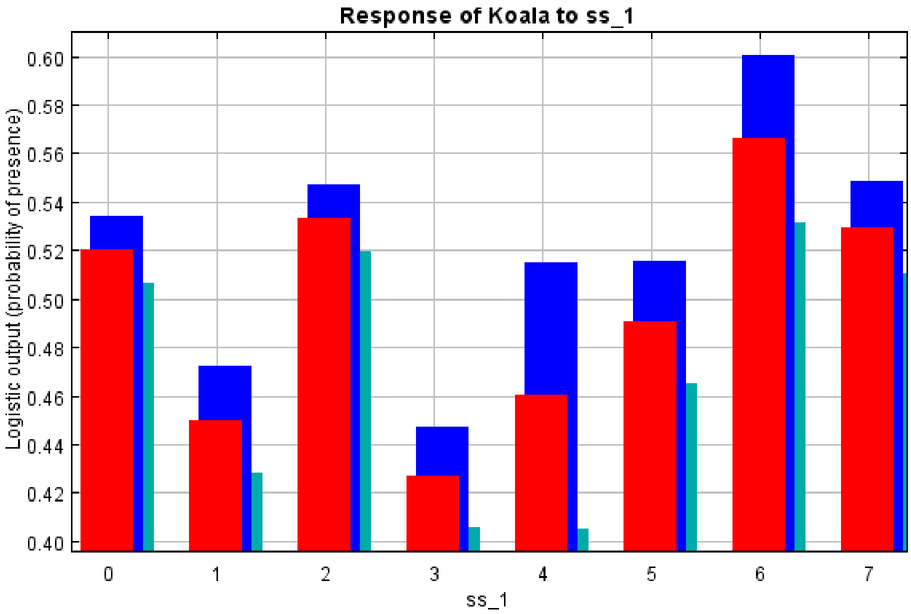

Figure A2. Example Successional Stage response curve for Sub-region 1. The red bar represents the mean response whilst the two shades of blue represent the mean +/- one standard deviation. Non forest = 0, Candidate old growth = 1, Disturbed Mature Forest = 2, Disturbed Old Growth = 3, Mature forest = 4, Rainforest = 5, Recently Disturbed = 6, Young = 7.

Reference

[1] UNE - LNE CRAFTI ACCURACY ASSESSMENT REPORT (1998). Unpublished report, NSW Government.

Appendix B

Sixty-five ground truth sites in northern NSW. Fire and logging descriptions were based on field assessments by B. Law. Number of Koala calls were those recorded by SongMeters over a seven night period after manually checking software generated ‘matches’ with a Koala call recogniser. Number of Koala scats refers to the total number recorded within a 1 m search area at the base of 40 trees (> 20 cm dbh) per site.

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
1H	WALLAROO SF	flat	25	light	10-15	Moderate	20	1	0	Small-fruited Grey Gum, Tallowwood
1L	PORT STEPEHENS	swamp	2	none		None		0	0	Swamp Oak, Swamp Mahogany
1M	WALLAROO SF	flat	17	light	10	None		0	0	Rough-barked Apple, Red Mahogany
1VH	TILLIGERRY SCA	swamp	10	moderate	10	none		1	0	Broad-leaved Paperbark, Blackbutt
2H	BULLS GROUND SF	mid slope	153	light	5-10	heavy	30	0	0	Blackbutt, Grey Ironbark
2L	COMBOYNE	upper slope	702	none		none	>50	0	0	Rainforest spp.

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
2M	BAGO BLUFF NP	lower slope	246	none		none	>50	0	0	Blackbutt, Tallowwood
2VH	COWARRA SF	flat	44	moderate	10-15	none		0	0	Narrow-leaved Red Gum, Rough-barked Apple
3H	ENFIELD SF	flat	1159	light	10	light	10-15	1	0	Messmate, Ribbon Gum
3L	COTTAN-BIMBANG NP	mid slope	1091	none		none		0	0	Rainforest spp.
3M	DOYLES RIVER SF	upper slope	1063	light	10	light	10	0	0	Sydney Blue Gum, eucalypt
3VH	ENFIELD SF	flat	1134	light	15	light	10	2	0	Messmate, Brown Barrel
4H1	CHICHESTER SF	ridge	326	none	10	moderate	20	0	40	Large-fruited Grey Gum, Tallowwood
4Ha	BARRINGTON TOPS NP	ridge	841	none		none		0	0	White-topped Box, Silver-top Stringybark

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
4M	CHICHESTER SF	ridge	490	none	20	heavy	30	0	0	Tallowwood, Sydney Blue Gum
4Ma	CHICHESTER SF	upper slope	845	none		heavy	30	1	0	Sydney Blue Gum, Silver-top Stringybark
5H	BALLENGARRA SF	upper slope	151	light	10	heavy	20	0	0	White Mahogany, Small-fruited Grey Gum
5Ha	MARIA RIVER SF	creek	25	light	10	moderate	15	0	0	Blackbutt, Ironbark
5M	MARIA RIVER SF	flat	21	moderate	5-10	moderate	15	0	0	Blackbutt, Stringybark
5VH	BALLENGARRA SF	upper slope	178	light	3-4	moderate	10	0	0	Tallowwood, Blackbutt
6H	GLENUGIE SF	mid slope	82	light	5-10	heavy	20	0	0	Spotted Gum, Narrow-leaved Ironbark

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
6L	BARCOONGERE SF	flat	22	none		heavy	10	0	0	Blackbutt
6M	GLENUGIE SF	simple slope	53	light	5-10	heavy	20	0	0	Red Ironbark, Spotted Gum
6VH	WEDDING BELLS SF	ridge	172	none		heavy	30	0	0	Blackbutt, Tallowwood
7H	WILD CATTLE CREEK SF	gully	570	none		heavy	30	0	0	Sydney Blue Gum, Forest Oak
7Ha	WILD CATTLE CREEK SF	lower slope	656	none		moderate	30	0	44	Flooded Gum, Tallowwood
7L	CASCADE NP	upper slope	808	none		heavy	40	0	3	Rainforest spp., Sydney Blue Gum
7M	CASCADE NP	upper slope	742	none		heavy	30	1	0	Brush Box, Sydney Blue Gum
8H	CLOUDS CREEK SF	upper slope	859	none		light	30	1	1	Sydney Blue Gum, Tallowwood

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
8Ha	CLOUDS CREEK SF	ridge	862	light	10	light	30	0	6	New England Blackbutt, Tallowwood
8VH	CLOUDS CREEK SF	upper slope	817	none		light	30	0	0	Sydney Blue Gum, Brush Box
8VHa	CLOUDS CREEK SF		800	none	10-15	light	5	0	0	Sydney Blue Gum, Tallowwood
9H	PINE CREEK SF	lower slope	26	light	10	heavy	30	0	22	Tallowwood, Blackbutt
9VH	PINE CREEK SF	lower slope	30	light	10	heavy	30	0	1	Blackbutt, Tallowwood
9VHA	BONGIL BONGIL NP	ridge	51	none	20	heavy	30	0	0	White Mahogany, Grey Ironbark
9VHb	PINE CREEK SF	mid slope	62	none	20	heavy	40	0	3	Flooded Gum, Turpentine
10H	INGALBA SF	ridge	78	none	10	heavy	30	0	0	White Mahogany, Small-fruited Grey Gum

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
10M	NAMBUCCA SF	gully	10	moderate	3-4	heavy	30	0	0	Red Bloodwood, Blackbutt
10MA	TAMBAN SF	lower slope	18	light	4-5	heavy	15	0	1	Blackbutt, Ironbark
10VH	NEWRY SF	lower slope	32	light	10	heavy	30	0	2	White Mahogany, Red Mahogany
10vHa	INGALBA SF	lower slope	37	none	10	heavy	20	0	0	Flooded Gum , Tallowwood
11Ha	GIBRALTAR RANGE SF	flat	1011	light	1	moderate	30	0	0	New England Blackbutt, Messmate
11Hb	MOOGEM SF	flat	962	moderate	15	heavy	30	0	1	Mountain Blue Gum, Messmate
11L	GIBRALTAR RANGE NP	flat	1059	light	1	none		0	0	Broad-leaved Stringybark, William's Stringybark

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
11M	MOOGEM SF	simple slope	1043	light	5	light	5	0	0	New England Blackbutt, Forest Ribbon Gum
12H	EWINGAR SF	saddle	755	none		heavy	25	0	0	New England Blackbutt, Tallowwood
12Ma	EWINGAR SF	upper slope	718	none		moderate	25	0	0	Brush Box, Sydney Blue Gum
12Mb	EWINGAR SF	ridge	412	light	5-10	moderate	20	0	1	Forest Oak, Mahogany
12VH	EWINGAR SF	upper slope	605	moderate	10	moderate	25	0	0	New England Blackbutt, Tallowwood
13H	ROYAL CAMP SF	flat	90	light	5	moderate	10	1	0	Spotted Gum, Small-fruited Grey Gum
13HB	CHERRY TREE SF	gully	120	light	10	heavy	25	0	7	Small-fruited Grey Gum, Grey Ironbark
13L	BUSBYS FLAT	lower slope	113	light	10	light		0	0	Broad-leaved Apple, Black She-Oak

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
13M	KEYBARBIN SF	flat	114	light	10	light		0	0	Forest Red Gum, Swamp Turpentine
14H	RICHMOND RANGE SF	upper slope	341	none		heavy	20	0	0	Spotted Gum, Grey Ironbark
14M	RICHMOND RANGE SF	simple slope	297	light	5	moderate	10	2	0	Small-fruited Grey Gum, White Mahogany
14VH	RICHMOND RANGE NP	ridge	448	none		heavy	30	0	8	Spotted Gum, Tallowwood
14VHb	RICHMOND RANGE NP	ridge	560	none		heavy	30	0		Tallowwood, White Mahogany
15H	YABBRA SF	upper slope	554	light	10	moderate	25	0	3	Pink Bloodwood, Sydney Blue Gum
15Hb	YABBRA SF	ridge	528	none	10	heavy	20	0	21	White Mahogany, Tallowwood

Site	Reserve	Topographic position	Elevation	Fire Severity	Estimated time since last fire (yrs)	Logging History	Estimated time since last harvesting event (yrs)	Number of Koala scats	Number of Koala calls	Dominant tree species
15M	TOONUMBAR NP	upper slope	689	none		moderate	>50	0	0	Rainforest spp.
15VH	YABBRA SF	ridge	513	none	10	moderate	25	0	0	Tallowwood, White Mahogany
16H	BRAEMAR SF	ridge	108	light	10	moderate	20	1	62	Red Gum, Grey Ironbark
16L	BANYABBA SCA	ridge	106	moderate	5-10	none		0	0	Bastard Tallowwood, Red Bloodwood
16M	MYRTLE SF	flat	51	light	10	heavy	20	1	6	Spotted Gum, Grey Box
16VH	BANYABBA SF	flat	89	light	10	light	20	0		Spotted Gum, Red Ironbark

Appendix C

Correlation matrix showing Pearson's correlation coefficients for all (n=27) continuous variables. See Table 1 in the main report for a description of the variables.

	tp	awc	bio01	bio08	bio09	bio10	bio11	bio12	bio14	bio17	bio20	bio28	biomass	cra%	dem	dep	fpc	ndvi_au	ndvi_sp	ndvi_su	ndvi_wi	npp	oc	p15	sea	slo	tor
tp	1	0.18	-0.02	-0.04	0.00	-0.05	0.00	0.31	0.22	0.31	-0.30	0.31	0.10	-0.07	0.04	0.13	0.15	0.24	0.24	0.26	0.20	0.11	0.38	0.10	-0.02	0.10	0.15
awc		1	-0.29	-0.17	-0.29	-0.24	-0.32	-0.20	-0.13	-0.15	0.15	-0.07	0.15	0.01	0.30	-0.06	-0.06	0.01	0.00	0.06	-0.03	-0.11	0.10	-0.09	-0.11	0.15	0.08
bio01			1	**0.90**	**0.89**	**0.98**	**0.99**	0.32	-0.01	-0.04	-0.19	0.01	-0.06	-0.09	**-0.97**	0.57	0.03	0.09	0.08	-0.03	0.13	0.20	0.21	-0.06	0.20	-0.17	-0.14
bio08				1	**0.76**	**0.94**	**0.84**	0.09	-0.23	-0.29	0.04	-0.21	-0.09	-0.02	**-0.84**	0.39	-0.15	-0.01	-0.04	-0.11	0.03	0.04	0.21	-0.07	0.10	-0.09	-0.06
bio09					1	**0.86**	**0.89**	0.35	0.13	0.13	-0.20	0.04	-0.08	-0.19	**-0.86**	0.59	0.03	-0.02	0.05	-0.10	0.06	0.16	0.11	-0.04	0.24	-0.25	-0.22
bio10						1	**0.93**	0.17	-0.11	-0.15	-0.06	-0.15	-0.10	-0.08	**-0.94**	0.49	-0.09	-0.02	-0.02	-0.12	0.04	0.09	0.19	-0.07	0.17	-0.16	-0.13
bio11							1	0.43	0.08	0.07	-0.30	0.14	-0.03	-0.11	**-0.96**	0.62	0.12	0.15	0.16	0.04	0.19	0.28	0.21	-0.05	0.23	-0.18	-0.15
bio12								1	0.58	**0.76**	**-0.86**	**0.85**	0.21	-0.12	-0.33	0.57	0.62	0.58	0.64	0.57	0.55	0.55	0.31	0.04	0.14	0.02	0.05
bio14									1	**0.86**	**-0.75**	0.60	0.13	-0.16	-0.09	0.29	0.48	0.28	0.38	0.27	0.28	0.31	0.12	0.03	0.13	-0.04	-0.03
bio17										1	**-0.81**	**0.77**	0.17	-0.17	-0.04	0.36	0.56	0.36	0.47	0.36	0.36	0.38	0.13	0.05	0.15	-0.04	-0.02
bio20											1	**-0.88**	-0.24	0.05	0.30	-0.45	-0.68	-0.61	-0.67	-0.58	-0.59	-0.56	-0.38	-0.03	-0.10	-0.09	-0.10
bio28												1	0.27	-0.02	-0.06	0.36	0.73	0.68	0.71	0.67	0.62	0.59	0.29	0.05	0.05	0.07	0.08
biomass													1	0.10	0.04	0.10	0.38	0.37	0.39	0.38	0.38	0.25	0.18	-0.29	-0.06	0.22	0.20
cra%														1	0.07	-0.25	0.11	0.23	0.15	0.16	0.28	0.14	0.12	-0.01	-0.20	0.18	0.17
dem															1	-0.58	-0.07	-0.11	-0.11	0.02	-0.16	-0.24	-0.22	0.10	-0.20	0.16	0.13
dep																1	0.30	0.18	0.23	0.13	0.18	0.33	-0.04	-0.17	0.24	-0.34	-0.34
fpc																	1	**0.76**	**0.80**	**0.75**	**0.75**	0.65	0.21	-0.01	0.00	0.07	0.08
ndvi_au																		1	**0.93**	**0.92**	**0.92**	0.58	0.41	0.00	-0.14	0.24	0.24
ndvi_sp																			1	**0.92**	**0.92**	0.60	0.40	0.00	-0.10	0.22	0.22
ndvi_su																				1	**0.83**	0.51	0.39	0.00	-0.16	0.27	0.26
ndvi_wi																					1	0.62	0.42	0.00	-0.13	0.25	0.24
npp																						1	0.25	0.00	0.06	0.04	0.04
oc																							1	0.14	-0.08	0.60	0.46
p15																								1	0.00	0.03	0.04
sea																									1	-0.18	-0.17
slo																										1	0.64
tor																											1

Appendix D

Frequency of the four *Wildfire* classes (**Class 0**: Areas that never burned and that are considered not flammable; **Class 1**: Areas that never burned; **Class 2**: Areas that burned 1 to 3 times; **Class 3**: Areas that burned more than 3 times) within each *Crafti floristic group* (**Class 1**: Primary browse species; **Class 2**: Secondary browse species; **Class 3**: Tertiary browse species; **Class 4**: Unsuitable habitat)