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Modelling the distribution and relative abundance of feral camels in the Northern Territory using count data

S. R. McLeod[A,C] and A. R. Pople[B]

[A]Vertebrate Pest Research Unit, Industry & Investment New South Wales – Primary Industries, Orange Agricultural Institute, Forest Road, Orange, NSW 2800, Australia.
[B]Biosecurity Queensland, Primary Industries and Fisheries, Department of Employment, Economic Development and Innovation, Alan Fletcher Research Station, PO Box 36, Sherwood, Qld 4075, Australia.
[C]Corresponding author. Email: steven.mcleod@industry.nsw.gov.au

Abstract. The objectives of this study were to predict the potential distribution, relative abundance and probability of habitat use by feral camels in southern Northern Territory. Aerial survey data were used to model habitat association. The characteristics of 'used' (where camels were observed) *v.* 'unused' (pseudo-absence) sites were compared. Habitat association and abundance were modelled using generalised additive model (GAM) methods. The models predicted habitat suitability and the relative abundance of camels in southern Northern Territory. The habitat suitability maps derived in the present study indicate that camels have suitable habitat in most areas of southern Northern Territory. The index of abundance model identified areas of relatively high camel abundance. Identifying preferred habitats and areas of high abundance can help focus control efforts.

Additional keywords: generalised additive model, habitat suitability, presence-only, pseudo-absence, resource selection function, habitat suitability, zero-inflated.

Introduction

Since their introduction to Australia in the late 1800s and subsequent release into the wild, camels (*Camelus dromedarius*) have increased and spread across arid Australia (Edwards *et al*. 2004). Their broad-scale relationship with habitat has not been examined, but a species distribution model (Guisan and Thuiller 2005) could have several uses in camel management. Importantly, identifying preferred habitats can help focus control efforts. Furthermore, as camel numbers continue to increase, further expansion in the camel range is likely and knowledge of habitat preference will indicate likely habitats at risk of invasion (Edwards *et al*. 2008).

Current broad-scale distribution is known only as snapshots in time from infrequent aerial surveys. These surveys provide useful regional estimates of abundance, but at fine scales (e.g. <10 000 km^2), density estimates are imprecise, leading to potentially misleading distribution patterns that may result in misdirected management effort. As an example, two identical surveys a short time period (e.g. 1 year) apart can yield quite different patterns of distribution, as only small numbers of camels are seen when both density and survey intensity are low. To overcome this problem, a spatial model linking habitat to the probability of occupancy can be used to predict camel distribution across the survey area.

Developments in statistical methods and the ease with which they can be linked to geographic information systems (GIS) has led to an increase in the number of studies using models to predict habitat distribution in recent years (Larson *et al*. 2008). Using a GIS, the attributes (biotic and abiotic characteristics) of sample sites can be easily recorded and used in resource selection function (RSF) models. Using this approach, predicted habitat distributions can be mapped and compared with other variables of interest such as areas of cultural or conservation importance.

A resource selection function is any function that is proportional to the probability of use of a resource unit (Manly *et al*. 2002). Resource selection functions have been used to infer habitat quality and their probability of use (Boyce and McDonald 1999) as well as for conservation and management planning (Mysterud and Ims 1999; McDonald 2003; Johnson *et al*. 2006; Allen *et al*. 2008). By predicting the probability of habitat use by camels, RSF models have the capacity to be powerful management tools that help allocate resources most effectively and efficiently to manage camel populations.

Generalised linear models (GLMs) have been used to model the habitat associations of a wide range of animals (Guisan and Zimmermann 2000). More recently, generalised additive models (GAMs) have become popular to describe habitat associations and preferences (Elith *et al*. 2006; Meynard and Quinn 2007).

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GAMs are frequently more flexible than GLMs when the linear predictor can best be described as a sum of smooth functions of covariates plus parametric linear predictors (Wood 2006).

In this paper we use GAMs to analyse the habitat associations of camels in central Australia. Our objectives were to predict the potential distribution and probability of habitat use by feral camels in southern Northern Territory. To make the predictions, we used a range of biotic and non-biotic predictors that were statistically related to locations where camels were observed during the most recent broad-scale aerial survey for camels in the Northern Territory. We then used the predicted habitat associations to identify areas of high cultural and ecological interest that may be heavily impacted by camels.

Materials and methods

Camel locations

In 2001, aerial surveys were flown over an area of ~260 000 km^2 of southern Northern Territory. The location of groups of camels along transects was recorded using a GPS connected to a handheld computer. The sampling intensity was 3.6% of the survey area. Full details of the survey design and results are given by Edwards *et al*. (2004).

Sample design and habitat associations

The locations of camels observed during aerial surveys provide information about habitats that camels use, but not about unused habitats, which may be unused because they are avoided or unused simply because there were no camels in the area at the time of the survey. Aerial survey locations represent a snapshot of association between animal and habitat at an instant in time. Using aerial survey data it is not possible to determine preference since there has been no measurement of choice or avoidance (Boyce *et al*. 2002). Thus, the locations of camels represent 'presence-only' data. Appropriate analyses characterise habitat association by presence *v*. availability whereby the characteristics of a sample of sites where camels occur is compared with a sample of what is available in the environment (Manly *et al*. 2002).

We modelled the relationship between camels and the environment by characterising a range of biotic and abiotic covariates (Table 1). The characteristics of 'used' (where camels were observed) *v*. 'unused' (pseudo-absence) sites were compared. The term 'pseudo-absence' is used since it refers to sites where camels were not observed, but this does not imply that those sites were avoided. There were 494 unique groups of camels identified during the aerial survey. An equal number of pseudo-absence sites were chosen. Pseudo-absence sites were chosen randomly without replacement along aerial survey transect lines within the aerial survey block and each site was at least 10 km from its nearest neighbour (average 18.5 km). Used sites were assigned the response variable of 1; unused sites were assigned the response variable 0.

We hypothesised that camels made decisions regarding their use of a habitat based on resources nearby. Studies of camel movements (Grigg *et al*. 1995; Edwards *et al*. 2001) indicated that they will range between ~0.1–30 km per day, but more commonly 1–10 km per day. Based on this information, we created two separate buffers around each sample location that we assumed were representative of the spatial scale over which camels made their short-term (i.e. daily to a few days) habitat choices. The buffers were, respectively, 1 and 5 km in radius, measured from the centre of each site.

The attribute values of covariates were then either based on the value at the centroid of each buffer (elevation and aspect), or the proportion of a covariate within the buffer area (vegetation type) or the nearest-neighbour distance (human population centres, water sources and roads).

Statistical methods

Following the general method described by Barry and Welsh (2002) for modelling zero inflated count data, we modelled the data in two steps. First, we modelled habitat association using habitat covariates and presence–absence data. Second, we modelled the relationship between abundance and the covariates, conditional on camels being present. The combination of two steps provides a flexible approach to the problem of modelling habitat suitability. The method also provides two predictions: (i) habitat suitability (presence–absence) and (ii) an index of abundance. The latter is only an index because the count data were point estimates of abundance, not density estimates in survey plots.

We modelled camel habitat association and abundance using generalised additive model (GAM) methods in the R statistical computing language (R version 2.9.0) (R Development Core Team 2008). Early exploratory analyses using GLMs were abandoned when we found they provided low explanatory power in comparison to GAMs. We fitted GAMs using the gam() function from the 'mgcv' package (version 1.5–5) (Wood 2009). For presence–absence, fitted models used a binomial error structure with a logit link. For abundance, fitted models used a Poisson error structure with a log link and a gamma value of 1.4. The gamma value inflates the degrees-of-freedom to help prevent over-fitting (Wood 2006). The best model was chosen by minimising un-biased risk estimator (UBRE). The UBRE score can be interpreted in the same way as AIC (Wood 2006).

Covariates

Nearest neighbour distance was calculated for human population centres, water sources and roads using GIS (Manifold System 8.0

Table 1. Covariates used to predict camel habitat suitability

Data type	Covariate	Range	Source
Nearest neighbour	Population centres	0–252 km	Manifold (www.manifold.net[A])
	Water sources (permanent and ephemeral)	0–58.8 km	Manifold (www.manifold.net[A])
	Major and minor roads	0–165 km	Manifold (www.manifold.net[A])
Proportion	Vegetation class	(see Table 2)	Wilson *et al*. (1990)

[A]Accessed 11 August 2009.

Table 2. Vegetation classes used in the model
Classes followed the classifications of Wilson *et al*. (1990). The percent of the total area of the study site made up by each vegetation class is included

Vegetation class	Code	Percent
Acacia with grass understorey/*Acacia georginae* low open woodlands	AC1	3.2
Acacia with grass understorey/mixed species low open-woodland	AC3	3.4
Acacia with grass understorey/sparse shrubland	AC4	4.7
Acacia with grass understorey/tall open shrubland	AC5	2.0
Chenopod low sparse-shrub/forbland	CH1	2.4
Eucalyptus with grass understorey	EU1	4.3
Eucalyptus with hummock grass understorey	EU2	15.1
Hummock grassland/mixed species low open-woodland	HU1	9.7
Hummock grassland/scattered shrub	HU2	0.7
Hummock grassland/tall open-shrubland	HU3	54.2
Melaleuca forest/woodland	ME	0.2

Professional Edition, Build 8.0.12.0) (Table 1). We hypothesised that camels might be attracted to water sources and avoid population centres and roads. The nearest neighbour distance was recorded as the Euclidean distance between the centroid of each used and unused sample location and the closest point in the covariate set.

Using the vegetation classifications (mapping units) described by Wilson *et al*. (1990), we used 11 simplified vegetation classes (Table 2). Camels were observed at least once in each class. The value of each vegetation class was calculated as the proportion of the total buffer area made up by each class.

Several climate variables, including temperature (mean annual, mean summer, maximum summer and minimum winter) and rainfall (mean annual and mean summer) were tested during preliminary model fitting and found to be unrelated to camel distribution. A range of topographic variables (elevation, slope and aspect) were also trialled and found to be unrelated to camel distribution.

Evaluation of predictive performance

Ideally, the predictive performance of the models would be tested using an independent data source. In the absence of independent data we evaluated the predictive performance of the models by internal validation using k-fold cross-validation (Kohavi 1995), with 10 folds. The details of the method are presented by Cowled *et al*. (2009).

Briefly, models were evaluated using the area under the receiver operator characteristic (ROC) curve (Pearce and Ferrier 2000; Wintle *et al*. 2005). The area under the ROC curve (AUC) is a measure of the model's ability to correctly distinguish between presence and absence. Thus, it is referred to as a measure of model discrimination (Pearce and Ferrier 2000). The statistic can be interpreted in a straightforward manner; a value of 1 indicates perfect discrimination, whereas a value of 0.5 indicates that the model performs no better than a random guess (Fawcett 2006). Swets (1988) considered values above 0.7 provided reasonable discrimination and the larger the AUC the better the model at predicting group membership. Calculation of AUC used the auc() function in the PresenceAbsence package (version 1.1.3) in R (Freeman 2007).

Predicting habitat suitability and relative abundance

Using the best overall models for each buffer we determined the habitat suitability and abundance for each point in Fig. 1. The predicted index of abundance was calculated from the product of

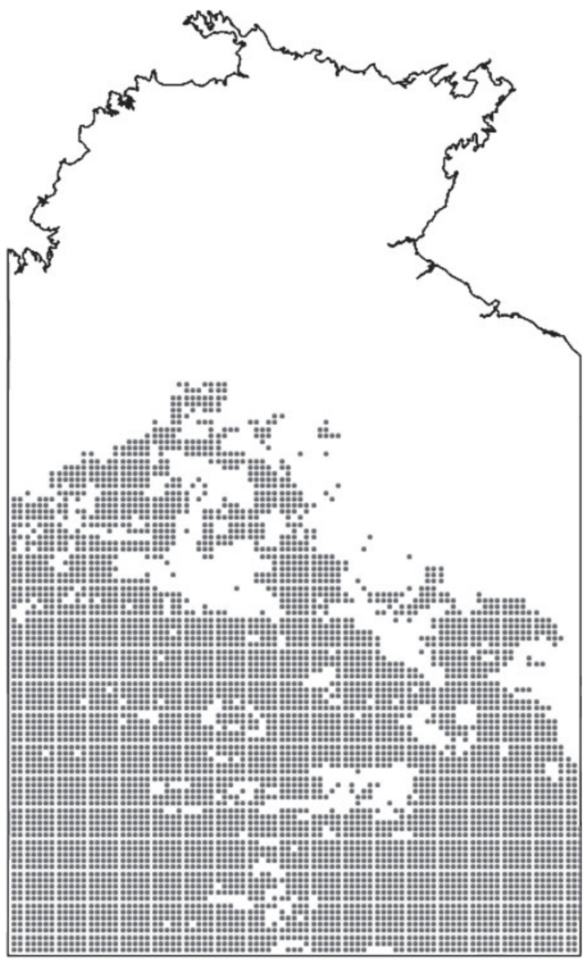

Fig. 1. Point locations for which camel habitat covariate values were measured.

the probability estimate from the presence–absence model and the modelled abundance (Barry and Welsh 2002). We used simple kriging with eight nearest neighbours to create smooth surfaces of predicted camel habitat suitability and relative abundance. These surfaces are estimates of the potential habitat suitability and abundance of camels in southern Northern Territory at the time of the survey.

Areas of importance

Using GIS, we overlaid the predicted habitat suitability maps on a map that included areas of indigenous, natural and historic significance recorded on the Register of the National Estate (RNE). The intersection of areas of high habitat suitability and RNE significance indicates potential priority regions for camel management.

Table 3. Significance of smooth and parametric model terms in the presence–absence model based on a 1 km buffer

s(lat, lon) is the smoothed model term representing location (latitude and longitude), s(popn) is the term representing distance from centres of population, s(tran) is the term representing distance from roads, and EU2 and HU1 are parametric terms representing vegetation classes (see Table 2). The model had an un-biased risk estimator (UBRE) score of 0.0758. The parametric term EU2 was included in the model since it was correlated with other model variables and resulted in a higher UBRE score if it was deleted

Model terms	Df/edf	Chi-square	*P*-value
s(lat, lon)	131.223	239.69	2.35e-08
s(popn)	5.252	62.04	6.50e-12
s(tran)	4.550	41.03	5.36e-08
EU2	1	2.884	0.0895
HU1	1	23.565	1.21e-06

Table 4. Significance of smooth and parametric model terms in the presence–absence model based on a 5 km buffer

s(lat, lon) is the smoothed model term representing location (latitude and longitude), s(popn) is the term representing distance from centres of population, s(tran) is the term representing distance from roads, and AC3, AC4, AC5, CH1, EU1, EU2, HU1, HU2 and HU3 are parametric terms representing vegetation classes (see Table 2). The model had an un-biased risk estimator (UBRE) score of 0.0693. The parametric term EU1 was included in the model since it was correlated with other model variables and resulted in a higher UBRE score if it was deleted

Model terms	Df/edf	Chi-square	*P*-value
s(lat, lon)	126.0	229.51	4.94e-08
s(popn)	5.47	64.69	2.47e-12
s(tran)	4.47	37.80	2.22e-07
AC3	1	6.282	0.01220
AC4	1	7.697	0.00553
AC5	1	8.895	0.00286
CH1	1	7.344	0.00673
EU1	1	3.041	0.08120
EU2	1	10.524	0.00118
HU1	1	10.819	0.00100
HU2	1	7.270	0.00701
HU3	1	7.329	0.00679

Results

Habitat suitability

The predicted habitat suitability surfaces indicate areas of suitable habitat for camels. For the 1 km buffer the model selected was:

$$\begin{aligned}\eta = {} & s(\text{latitude, longitude}) \\ & + s(\text{distance from population centres}) \\ & + s(\text{distance from roads}) + \text{EU2} + \text{HU1}\end{aligned} \tag{1}$$

where η is the probability of occurrence and s() is a smooth function. The model explained 43.4% of the deviance. The statistical significance of parametric and smooth model terms is presented in Table 3. An explanation of the parametric terms is presented in Table 2.

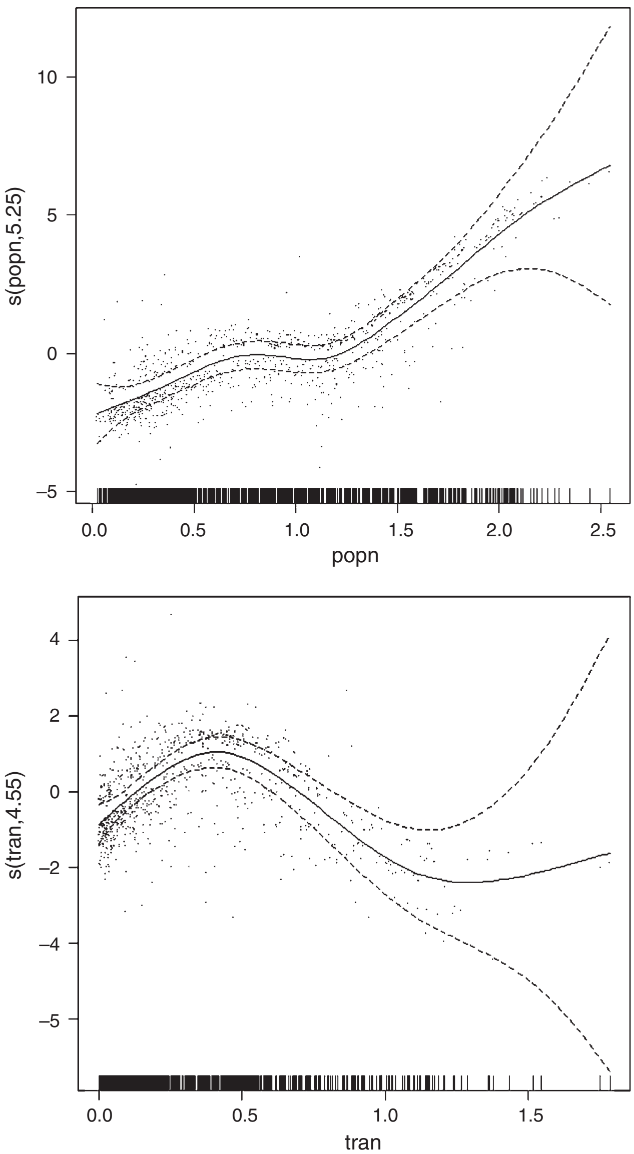

Fig. 2. Smoothed fits to the covariates distance to population centres (popn) and distance to roads (tran) used in the final habitat suitability model with a 1 km buffer. Dashed lines give ~95% confidence intervals. The units of the *x*-axis are decimal degrees.

For the 5 km buffer, the model selected was:

$$\begin{aligned}\eta = {} & s(\text{latitude, longitude}) \\ & + s(\text{distance from population centres}) \\ & + s(\text{distance from roads}) + AC3 + AC4 + AC5 \\ & + CH1 + EU1 + EU2 + HU1 + HU2 + HU3\end{aligned} \tag{2}$$

where η is the probability of occurrence and s() is a smooth function. The model explained 44.2% of the deviance. The statistical significance of parametric and smooth model terms is presented in Table 4. An explanation of the parametric terms is presented in Table 2.

The differences between these two models was the inclusion of a large number of vegetation categories in the 5 km buffer model, which were absent from the 1 km buffer model. The most likely reason would be the substantial increase in area of the 5 km buffer relative to the 1 km buffer. Consequently, the buffer area from the 5 km buffer intersected with a greater range of vegetation classes.

The smooth terms latitude, longitude, distance to population centres and distance to roads were common to both models. Examples of smoothed fits to the covariates distance to population centres and distance to roads are given in Fig. 2. The fitted splines indicate that the probability of presence of camels increases with distance from either a population centre or a road, but with probability of presence declining at large distances from roads.

The significance of the terms for smoothed latitude and longitude in the models reflects some of the (2-dimensional) spatial variation in occupancy that has not been captured by the environmental covariates. Locations can only be a proxy for biologically important variables, and they are included in the model because they are correlated with some underlying process.

The largest difference in the predicted habitat suitability surfaces occurs on the eastern sector (Figs 3, 4). The model based on a 5 km buffer included extensive areas in the east that ranked as medium-high suitable habitat. These areas contained *Acacia* with grass understorey and *Acacia georginae* low open woodlands (AC1, Table 2).

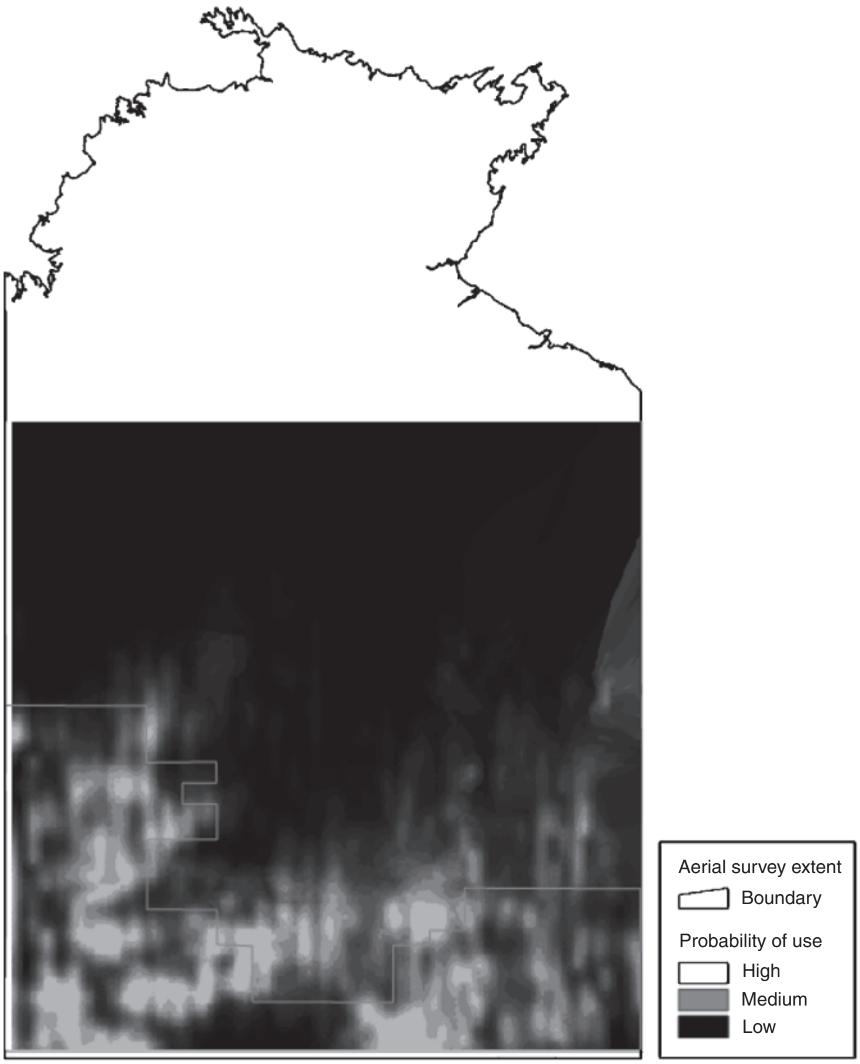

Fig. 3. Predicted camel habitat suitability based on a 1 km buffer around sample locations. The extent of the aerial survey conducted in 2001 by Edwards *et al*. (2004) is also shown on the map.

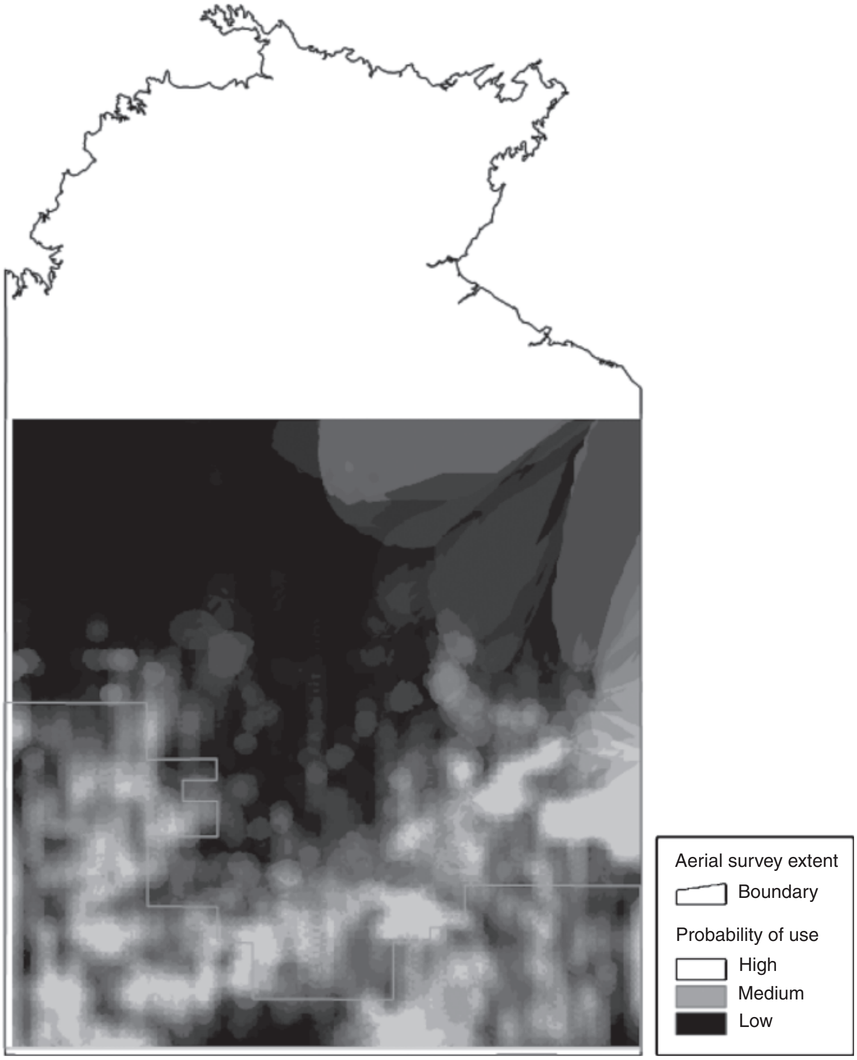

Fig. 4. Predicted camel habitat suitability based on a 5 km buffer around sample locations. The extent of the aerial survey conducted in 2001 by Edwards *et al*. (2004) is also shown on the map.

The habitat suitability surfaces indicated that the majority of southern Northern Territory is predicted to be suitable for camels.

Relative abundance

There was no difference in the structure of the best models fitted to the count data. For both the 1 km and 5 km buffers the selected model was:

$$\begin{aligned}\eta = {} & \mathrm{s(latitude, longitude)} + \mathrm{s(distance\ from\ water)} \\ & + \mathrm{AC1} + \mathrm{AC3} + \mathrm{AC4} + \mathrm{AC5} + \mathrm{CH1} \\ & + \mathrm{EU1} + \mathrm{HU1} + \mathrm{HU3}\end{aligned} \tag{3}$$

where η is the camel abundance and s() is a smooth function (Tables 5 and 6). An explanation of the parametric terms is presented in Table 2. The fitted models explained 69 and 71.6% of the deviance in the data for the 1 and 5 km buffers, respectively. The predicted count surfaces (Figs 5, 6) indicate that there are a few 'hotspots' of camel abundance. Keeping in mind that the predicted abundance surfaces are the product of the predictions of the presence–absence model and the count model, the surfaces are remarkably similar. Also, the region to the east that was of medium-high suitability is not predicted to sustain a high abundance of camels.

The predicted abundance surface indicates that camels will probably occur at low density across southern Northern Territory and occasionally reach very high density. However, these 'hotspots' of abundance cover on average ~1000 km^2 and biodiversity impacts by camels over such a large area can be substantial (Edwards *et al*. 2008).

Hotspots coincided with a wide range of vegetation classes including *Acacia* with grass understorey/sparse shrubland (AC4), *Acacia* with grass understorey/tall open shrubland (AC5), chenopod low sparse-shrub/forbland (CH1), *Acacia* with grass understorey/*Acacia georginae* low open woodlands (AC1), hummock grassland/tall open-shrubland (HU3) and hummock grassland/mixed species low open-woodland (HU1). These vegetation types are widespread across southern Northern

Table 5. Significance of smooth and parametric model terms in the count model based on a 1 km buffer

s(lat, lon) is the smoothed model term representing location (latitude and longitude), s(water) is the term representing distance from water sources, and AC1, AC3, AC4, AC5, CH1, EU1, HU1 and HU3 are parametric terms representing vegetation classes (see Table 2). The model had un-biased risk estimator (UBRE) score of 1.566. The parametric terms AC3 and HU1 were included in the model since they were correlated with other model covariates and deleting them resulted in a higher UBRE score

Model terms	Df/edf	Chi-square	*P*-value
s(lat, lon)	165.801	227.44	0.00106
s(water)	8.745	35.62	3.79e-05
AC1	1	5.480	0.01924
AC3	1	0.723	0.39513
AC4	1	4.896	0.02691
AC5	1	7.080	0.00779
CH1	1	5.628	0.01768
EU1	1	7.505	0.00615
HU1	1	2.942	0.08632
HU3	1	5.620	0.01775

Table 6. Significance of smooth and parametric model terms in the count model based on a 5 km buffer

s(lat, lon) is the smoothed model term representing location (latitude and longitude), s(water) is the term representing distance from water sources, and AC1, AC3, AC4, AC5, CH1, EU1, HU1 and HU3 are parametric terms representing vegetation classes (see Table 2). The model had un-biased risk estimator un-biased risk estimator (UBRE) score of 1.470. The parametric terms EU1 and HU1 were included in the model since they were correlated with other model covariates and deleting them resulted in a higher UBRE score

Model terms	Df/edf	Chi-square	*P*-value
s(lat, lon)	172.0	283.75	1.58e-07
s(water)	8.66	36.96	2.03e-05
AC1	1	2.497	0.11403
AC3	1	10.654	0.00110
AC4	1	5.796	0.01607
AC5	1	7.018	0.00807
CH1	1	6.763	0.00931
EU1	1	1.042	0.30745
HU1	1	2.446	0.11786
HU3	1	7.308	0.00686

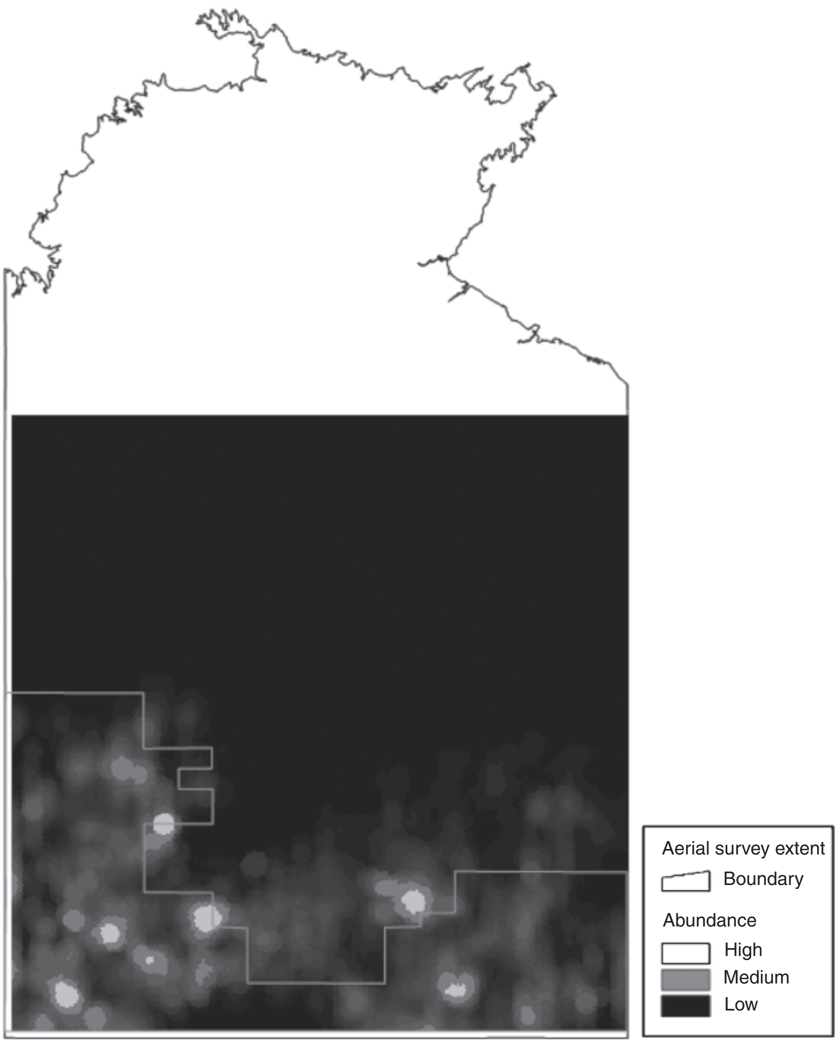

Fig. 5. Predicted abundance of camels based on a 1 km buffer around sample locations. The extent of the aerial survey conducted in 2001 by Edwards *et al*. (2004) is also shown on the map.

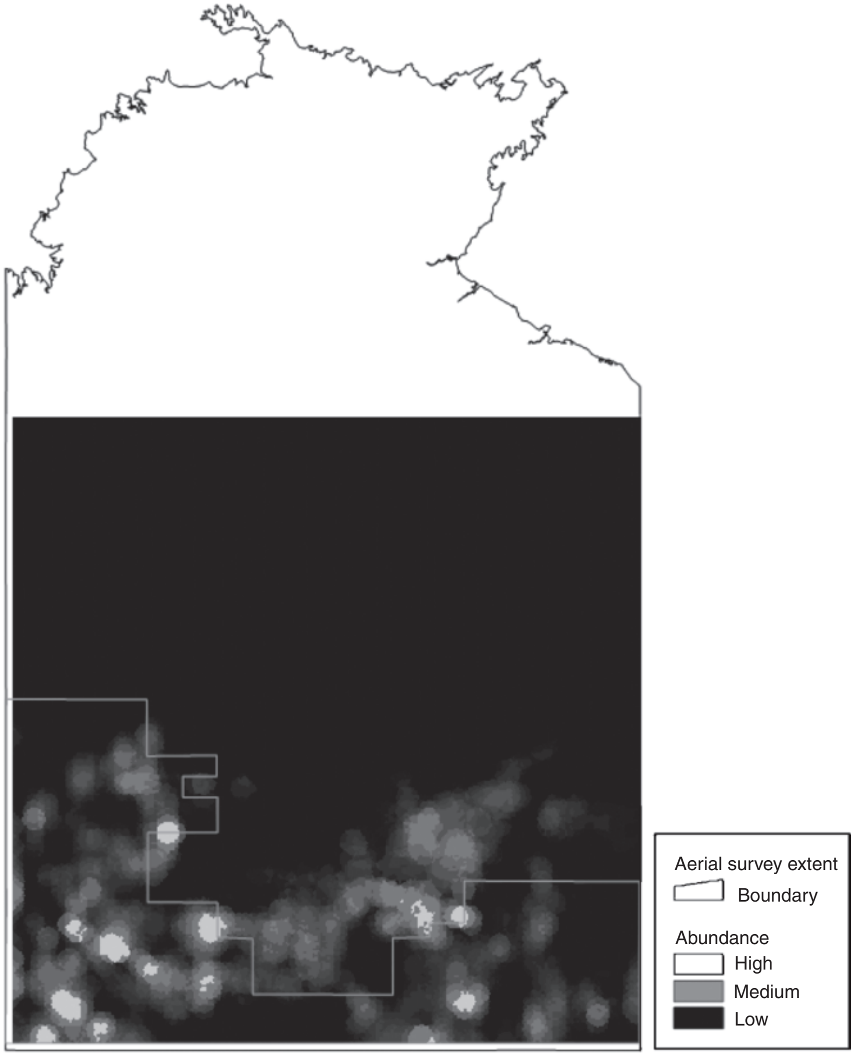

Fig. 6. Predicted abundance of camels based on a 5 km buffer around sample locations. The extent of the aerial survey conducted in 2001 by Edwards *et al*. (2004) is also shown on the map.

Territory and may indicate why camels have been so successful in this region.

Evaluation of predictive performance

The AUC values for the 1 and 5 km buffers were 0.77 and 0.79, respectively. The slightly higher value for the 5 km buffer model indicates slightly better cross-validation agreement between the predicted and observed presence-absence data, but this difference is still small. Following the classification described by Hosmer and Lemeshow (2000) the level of predictive ability for these models is 'acceptable', but keeping in mind that values greater than 0.8 are 'excellent' the models are at the right end of 'acceptable'.

Areas of importance

Given that suitable habitats for camels are widespread in southern Northern Territory it is not surprising that there are substantial areas of natural and indigenous significance that are at risk. Of particular concern is the south-eastern region that includes the Simpson Desert (Figs 7, 8). This is a large area of natural significance that contains large regions of suitable habitat for camels. Fortuitously, the region does not include many hotspots of predicted high abundance. Nevertheless, given the logistical difficulties controlling camels in remote locations it will probably be difficult to manage camels in this region. Areas of significance that coincide with hotspots in the south-west include Lake Amadeus, Watarrka (Kings Canyon) National Park, the George Gill Range and Finke Gorge National Park.

Discussion

The predicted habitat suitability surfaces indicate that highly suitable habitats for camels are widespread across southern Northern Territory. However, with the exception of the south-west region, these areas did not have very high numbers of camels in 2001 (Edwards *et al*. 2004). It may be difficult to limit the immigration of camels following control operations owing to

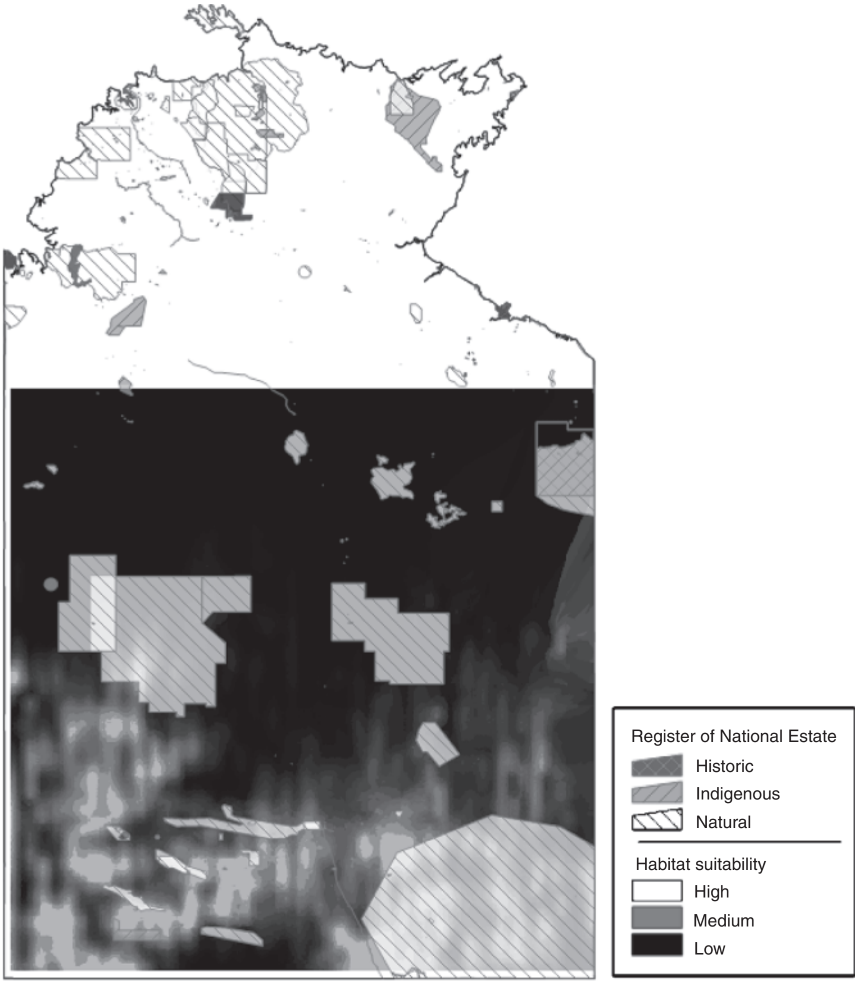

Fig. 7. Overlap between areas of significance on the Register of National Estate and camel habitat suitability based on a 1 km buffer around sample locations.

their ability to move quickly over large distances (Grigg *et al*. 1995; Edwards *et al*. 2001; Saalfeld and Edwards 2008) and the widespread availability of suitable habitat in southern Northern Territory. However, the predicted suitability and abundance surfaces are based on surveys that had low sampling intensity and camels were at low density. This combination may have conspired to provide a deceptive picture of camel distribution.

Discrepancies between predicted habitat suitability and abundance and observed distribution may be due to the fact that camels are not near carrying capacity in the Northern Territory. Camel populations are still growing at, or close to, their maximum rate (Pople and McLeod 2010) and it may take many more years until some type of equilibrium is reached between camel abundance and the environment. Even at low density, camels can have damaging impacts and holding the long-term density to the recommended level of 0.1–0.2 camels/km^2 (Edwards *et al*. 2008) will pose a difficult challenge. Given the large areas of suitable habitat for camels, planning of management will be hindered without more up-to-date information regarding their current distribution and abundance.

Errors in either the model, such as important covariates not being included, or data, such as misidentification of true absence, can lead to prediction errors (Fielding and Bell 1997; Barry and Elith 2006). For example, normalised difference vegetation index (NDVI), which measures live green vegetation (Schowengerdt 2007), has been used as a proxy for plant productivity and habitat quality of ungulates (e.g. Verlinden and Masogo 1997; Pettorelli *et al*. 2006) and birds (e.g. Osborne *et al*. 2001). Green vegetation may be an important influence on the distribution of camels that are able to move large distances in search of food (Iqbal and Khan 2001). Unfortunately, we were unable to obtain NDVI for the time of the aerial survey. The models presented in this paper make specific predictions regarding the suitability of habitat and relative abundance of camels in the Northern Territory at the time of the survey in 2001. It would be timely to conduct additional surveys to determine current camel density in specific habitats and validate this model and collect data on other co-variates, such as NDVI, which may be important predictors of camel distribution and abundance.

Latitude and longitude were important predictors of camel habitat association and abundance. It is very unlikely that location

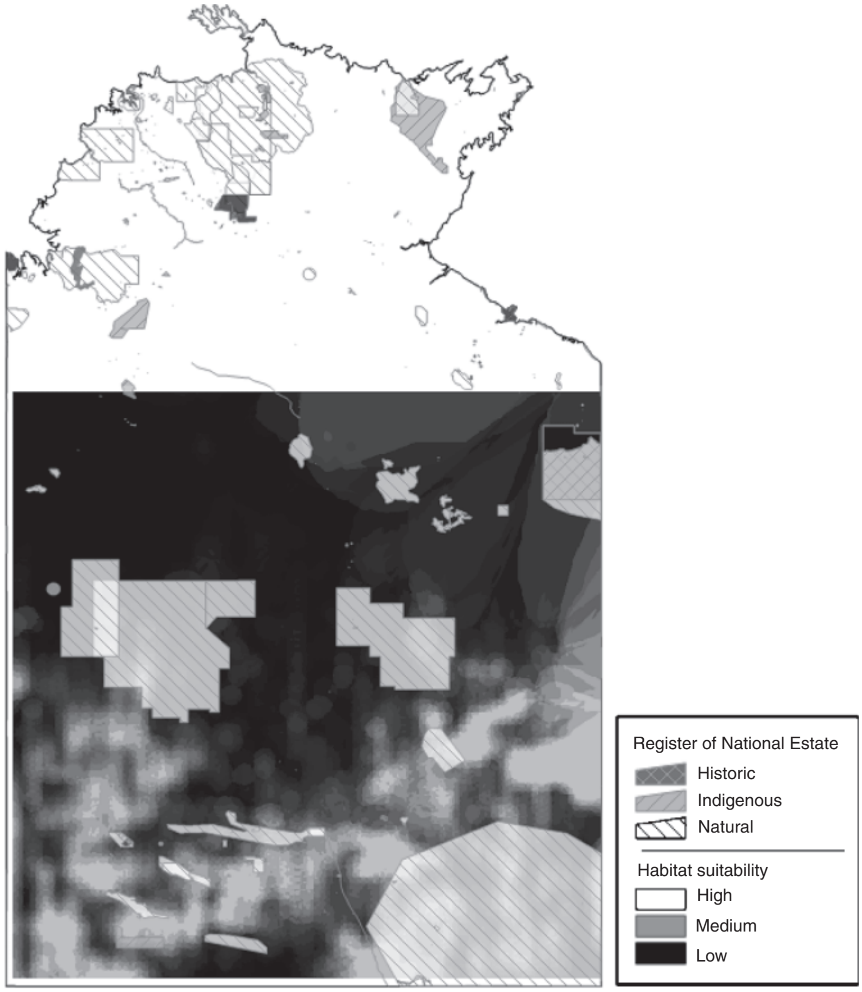

Fig. 8. Overlap between areas of significance on the Register of National Estate and camel habitat suitability based on a 5 km buffer around sample locations.

per se would be an important determinant of habitat association. Rather, location is likely to be correlated with important variables that influence habitat suitability. Although we examined a range of climate variables likely to be correlated with latitude and longitude, none were significantly related to the observed distribution of camels. This result highlights our general lack of knowledge regarding the ecology of wild camels in Australia. Increased knowledge of the most important factors influencing their rate of increase are likely to provide a much more focused method of selecting variables that influence distribution. It will also lead to greater generality of the predictions of the models.

Until more information regarding the physiology and ecology of camels becomes available and we can make predictions without the use of explicit spatial variables, such as latitude and longitude, there remains a caveat on the predictions: the model's predictions outside of surveyed areas are unreliable. However, within surveyed areas the predictions of the model were robust to cross-validation and can be considered to be valid.

There have been suggestions that commercial use of camels may be a useful form of control (Zeng and McGregor 2008). However, commercial use of wildlife requires infrastructure for harvested animals to be held, handled and transported from often remote field locations. In addition, the profitability of commercial enterprises is improved by camels being at high density. The analysis of habitat suitability and relative abundance indicated that many suitable habitats and areas of potentially high relative abundance are large distances from the necessary infrastructure, such as roads and population centres. The models of relative abundance predict that camels will occur at low density across most of southern Northern Territory. In combination, these factors are likely to reduce profitability and might make commercial use nonviable in many areas.

The management of camels in Central Australia poses unique problems, the solutions to which are not clear. Camels can have large impacts even when they are at low density (Edwards *et al*. 2008) and they are difficult and costly to manage (Drucker 2008). The habitat suitability maps derived in the present study indicate that camels have suitable habitat in most areas of southern Northern Territory. Maps of suitable habitats and abundance can play a major role in strategic approach to managing camels and their impacts. However, to maximise their usefulness we need better information on the ecology of camels so that these maps can be refined and generalised.

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