Mapping the stray domestic cat (*Felis catus*) population in New Zealand: species distribution modelling with a climate change scenario and implications for protected areas

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Abstract

Species distribution models of stray cats were developed using two types of occurrence data, one using a combined dataset of stray cats and cat colonies in Auckland and projected to the larger New Zealand area and a second based on population density as an analogue for country wide stray cat occurrence. Environmental variables used for running the models consist of current bioclimatic conditions and a future climate scenario (RCP8.5 for year 2070 CCSM model). Commonly occurring bias due to latitude, the background area used to derive points for model evaluation, inherent spatial autocorrelation of occurrence points and correlated bioclimatic variables were addressed before Maxent was used to produce the suitability maps for the models. Results show that the North Island consistently provide more suitable areas for stray cats with increased suitable areas in a high emission climate change condition. The important protected areas at risk from the increased suitability to stray cats are also presented.

Keywords: stray cats, cat colonies, species distribution modelling, Maxent, climate change, New Zealand

1.0 Introduction

The cat (*Felis catus*) has been identified as one of the world's most invasive species (Lowe et al., 2000). However, it is also the most common, and popular, companion animal in countries like New Zealand (MacKay, 2011). This means that the cat population, and issues associated with both predation by cats and the welfare of the cats themselves are anthropogenic in nature. The population densities of urban free-living, un-owned cats (also known as 'stray cats'; see Farnworth et al., 2010), have been demonstrated to be closely linked to human population density (Aguilar and Farnworth 2012; 2013). These populations of unowned individuals, including loose aggregations around ad hoc provision of food and shelter known as cat colonies (Sparkes et al., 2013), are concomitantly protected by their carers, perceived as a public nuisance (Ash et al., 2013) and predators of localised populations of wildlife (Gillies and Clout 2003; Woods et al., 2003; van Heezik et al., 2010). Therefore the management of stray cats is consistently identified as challenging and difficult. Not leaset because it is reported from a wide range of perspectives which include animal welfare, landscape ecology and environmental and biodiversity conservation (Marston & Bennett 2009; Loss et al., 2013; van Heezik 2010). The issue is further confounded by the multifaceted human-cat relationship which is dominated by emotional attachments to domestic cats or their perceived prey. Cat management is particularly difficult in New Zealand because the cat is the most common companion (pet) animal (Argante 2008) and therefore exists in most complex spatial environments. Associated concerns around stray cat populations include, but are not limited to, threats to wildlife and biodiversity, the spread of pathogens to the companion (pet) cat population and other species and economic considerations in the implementation of management measures (Levinthal, 2010; Simking et al., 2010; Dickman et al., 2010). Practical management approaches such as Trap-Neuter-Return (TNR), capture and rehoming and euthanasia seek to address the growth of stray cats in a humane way. (Farnworth et al., 2011, 2013). Despite these measures there is no clear evidence that the management of urban cat populations has been effective. Marston and Bennett

(2009) suggest that, in Melbourne Australia, the urban cat population is driven by unowned individuals that have not been sterilised. Within New Zealand, studies show that the sterilisation rate for owned cats is approximately 90% (McKay et al., 2009; Farnworth et al., 2010) and the seeming growth of the stray cat population whose density may exceed 50 cats/Km2 (Aguilar and Farnworth, 2012) must therefore be self-perpetuating. This is of concern as anthropogenic food sources likely provide enough nutrition to ensure increased fecundity and survival rates while reducing home ranges of stray cats (Schmidt et al., 2007) which are not curtailed in the same way as feral cats (i.e. those that live in a wild state away from human populations and responsible for at least 14% of extinctions of global bird, mammal and reptile species and 8.2% of these species becoming endangered (Medina et al., 2011). A thriving stray cat population may also present substantial problems as, although large, the ability of urban areas to support the cat population is finite (Ferreira et al., 2011). Urban environments may therefore act as centres from which stray cats disperse into the surrounding environments which may be either semi-urban or rural. Dispersing individuals may use human habitations as a staging source which is particularly problematic when human environments are closely associated with protected areas of ecological value.

The growth of the urban stray cat population is of concern because urban areas are not isolated. They contain within them and at their boundaries areas of potential, and categorical, ecological value. Such areas may be protected by law but incursion by local cats cannot be curtailed (van Heezik et al., 2010). Pet cats tend to have a limited home range and reduced likelihood of dispersal as their territory is centred around food and shelter provided by the owner (Kays et al., 2004). However, stray cats may experience significant pressure to disperse dependent upon a number of factors: for example, the frequency and availability of food (Liberg et al., 2000), the carrying capacity of the location and the level of habituation towards humans of the individual cat. In the latter example it is reasonable to say that an unsocialised individual that is fearful of humans may actively disperse to avoid contact with people. Stray cats may also experience a greater need to hunt than pet cats although this is difficult to quantify. As such there is a need to be able to understand how human population, stray cat population and proximity to areas of ecological interest may overlap which is best presented as a GIS model.

New Zealand is considered a leader in eradication efforts of mammalian pests such as rats, possums and stoats (Keitt et al., 2011). Considerable resources and pest management strategies are in place at both national and regional bodies in charge of conservation. No measures however, are in place for the particular challenge arising from stray cats preying on wildlife which will include both small mammals, birds, reptiles, insects and amphibians (Gillies and Clout 2004; Flux 2007). The predation of birds, particularly in reserves adjacent to human habitation, was recorded and quantified for Dunedin (New Zealand) and it was noted that owned cats alone may place an unsustainable burden upon a range of urban bird populations (van Heezik et al., 2010).

Using a species distribution modelling approach to produce maps showing the suitability of areas for a particular species has become widespread in application with a rapidly growing volume of work reporting improved or newer algorithms and software tools, applications for important species at different geographic and timescales with social-economic or non-biological information layers (Guisan et al., 2013, Booth et al., 2014, Sherrouse et al., 2014). In this effort, we used methods and modelling practice in species distribution modelling proven to reduce several bias types and produce robust model measurement metrics. The combination of ArcGIS and Maxent (Phillips, 2006) was used for processing available stray cat and cat colony data used in earlier studies (Aguilar & Farnworth 2012; Aguilar & Farnworth 2013). Maxent (version 3.3.3k) is a presence-only tool based on optimization algorithms reported to provide better performance compared to other tools (Elith et al., 2006). Maxent has become one of the most widely used species distribution modelling tool (Fourcade et al., 2014) with example of work on models for the distribution of invasive species (Domíguez-Vega et al., 2012; Elith et al., 2006; De Queiroz et al., 2013), endangered and threatened flora and fauna (Sochat et al., 2010), organisms with economic significance (Blanchard et al., 2014) and even ancient species (Connolly et al., 2012). Since the software was first made available by Phillips et al., (2006), techniques, evaluation methods and various measures of performance and interfaces with other GIS software resulted in addressing recognised concerns with the 'presence-only' modelling approach that is implemented. These include techniques to address spatial autocorrelation, background data bias, environmental heterogeneity and latitudinal bias that contributed to assurance or confidence from the results of modelling potential species distribution using Maxent. (Brown 2014)

This work contributes to the effort in developing a stray cat management strategy through the establishment of NZ wide maps of suitability for stray cats and cat colonies under current conditions and future climate scenarios.

2.0 Methodology

Maxent requires the geographic locations of occurrences and a set of environmental layers used to determine the probability of occurrence for each cell represented in the area covered. We used stray cat and cat colony data sourced from animal welfare organisations and reported in previous papers (Aguilar & Farnworth, 2012; Aguilar & Farnworth, 2013) as the basis running two models, one based solely from actual data modelled in Auckland and projected to the entire country and another using population as an analogue for presence data. The first model (A) was run with the Auckland stray cat data with the Bioclim layers as environmental layers. The Auckland model was then projected into the entire New Zealand land mass with the same layer set at a larger, country wide coverage and similarly projected into a future climate scenario. This approach is similar to the process used when projecting locally occurring species to a global or wider regional scales such as the spread of invasive species (Ficetola et al., 2007; Thuiller et al., 2005), determining suitable areas for future translocations (Fouquet et al., 2010) and focussing efforts on areas that were previously unexplored (Raxworthy et al., 2003).

For the other model (B), Auckland based stray cat and population density was used to determine the minimum non-zero value for stray cat density to determine the cut-off value of population density in order to select the New Zealand mesh blocks serving as basis for occurrence points. This was premised on the work of Aguilar and Farnworth (2012) where population density was identified as major factor indicating the presence of these cats. The mesh blocks were then converted to point features located at the centroid of each polygon to represent stray cat occurrence. Centroids of municipal polygonal area were used as presence points for modelling of locust species in Spain due to the varying spatial resolution of the species presence records derived secondary sources (Aragon et al., 2013). Similarly, tracks from GPS capuchin monkey daily routes where points at least 30m distances apart were extracted and used as presence or occurrence data in Maxent (Howard et al., 2012).

Evident clustering of the stray cat data and the concentration of smaller mesh blocks at high population density areas hints at spatial autocorrelation that may result in the inability of the model to predict spatially independent data and lead to inflated performance measure values (Veloz 2009; Nazeri et al., 2014; Hijmans et al., 2012; Boria et al., 2014; Syfert et al., 2013). A tool in Arcmap named Spatially Rarefy Occurrence data was used to filter the occurrence points by eliminating redundant points and removing spatially autocorrelated points within a range of specified distances (Brown 2014). This also included the grouping of occurrence points based on specific habitats or, in this case, suitable land class types for the stray cats grouped using the land cover classes specified in the Land Cover Database of New Zealand (LCDB Version 4.0) (Table 1). The tool creates groups of occurrence points which are used as input into a preliminary Maxent run. Using the common evaluation metric for predictive performance Area Under Curve or AUC (Swets, 1988), the group with the highest AUC value is selected for running the final model and projection.

Table 1. Land cover classification from based on distances from LCDB grouped into favourable environments for stray cats.

Land Class Name	Group
Urban Parkland/Open Space, Transport Infrastructure Built-up Area (settlement)	5
Orchard, Vineyard or Other Perennial Crop Indigenous Forest, High Producing Exotic Grassland	4
Tall Tussock Grassland, Manuka and/or Kanuka, Low Producing Grassland, Exotic Forest, Deciduous Hardwoods, Broadleaved Indigenous Hardwoods	3
Short-rotation Cropland, Mixed Exotic Shrubland, Gorse and/or Broom, Forest – Harvested, Flaxland, Fernland, Depleted Grassland	2
Surface Mine or Dump, Sub Alpine Shrubland, Sand or Gravel River, Permanent Snow and Ice Matagouri or Grey Scrub, Mangrove, Landslide, Lake or Pond, Herbaceous Saline, Vegetation, Herbaceous Freshwater Vegetation, Gravel or Rock, Estuarine Open Water, Alpine Grass/Herbfield	1

Environmental layers, which consisted of current bioclimatic variables, were downloaded from the WorldClim database (Hijmans 2005). This Bioclim set consisted of 11 temperature and 8 precipitation variables representing a 50-year mean for each. Most Bioclim variables were found to be highly correlated (Metzger et al., 2013) leading to difficulties in interpreting the contribution of each to the model. A tool included in the SDMToolbox allowed identification of correlated variables that can be excluded when Maxent is run. A range Spearman’s r correlation values (0.6, 0.7, 0.8 and 0.9 - higher values represent higher correlation) was used to identify which environmental variables combination is to be used for both models.

To overcome the commonly encountered overfitting problem (Philipps et al., 2011; Elith et al., 2011) bias files were created that limit the area from which background points used for model measurement and evaluation were selected. The bias file resulted from two correction rasters, one for latitudinal correction and the other for limiting the background used based on the presence locations used. Normally, Maxent uses the entire area for deriving background points resulting in a higher percentage of commission errors or false positives due to the selection of background points from localities that may be environmentally suitable but not occupied by the species. Several approaches to limit the area ranged from simple radial distances from known occurrences to minimum convex polygons from occurrences to more elaborate combinations of area definitions (Brown 2014; Barbet-Massin et al., 2012; Phillip et al., 2009). We used the convex hull radial area connected with radial buffers from the occurrences. The radial buffer distances was based on home ranges collated from previous stray cat studies and calculated as the distance between the centres of circles that have areas equal to the maximum home range. (Table 1) Compared to mainly urban stray cats, feral cats in rural areas have greater home ranges as reported by different authors with the minimum of 42 ha reported in (Pierce et al., 1987) and a maximum of 2486 ha (Recio et al., 2010). This translates to a range from 0.07 to 56.2 kilometre using the radius of the home range area as the end to end distance that the feral cat potentially travels. While rural feral home ranges are a magnitude greater than urban stray cats' home range, we use these maximum estimates considering the potential for stray cats to become feral. This value was used to limit the area from which background points were derived by Maxent in order to address a commonly observed overfitting characteristic of the algorithm (Radosavljevic & Anderson 2014, Elith et al., 2010, Brown 2014).

Table 2. Distances reported as home ranges in previous studies.

Reported home range (Ha)		Rarefy Distance	Location	Reference
Stray cats	0.07-2.86	2.99	Perth, Australia	Lilith 2007
	2.70-7.9	4.98	Canberra, Australia	Barrat 1997
	0.1-10.1	5.63	Christchurch	Morgan 2002

	0.5-21.8	8.27	Dunedin, NZ	van Heezik et al., 2010
Feral cats	80-990	55.77	NW Victoria, Australia	Jones & Coman 1982
	490.2-1571.4	70.26	Mackenzie Basin, South Island, New Zealand	Pierce 1987
	82-840	51.37	Mackenzie Basin, South Island, New Zealand	Norbury et al., 1998
	178-2486	56.26	Central South Island, New Zealand	Recio et al., 2010

The availability of the latest scenarios for different future bioclimatic conditions based on the 5th IPCC report made the modelling of future suitability of stray cats possible (IPCC 2013; Carraro et al., 2014). Using the worst case scenario of RCP 8.5, Bioclim layers for the year 2070 (NCAR 2012) was included as a projection to enable the comparison between current and future suitability conditions for both Model A and B.

The set of resulting suitability maps were overlayed over the protected areas of New Zealand as categorised in the IUCN system. Consisting of 3,954 areas over an area of 108,327 square kilometres, the categories include Ia - Strict Nature Reserve, Ib – Wilderness Area, II – National Park, III – National Monument, IV – Habitat Species Management Area, V – Protected Landscape and Seascape. Included in the data available were categories Not Applicable and Not Reported. For purposes of presenting the suitability of these areas to stray cats, all of the protected areas were used. The result show which protected area are most suitable to stray cats based on the output of the two models for current and future conditions.

Results and Discussion

Environmental Data

Consistent with the finding of Warren and Siefert (2011) that over-parameterization presents lesser problems than under-parameterization, we use groups produced at the maximum value of Spearman's r coefficient less than 1. Also, since the geographical area of the New Zealand model enclosed the Auckland area, a lesser set of non-correlated variables resulted for Auckland with an extra 2 variables reported as non-correlated for the New Zealand map. (Model B with r=0.9 in Table 2) This set of variables was used to run both Model A and Model B as the extra variables in the former do not contribute significantly to model outputs while the evaluation of comparative measures between model is better served with a common set of environmental variables.

Table 3. Bioclim variables that were not correlated at different Spearman's r values

Models	Spearman's r values			
	0.6	0.7	0.8	0.9
Model A (Bioclim Auckland)	bio15nz.asc	bio15nz.asc	bio15nz.asc	bio15nz.asc
	bio12nz.asc	bio12nz.asc	bio12nz.asc	bio12nz.asc
	bio9nz.asc	bio9nz.asc	bio9nz.asc	bio9nz.asc
	bio3nz.asc	bio3nz.asc	bio4nz.asc	bio4nz.asc
	bio2nz.asc	bio2nz.asc	bio3nz.asc	bio3nz.asc
	bio1nz.asc	bio1nz.asc	bio2nz.asc	bio2nz.asc
			bio1nz.asc	bio1nz.asc
Model B (Bioclim New Zealand)	bio15nz.asc	bio15nz.asc	bio15nz.asc	bio15nz.asc
	bio12nz.asc	bio12nz.asc	bio12nz.asc	bio12nz.asc
	bio11nz.asc	bio11nz.asc	bio11nz.asc	bio11nz.asc
	bio9nz.asc	bio9nz.asc	bio9nz.asc	bio9nz.asc
	bio8nz.asc	bio8nz.asc	bio8nz.asc	bio8nz.asc
	bio5nz.asc	bio6nz.asc	bio6nz.asc	bio6nz.asc
	bio3nz.asc	bio5nz.asc	bio5nz.asc	bio5nz.asc

	bio2nz.asc	bio3nz.asc	bio3nz.asc	bio4nz.asc
	bio1nz.asc	bio2nz.asc	bio2nz.asc	bio3nz.asc
		bio1nz.asc	bio1nz.asc	bio2nz.asc
				bio1nz.asc

Occurrence Data

Presence reports of stray cats (Aguilar & Farnworth 2012) and cat colonies (Aguilar & Farnworth 2013) showed high levels of clustering in the central city districts of Auckland (Figure 1)

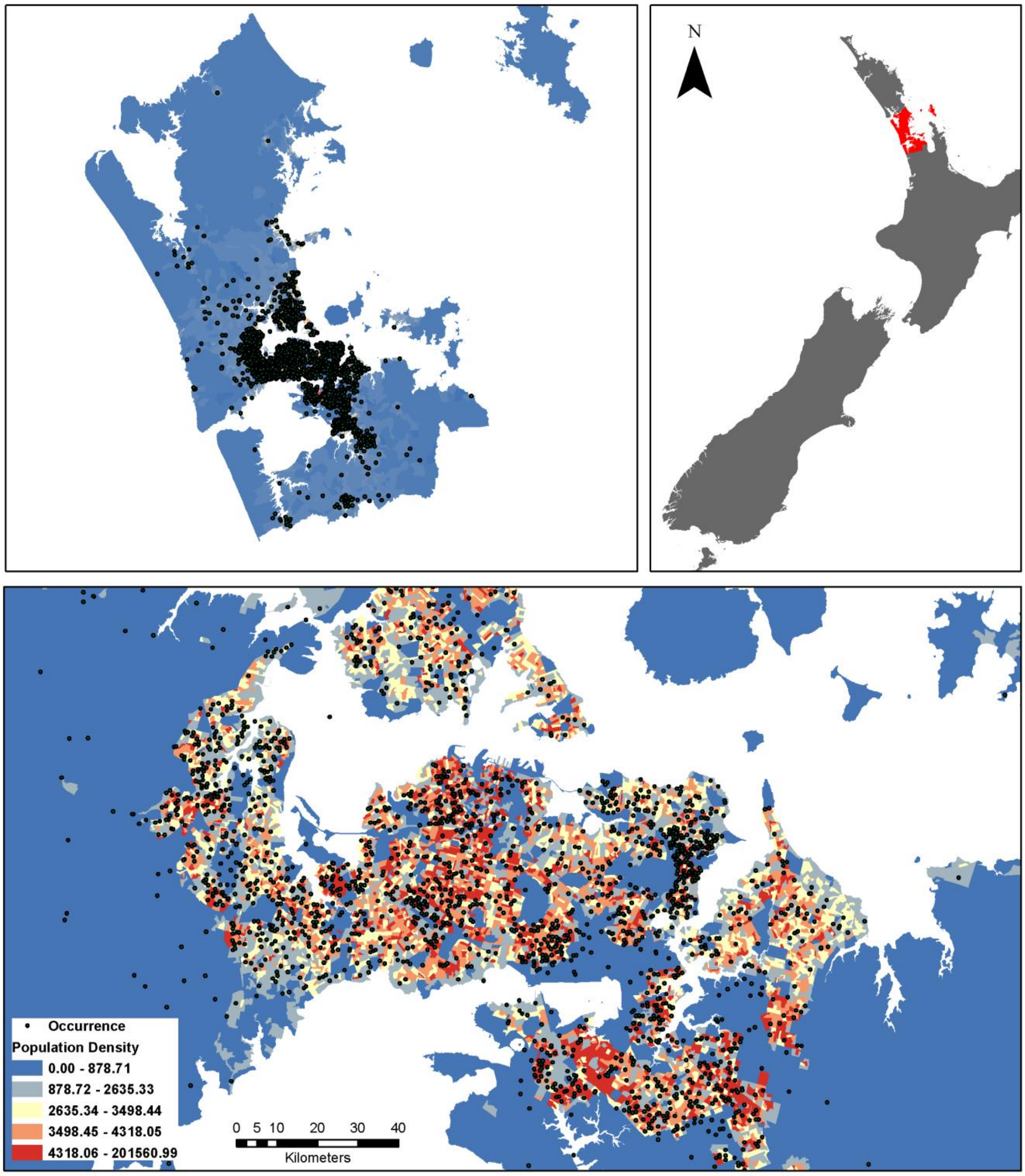

Figure 1. Stray cats and cat colony occurrences in the city center (bottom) of Auckland (top-left), New Zealand (top-right)

Spatial rarefication of location data for Auckland for Model A resulted in 131 points that were not spatially autocorrelated. This represents only 4% of the original 2953 occurrences. Majority of the rarefied points were found within or nearest to the group

5 landcover classes, an expected result considering the significant correlation between stray cat density and population density. (Table 4)

For the occurrence data requirements of Model B, Auckland population mesh blocks with the minimum population density where there was non-zero stray cats or cat colony wwere found to be at 0.091 persons per square kilometre (the cut-off value). A total of 41,127 mesh blocks with population densities greater than the cut off value were converted into point features located at the centroid of each polygon. When the Spatially Rarefy Occurrence Data included in the SDMToolbox was run, a total of 5,888 points resulted showing that 14% were non-spatially correlated.

A Maxent run for Models A and B was conducted for each set of rarefied occurrences to determine comparative performance in terms of AUC. Resulted show that Group 5 has better performance compared to other Groups. This is to be expected as the land cover types associated with higher human population densities are mainly under the land cover class for Group 5 (Buit-up area (settlements)) (Figure 2 and Table 4).

Table 4. AUC values for the spatially rarefied data from the initial Maxent run.

	Raster Value	AUC Training	AUC Test	No of Pts
Model A	Group 1	-	0.5	1
	Group 2	0.906	0.811	3
	Group 3	0.829	0.901	11
	Group 4	0.838	0.605	38
	Group 5	**0.906**	**0.827**	**78**
	All Points	0.836	0.737	131
	Original Points from Stray Cat Data			2,953
Model B	Group 1	0.697	0.602	56
	Group 2	0.804	0.781	713
	Group 3	0.729	0.724	4663
	Group 4	0.853	0.655	80
	Group 5	**0.919**	**0.900**	**376**
	All Points	0.697	0.691	5,888
	Original Points from NZ Population Data			41,127

The bias files included in the Maxent model resulted from combining latitudinal bias with and area coverage based on occurrence data (Figure 2)

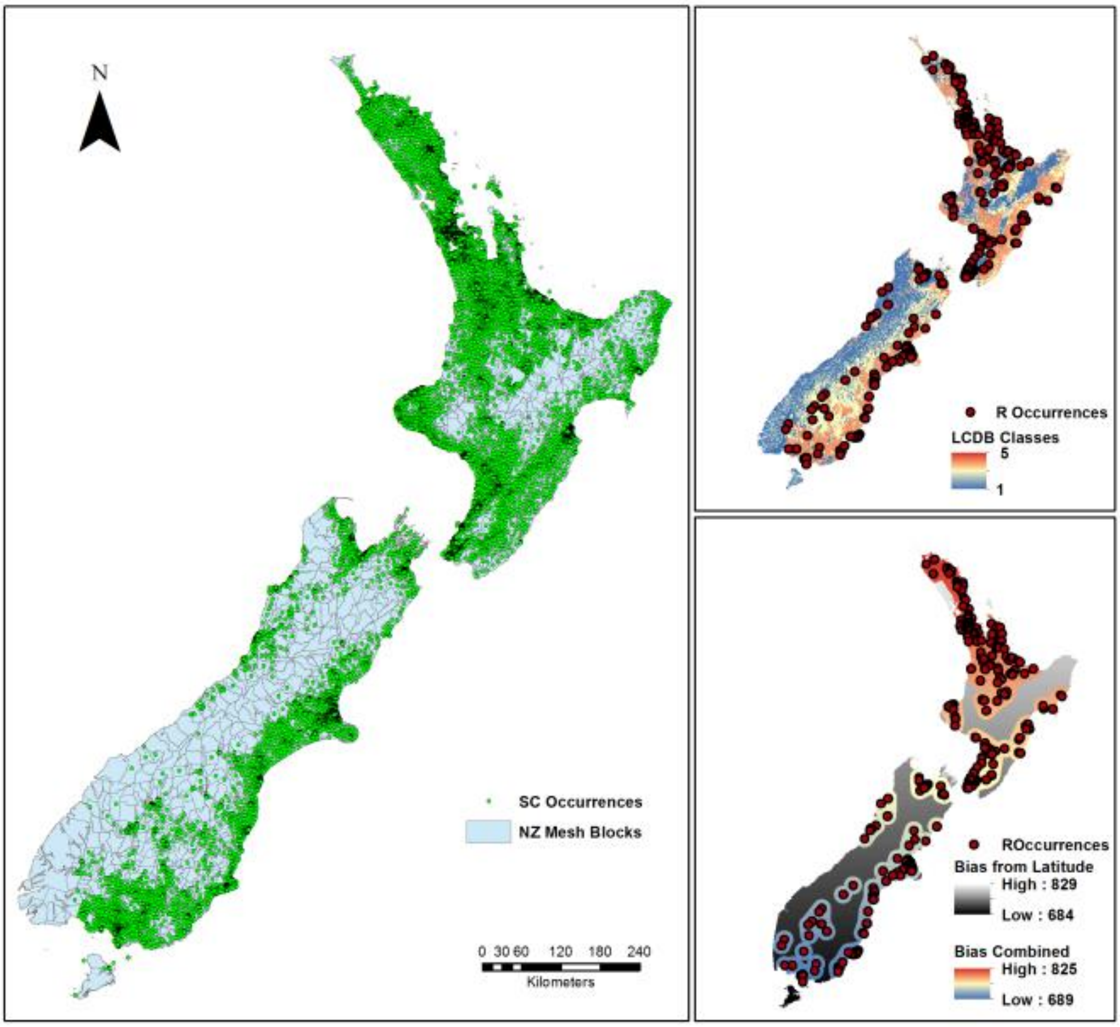

Figure 2. Occurrence data derived from NZ mesh blocks (Left) with rarefied group 5 (Top right) and bias files (Bottom right).

Results of the Maxent model using the Auckland stray cat data and projected into the entire New Zealand land mass with current and future climate conditions show some changes in the suitability for stray cats (Figure 3). Areas in the North Island are shown to have much more favourable conditions compared to the South Island with increasing areas for both in the future climate scenario. When a 10th percentile presence logistic threshold for both current and future conditions was used, an increase in the areas predicted to be presence areas for stray cats is evident (Figure 3).

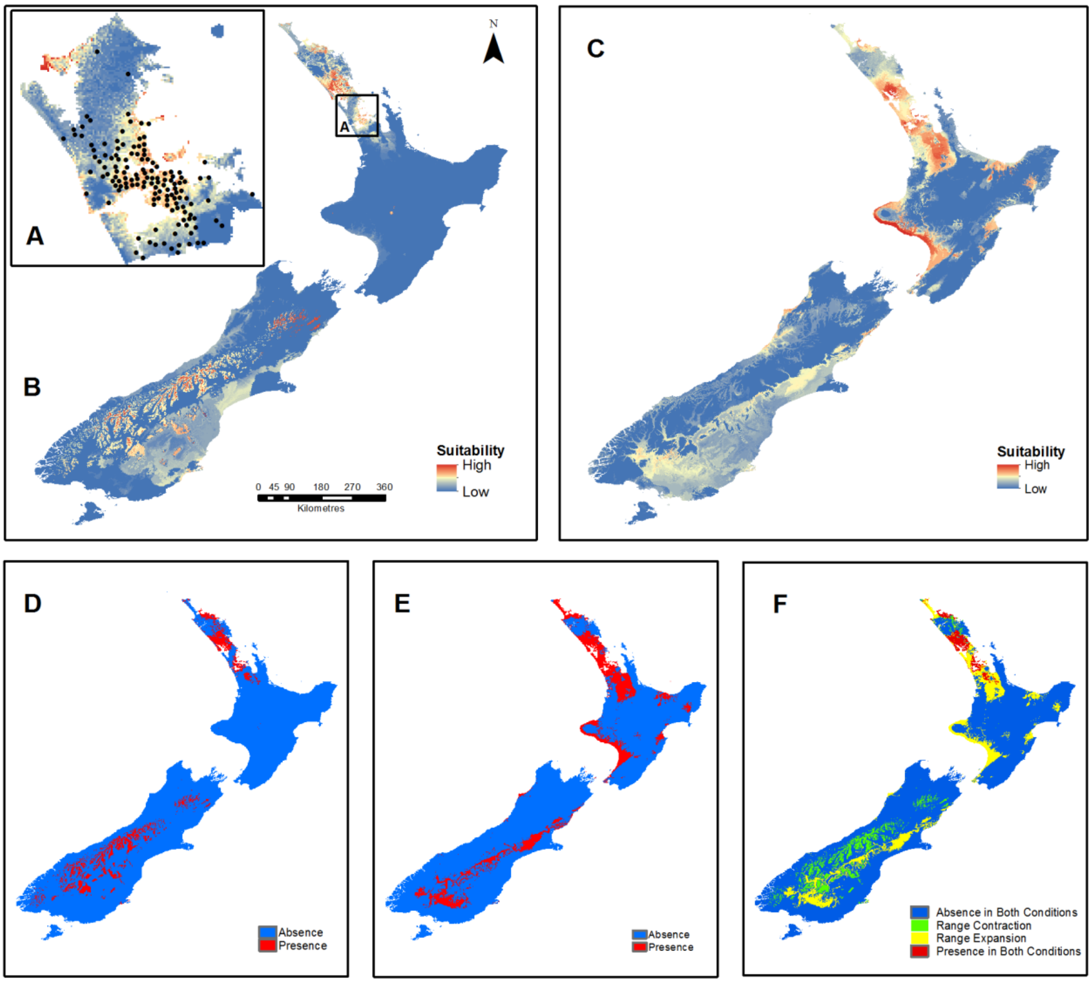

Figure 3. Maxent results with corrected occurrence data from Auckland stray cats (A), projected into the New Zealand terrestrial area under current conditions (B) and RCP8.5 climate conditions for 2070 (C), thresholded presence under current conditions (D), thresholded presence under RCP8.5 climate conditions for 2070 and (E) presence/absence and range contractions/expansions between D and E (F).

Results of the population based model show similar characteristics of the environmental suitability of New Zealand to stray cats. Many of the population centers have greater values while higher altitudes, remote wilderness and the majority of the South Island are not as favourable. When the model was projected to RCP8.5 for the year 2070, a result consistent with Model A is shown, depicting a wider and more intense favorable suitability of the area covered. (Figure 4).

A simple comparison of the two models show better AUC reported by Model B. For this instance, better performance measures for using population density as an analogue for stray cats compared to using actual presence data from a local region and expanding to a larger extent is implied. Caution is still warranted in this result however, and further model validation as well as testing with other occurrence data is required.

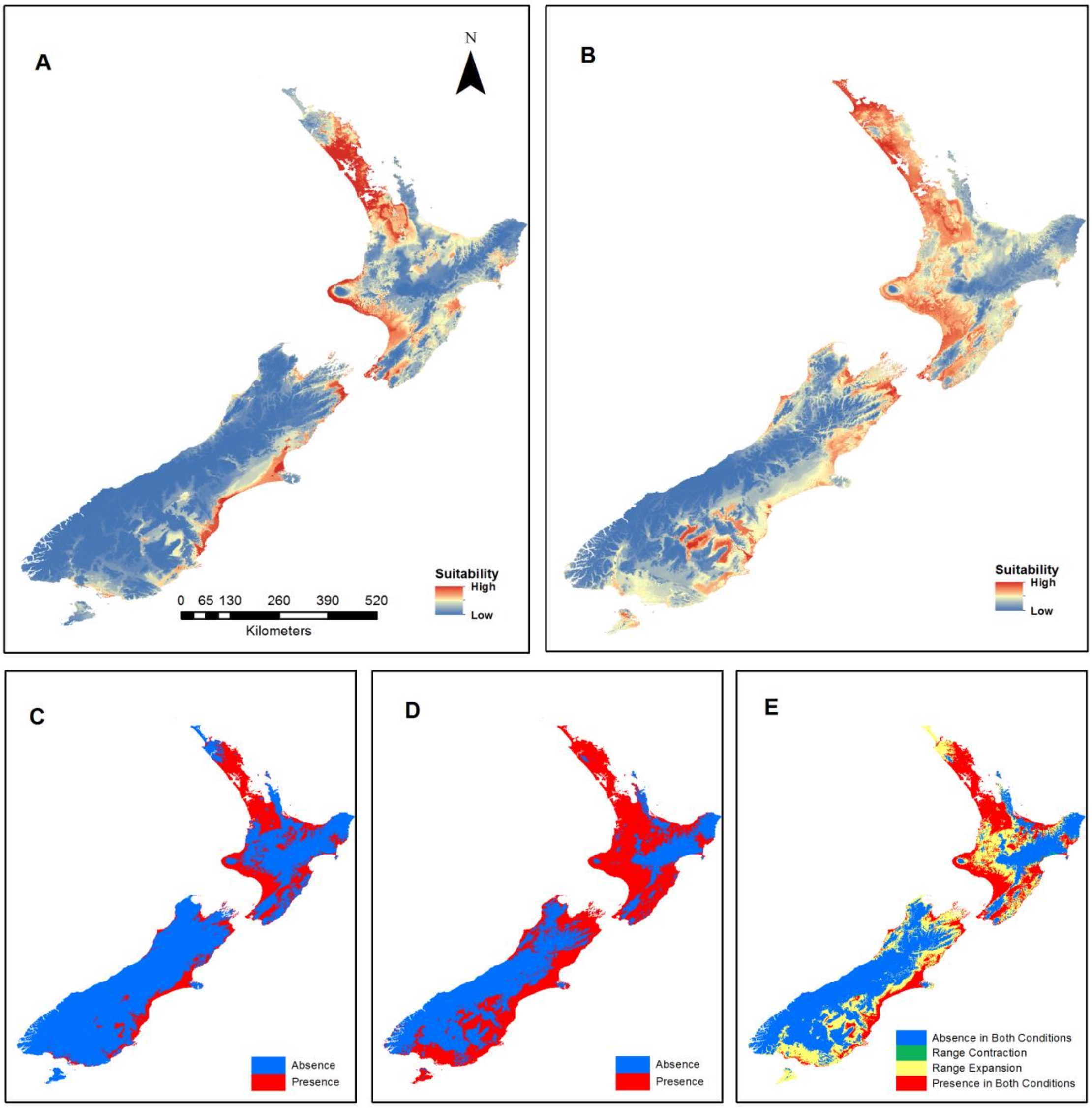

Figure 4. Results of Model B using data from mesh block data based New Zealand population for current conditions (A) projected into RCP8.5 climate conditions for 2070 (B), thresholded presence under current conditions (C), thresholded presence under RCP8.5 climate conditions for 2070 and presence/absence and range contractions/expansions between C and D (E).

Both Models A and B show an increase in the number of presence cells in future conditions with Model B reporting presence et almost double the number of cells as Model A (Table 3).

Table 3. Number of raster cells representing presence and absence resulting from thresholding current and future suitability maps.

	Absent in Both (Non-Occupancy)	Range Contraction (Presence: current conditions only)	Range Expansion (Presence: future conditions only)	Present in Both (Occupancy)
Model A	325,741	26,240	54,824	9,443
Model B	200,962	1,489	117,260	95,606

Clipping the resulting suitability maps with existing IUCN categories of protected areas of New Zealand (Figure 4) show the differences between the models (CD and EF in Figure 5) and the changes of suitability in current conditions and the future scenario of RCP8.5 for the year 2070 (CE and DE). A major difference between the two models is the greater proportion of suitable areas found in the North Island compared to the South Island for Model B. In terms of the climate change scenario, a movement of suitable areas to the South seems to be present in Model A while in Model b, an increased concentration of suitability to the South but limited in the North Island seems evident.

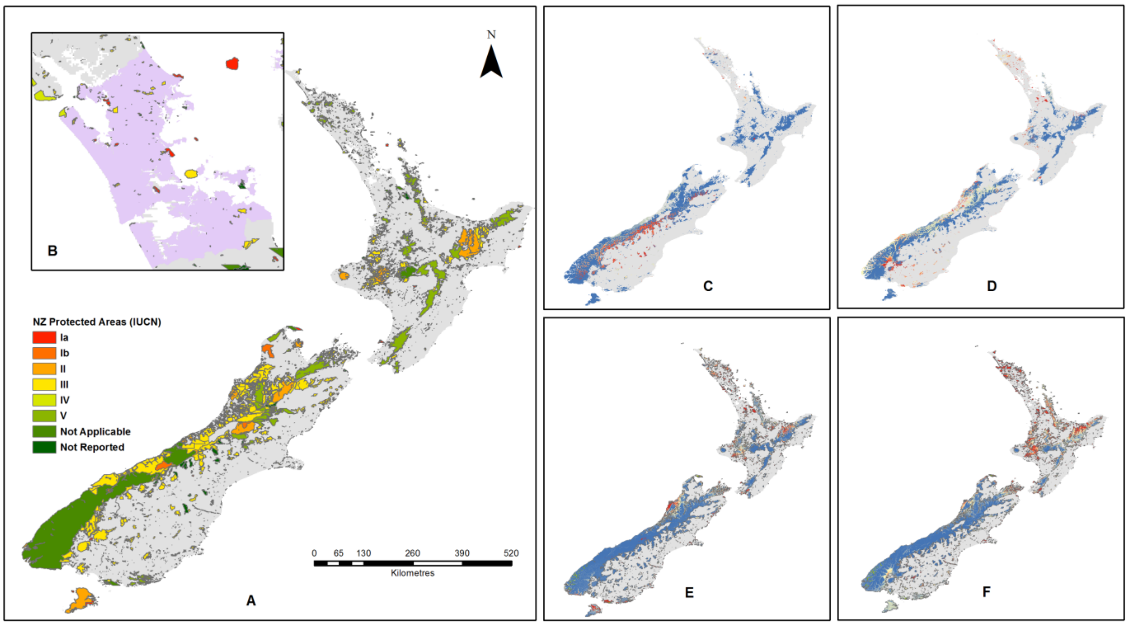

Figure 5. IUCN categories of protected areas of New Zealand (A) with areas in Auckland (B) clipped with suitability of stray cats from Model A current conditions (C), Model A RCP 8.5 projected to 2070 (D), Model B current conditions (E) and Model B RCP 8.5 projected to 2070 (F).

Conclusion

Species distribution modelling provide a convenient approach to the visualization of the spatial characteristics of stray cats in New Zealand that may impact areas that are considered to be environmentally significant and protected under various categories. Modelling based on two data sources, one from actual occurrence data and another using population density as an analogue, provides a comparison of performance that hints at the advantages of the latter in cases when attempting to project from a smaller region to a much wider geographical area. Projections to a climate change based scenario show consistent increase in the area and intensity of suitability for stray cats. Overlaying the protected areas of the country into the suitability maps help identify which protected areas are more suitable for stray cats for the entire country in current and a future climatic condition.

References

Aguilar, G. D., & Farnworth, M. J. (2012). Stray cats in Auckland, New Zealand: Discovering geographic information for exploratory spatial analysis. Applied Geography, *34*, 230–238. doi:10.1016/j.apgeog.2011.11.011

Aguilar, G. D., & Farnworth, M. J. (2013). Distribution characteristics of unmanaged cat colonies over a 20 year period in Auckland, New Zealand. Applied Geography, *37*, 160–167. doi:10.1016/j.apgeog.2012.11.009

Anderson, R. P. & Raza, A. (2010) The effect of the extent of the study region on GIS models of species geographic distributions and estimates of niche evolution: preliminary tests with montane rodents (genus Nephelomys) in Venezuela. *Journal of Biogeography*, *37*, 1378-1393.

Aragón, P., Coca-Abia, M. M., Llorente, V., & Lobo, J. M. (2013). Estimation of climatic favourable areas for locust outbreaks in Spain: integrating species' presence records and spatial information on outbreaks. *Journal of Applied Entomology*, *137*(8), 610–623. doi:10.1111/jen.12022

Ash, S. J., Adams, C. E., Ash, S. J., & Adams, C. E. (2011). Public preferences for free-ranging domestic cat (*Felis catus*) management options, *Wildlife Society Bulletin. 31*(2):334-339.

Barbet-Massin, M., Jiguet, F., Albert, C. H. & Thuiller, W. (2012) Selecting pseudoabsences for species distribution models: how, where and how many? *Methods in Ecology and Evolution*, *3*, 327–338.

Blanchard, R., O'Farrell, P. J., & Richardson, D. M. (2014). Anticipating potential biodiversity conflicts for future biofuel crops in South Africa: incorporating spatial filters with species distribution models. *GCB Bioenergy*, n/a-n/a. doi: 10.1111/gcbb.12129

Boria, R.A., Olson, L.E., Goodman, S.M., Anderson, R.P. (2014) Spatial filtering to reduce sampling bias can improve the performance of ecological niche models. *Ecological Modelling*, *275,* 73–77. doi: 10.1016/j.ecolmodel.2013.12.012

Brown, J. L. (2014). SDMtoolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *Methods in Ecology and Evolution*, *5*(7), 694-700. doi:10.1111/2041-210X.12200

Carraro, C., Lanza, A., & Tavoni, M. (2014). All You Need to Know About the IPCC 5th Assessment Report. Mitigation of Climate Change. *Review of Environment, Energy and Economics*-Re3.

Conolly, J., Manning, K., Colledge, S., Dobney, K., & Shennan, S. (2012). Species distribution modelling of ancient cattle from early Neolithic sites in SW Asia and Europe. *The Holocene*, *22*(9), 997-1010.

De Queiroz, D. L., Majer, J., Burckhardt, D., Zanetti, R., Fernandez, J. I. R., de Queiroz, E. C., … dos Anjos, N. (2013). Predicting the geographical distribution of *Glycaspis brimblecombei* (Hemiptera: Psylloidea) in Brazil. *Australian Journal of Entomology*, *52*(1), 20–30. doi:10.1111/aen.12001

Dickman, C.R. Denny, E. & Buckmaster, T. (2010) Identification of sites of high conservation priority impacted by feral cats. Report for the Australian Government Department of the Environment, Water, Heritage and the Arts. Canberra, Australia

Domíguez-Vega, H., Monroy-Vilchis, O., Balderas-Valdivia, C. J., Gienger, C. M., & Ariano-Sánchez, D. (2012). Predicting the potential distribution of the beaded lizard and identification of priority areas for conservation. *Journal for Nature Conservation*, *20*(4), 247–253. doi:10.1016/j.jnc.2012.04.003

Dunn,W. C., & Milne B. T. (2014) Implications of climatic heterogeneity for conservation of the Lesser Prairie-Chicken (Tympanuchus pallidicinctus). *Ecosphere* *5*(5):64. http://dx.doi.org/10.1890/ES13-00333.1

Elith, J., H Graham, C., P Anderson, R., Dudík, M., Ferrier, S., Guisan, A., … E Zimmermann, N. (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, *29*(2), 129–151. doi:10.1111/j.2006.0906-7590.04596.x

Ferreira, J. P., Leitão, I., Santos-Reis, M., & Revilla, E. (2011). Human-related factors regulate the spatial ecology of domestic cats in sensitive areas for conservation. *PloS One*, *6*(10), e25970.

Ficetola, G. F., Thuiller, W., & Miaud, C. (2007). Prediction and validation of the potential global distribution of a problematic alien invasive species - the American bullfrog. *Diversity and Distributions*, *13*(4), 476–485. doi:10.1111/j.1472-4642.2007.00377.x

Fourcade, Y., Engler, J. O., Rödder, D., & Secondi, J. (2014). Mapping Species Distributions with MAXENT Using a Geographically Biased Sample of Presence Data: A Performance Assessment of Methods for Correcting Sampling Bias. *PloS One*, *9*(5), e97122. doi:10.1371/journal.pone.0097122

Howard, A. M., Bernardes, S., Nibbelink, N., Biondi, L., Presotto, A., Fragaszy, D. M., Madden, M. (2012). A maximum entropy model of the bearded capuchin monkey habitat incorporating topography and spectral unmixing analysis, In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2012 XXII ISPRS Congress, 25 August – 01 September, Melbourne, Australia, (I-2), 7-11.

Gillies, C. and Clout M.N. (2003). The prey species of domestic cats in two suburbs of Auckland City, New Zealand. *Journal of Zoology*, *259*, 309-315.

Ihlow F, Dambach J, Engler JO, Flecks M, Hartmann T, et al.,. (2012) On the brink of extinction? How climate change may affect global chelonian species richness and distribution. *Global Change Biology, 18*, 1520–1530. doi: 10.1111/j.1365-2486.2011.02623.x

Kays, R. W., & DeWan, A. a. (2004). Ecological impact of inside/outside house cats around a suburban nature preserve. *Animal Conservation*, *7*(3), 273–283. doi:10.1017/S1367943004001489

Keitt, B., Campbell, K., Saunders, A., Clout, M., Wang, Y., Heinz, R., Newton H.K., & Tershy, B. (2011). The Global Islands Invasive Vertebrate Eradication Database: A tool to improve and facilitate restoration of island ecosystems. In: Veitch CR, Clout MN and Towns DR (eds). *Island invasives: eradication and management*, (pp 74-77), Switzerland: IUCN.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V., … Wilting, A. (2013). The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions*, *19*(11), 1366–1379. doi:10.1111/ddi.12096

Levy, J. K., & Crawford, P. C. (2004). Humane strategies for controlling feral cat populations*. Journal of the American Veterinary Medical Association*, *225*(9), 1354-1360.

Liberg, O., Sandell, M., Pontier, D., & Natoli, E. (2000). Density spatial organisation and reproductive tactics in the domestic cats and other felids. In D. C. Turner, & P. Bateson (Eds.), *The domestic cat: The biology of its behaviour* (pp.119-147). UK: Cambridge

Loss, S. R., Will, T., & Marra, P. P. (2013). The impact of free-ranging domestic cats on wildlife of the United States. *Nature Communications*, *4*, 1396. doi:10.1038/ncomms2380

Lowe, S., Browne, M., Boudjelas, S., De Poorter, M. (2000). 100 of the World's Worst Invasive Alien Species: A selection from the Global.Invasive Species Database. The Invasive Species Specialist Group (ISSG), a specialist group of the Species Survival Commission (SSC) of the World Conservation Union (IUCN), 12 p.

MacKay, J., & NZCAC (New Zealand Companion Animal Council Incorporated). (2011). *Companion animals in New Zealand.*

McDowell, W. G., Benson, A. J., & Byers, J. E. (2014). Climate controls the distribution of a widespread invasive species: implications for future range expansion. *Freshwater Biology*, *59*(4), 847-857. doi: 10.1111/fwb.12308

Medina, F. M., Bonnaud, E., Vidal, E., Tershy, B. R., Zavaleta, E. S., Donlan, C. J., Keitt, B. S., Le Corre, M., Horwath, S. V., Nogales, M. (2011). A global review of the impacts of invasive cats on island endangered vertebrates. *Global Change Biology*, *17*(11), 3503–3510. doi:10.1111/j.1365-2486.2011.02464.x

Miller, G. , Slater, M. and Weiss, E. (2014) Effects of a Geographically-Targeted Intervention and Creative Outreach to Reduce Shelter Intake in Portland, Oregon. *Open Journal of Animal Sciences*, *4*, 165-174. doi: 10.4236/ojas.2014.44021.

NCAR GIS Program (2012). Climate Change Scenarios, version 2.0. Community Climate System Model, June 2004 version 3.0. http://www.cesm.ucar.edu/models/ccsm3.0/ was used to derive data products. NCAR/UCAR. URL:http://www.gisclimatechange.org. Accessed 01 June 2014.

Norbury G.L., Norbury D.C., Heyward R.P. (1998). Space use and denning behaviour of wild ferrets (*Mustela fero*) and cats (*Felis catus*). *New Zealand Journal of Ecology, 22*, 149–159

Phillips SJ, Dudík M, Elith J, Graham CH, Lehmann A, Leathwick J, Ferrier S (2009) Sample selection bias and presence-only distribution models: implications for background and pseudoabsence data. *Ecological Applications*, *19*, 181-197.

Radosavljevic, A. and Anderson R.P. (2014) Making better MAXENT models of species distributions: complexity, overfitting and evaluation. *Journal of Biogeography*, *41*, 629–643

Schmidt, P. M., Lopez, R. R., & Collier, B. A. (2007). Survival, Fecundity, and Movements of Free-Roaming Cats. *Journal of Wildlife Management*, *71*(3), 915–919. doi:10.2193/2006-066

Sherrouse, B. C., Semmens, D. J., & Clement, J. M. (2014). An application of Social Values for Ecosystem Services (SolVES) to three national forests in Colorado and Wyoming. *Ecological Indicators*, *36*, 68–79. doi:10.1016/j.ecolind.2013.07.008

Shochat, E., Lerman, S. B., Anderies, J. M., Warren, P. S., Faeth, S. H., & Nilon, C. H. (2010). Invasion, competition, and biodiversity loss in urban ecosystems. *BioScience*, *60*(3), 199e208.

Sparkes, A. H., Bessant, C., Cope, K., Ellis, S. L. H., Finka, L., Halls, V., … Yeates, J. (2013). ISFM guidelines on population management and welfare of unowned domestic cats (Felis catus). *Journal of Feline Medicine and Surgery*, *15*(9), 811–7. doi:10.1177/1098612X13500431

Swets, J.A. 1988. Measuring the accuracy of diagnostic systems. *Science*. *240*, 1285-1293.

Syfert, M. M., Smith, M. J., & Coomes, D. a. (2013). The effects of sampling bias and model complexity on the predictive performance of MaxEnt species distribution models. *PloS One*, 8(2), e55158. doi:10.1371/journal.pone.0055158

Thuiller, W., Lafourcade, B., Engler, R. & Araujo, M. B. (2009) BIOMOD – a platform for ensemble forecasting of species distributions. *Ecography*, *32*, 369–373.

Veloz S.D. (2009) Spatially autocorrelated sampling falsely inflates measures of accuracy for presence-only niche models. *Journal of Biogeography*, *36*: 2290–2299. doi: 10.1111/j.1365-2699.2009.02174.x

Warren, D. L., & Seifert, S. N. (2011). Ecological niche modeling in Maxent: the importance of model complexity and the performance of model selection criteria. *Ecological Applications*, *21*(2), 335–342. doi:10.1890/10-1171.1

Woods, M., McDonald, R., & Harris, S. (2003). Predation of wildlife by domestic cats Felis catus in Great Britain. *Mammal Review*, *33*(2), 174–188. Retrieved from http://onlinelibrary.wiley.com/doi/10.1046/j.1365-2907.2003.00017.x/full