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Spatial Modelling for the Northern Quoll in the Pilbara:

Informing the Management of a Unique and Isolated Population of an Endangered and Iconic Species.

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CENTRE for ECOSYSTEM MANAGEMENT

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Executive Summary

BACKGROUND

The northern quoll (*Dasyurus hallucatus*) is an endangered, medium-sized marsupial carnivore once widespread across northern Australia, but now restricted to several disjunct populations within its former range. This decline is largely attributed to invasion by the introduced cane toad (*Rhinella marina*). The cane toad emits a lethal toxin, and when the quoll naïvely predates on the toad, it succumbs to this toxin. Subsequently, the northern quoll is now classified as an endangered species.

The Pilbara population of the northern quoll is isolated and disjunct differentiating strongly from other populations in that:

1. There are marked genetic, behavioural and ecological differences from other populations,
2. Habitats are largely intact, giving a high probability of persistence, and
3. To date, it has been spared the devastation that cane toad invasion has brought to other populations.

OBJECTIVE

In this project we have used a variety of spatial modelling tools to develop a predictive model identifying northern quoll refugia within the Pilbara and to determine how impacts such as cane toad invasion and climate change will impact on that refugia.

METHODS

a) Identifying potential distribution for the northern quoll
At the Pilbara scale, from an initial group of 48 bioclimatic, topographic, geological and biotic potential predictive variables, a combination of statistical tests were used to identify nine variables to be used in the development of a species distribution model (SDM) for the northern quoll. This model was developed using MaxEnt software. To account for sample bias (a common problem with MaxEnt modelling) a pseudo-absence bias layer was developed from presence records for critical weight range non-volant mammals. This resulting model was then tested using an ensemble process, where five other models were constructed using a group of modelling packages and an ensemble package was created by combining these models. This ensemble model was then compared with the MaxEnt model and conclusions drawn. The resulting preferred model is presented below (Figure 1).

b) Climate change impacts on the northern quoll
MaxEnt models were run at the national scale using a suite of eight bioclimatic variables. We elected to use the Australian Community Climate and Earth-System Simulator (ACCESS) 1.0

coupled model. Coupled models evaluate individual climate models and combine them. In this instance it combines 46 largely conflicting CMIP 5 models. The timeframes selected were 2050 and 2070 as it was felt that lower timeframes would not show significant changes in the quolls potential distribution and timeframes beyond 2070 gave ample opportunity to create SDMs with improved tools and projections. All modelled changes are measured against baseline of 1986–2005 averages using medium and high emission scenarios.

c) Can the cane toad reach the Pilbara?

There have been quite a few predictive, national scale, national scale SDMs constructed to demonstrate the potential distribution of the cane toad and how this will change with the predicted impacts of climate change. These SDMs vary greatly both in methodology and in the sophistication of their design and implementation. Therefore, it is not surprising to find that their outputs vary enormously, both in current and predicted future potential distributions.

The cane toad is also a range shifting species in Australia, therefore a successful SDM must account for the following limitations.

1. We do not have a historical distribution of this species in Australia.
2. Potential distribution appears to be largely defined by “cryptic” variables.
3. The cane toad has been known to “hitch hike” to overcome barriers.
4. The Olympic village phenomenon.
5. Previous SDMs used outdated climate scenarios.

To determine the cane toad’s capacity to invade the Pilbara, and the impacts of climate change on this species, a simple sum overlay model was constructed in a GIS environment, where the parameters of this species actual distribution within ten different variables were derived and scores given to 1km^2 pixels based on the number of times variable parameters were met nationally. This SDM was then repeated using the ACCESS 1.0 climate scenarios.

CONCLUSIONS

- The Pilbara population of the northern quoll is an appropriate subject for species distribution modelling in that it multiple modelling tools provide consistent outputs given an appropriate suite of predictive variables.
- Our models indicate that, under the scenarios identified in the ACCESS 1.0 model, the potential distribution of northern quoll will shift inland and while that of the cane toad will contract towards the coast. This will bring about a divergence in the distributions of these two species.

- Modelling habitat for the northern quoll at a very fine scale remains beyond the capacity of this project

- Our understanding of the cane toad's capacity to adapt remains inadequate.

- The outputs of this project should be tested and refined through field studies.

- The capacity to model the effects of threats to the Pilbara population of the northern quoll in response to impacts associated with mining activities, inappropriate fire regimes, pastoral activities and feral predators, requires additional data capable of quantifying the impacts of these threats.

RECOMMENDATIONS

- Targeted research should be undertaken to address knowledge gaps in regard to the habitat preferences of the northern quoll and the impacts of threatening processes on this species.

- There remains significant conflict between climate models. It is recommended that these exercises be repeated and re-evaluated using the best available models as they come to hand.

- It is expected that new and improved spatial modelling tools and methodologies should also be applied to the conservation of the Pilbara population of the northern quoll as they come to hand.

- Quarantine activities such as blocking toad access to key bodies of permanent fresh water and public awareness programs of the dangers of transporting cane toads may prove effective in delaying their invasion of the Pilbara, thereby diminishing their impact on the Pilbara population of the northern quoll.

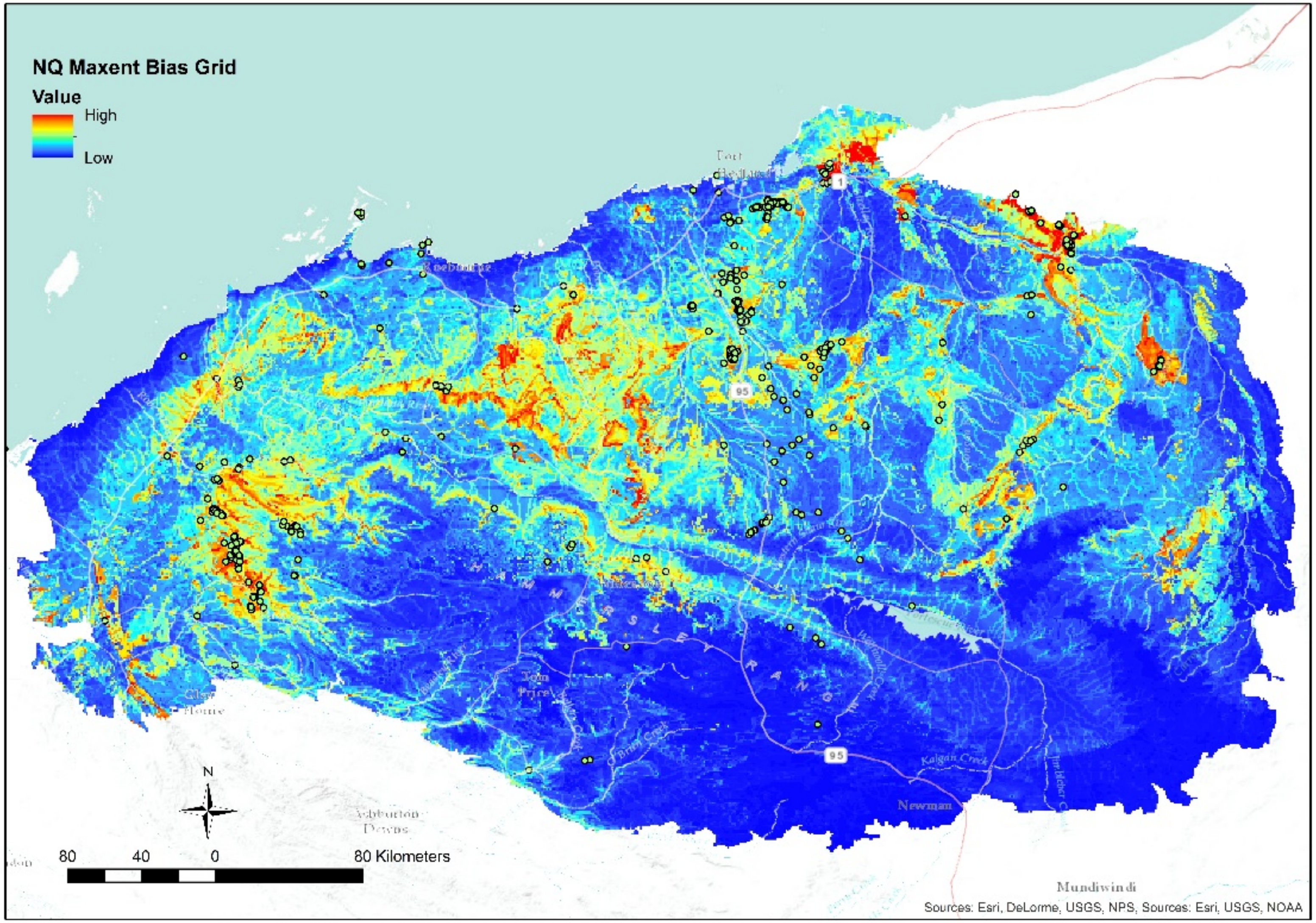

Figure 1: The current potential distribution for the Northern Quoll in the Pilbara (Preferred model)

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1 Introduction

1.1 Project background

In 2011 the Department of Parks and Wildlife embarked on a ten year northern quoll regional monitoring project within the Pilbara. In 2012, a workshop hosted a workshop to define research priorities for the northern quoll (Cramer et al., 2015). The workshop was attended by researchers from universities and government, environmental consultants, mining industry representatives and representatives of Western Australian and Australian government departments responsible for environmental regulation and approvals. This conference identified the need for a better understanding of northern quoll distribution as a priority action. This reflected a general consensus that effective management of this endangered species relies on a good baseline knowledge of the distribution of this species, an understanding of how and why that distribution has changed, the extent of that change, and how it may be altered by threatening processes in the future.

As a consequence of the findings of the northern quoll workshop, a collaboration was entered into between Department of Parks and Wildlife and research staff with the Edith Cowan University School of Natural Sciences on ways by which the School apply its expertise in species distribution modelling to the conservation of the northern quoll. To that end, a conceptual model was developed that demonstrated the potential application of species distribution modelling to northern quoll conservation in the Pilbara (Figure 2) and this model was used as a basis for the development and implementation of this project.

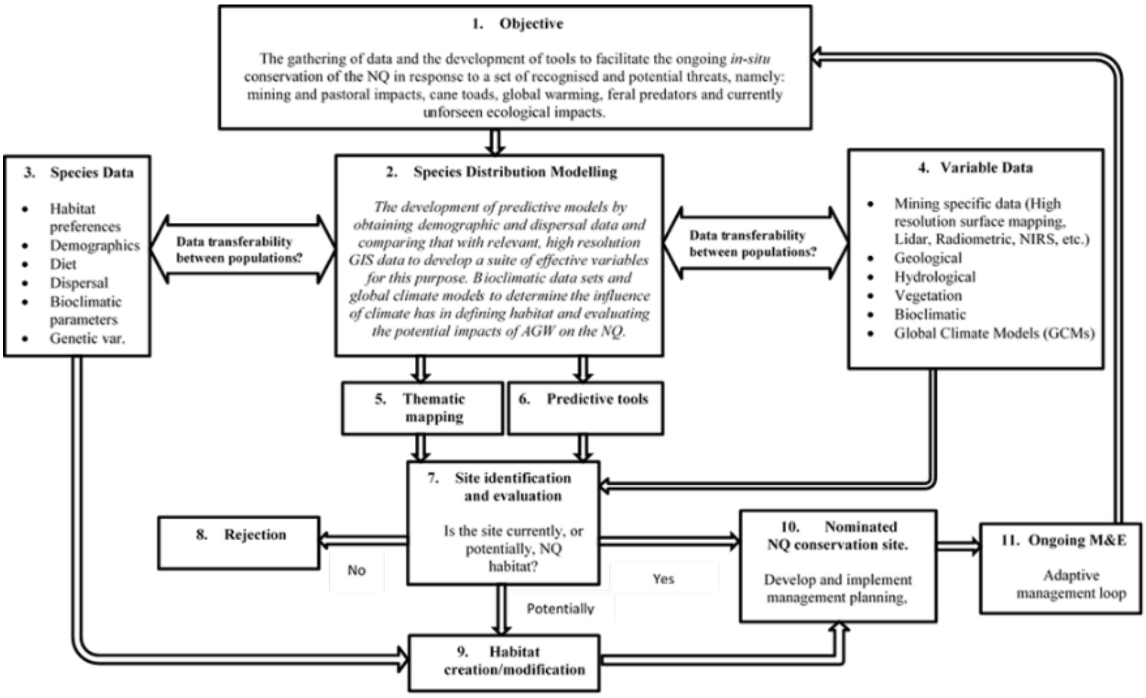


Figure 2: A conceptual model for the application of species distribution modelling to the conservation of northern quoll in the Pilbara

1.2 Objectives

The objective of this project is the development of tools to facilitate the ongoing in-situ conservation of this species in response to a set of recognised and potential threats, namely; mining and pastoral impacts, cane toads, global warming, feral predators and currently unforeseen ecological impacts.

To that end, we aimed to concentrate our activities in the following areas:

- Develop a predictive model of Northern Quoll habitat on a finer scale than is currently available based on a combination of DPaW monitoring data, existing survey data, improved habitat data and dispersal estimates.

- Evaluate known threats to this species, such as climate change, fire regimes, pastoralism, mining infrastructure and cane toads, and, where appropriate, incorporate these threats into models to identify important future/core habitat.

- Develop a data set which identifies areas of key/core habitat to support conservation planning and mining offsets.

1.3 Outputs

In response to the above this project has delivered the following:

- A suite of landscape attributes (predictive variables) which define northern quoll habitat and the degree to which these attributes contribute to habitat value.

- A predictive species distribution model (SDM) to quantify northern quoll habitat value within the Pilbara.

- SDMs which quantify how impacts such as cane toad invasion and climate change will affect northern quoll habitats.

- Future research directions.

1.4 The northern quoll (*Dasyurus hallucatus*)

Weighing only 300-1200g the northern quoll *Dasyurus hallucatus* is the smallest of Australia’s four quoll species, it is the largest predatory marsupial left in northern Australia (Cooper &

Withers, 2010; Cramer et al., 2015; Oakwood, 2008). It is an opportunistic carnivore that consumes a wide variety of fruit, insect, and vertebrate species (Pollock, 1999; Schmitt et al., 1989). Both males and females mature at approximately six months of age with females breeding during their first year, with mean litter sizes of seven young (Nelson & Gemmell, 2003; Oakwood, 2000). The northern quoll is considered to be largely semelparous, having one breeding season each year (Fisher et al., 2013). Although females may live for several years, many females and almost all males die following reproduction in their first year (Begg, 1981; Cooper & Withers, 2010; Dickman, 1996; Oakwood, 2008). Northern quolls are largely nocturnal, denning inside rock crevices, tree hollows, logs, termite mounds, grasses and in the burrows of other animals, during daylight hours (Oakwood 1997).

Once widely distributed from the Western Australian Pilbara across northern Australia to southern Queensland (Figure 3), the mainland distribution of the northern quoll has contracted to several disjunct populations in recent years (Burbidge et al., 2009; Oakwood, 2008). For some time this collapse has largely been linked to cane toad *Rhinella marina* invasion (Braithwaite & Griffiths, 1994; How et al., 2009; Oakwood, 2004; Woinarski, 2010). Where these species coincide northern quolls naively predate on cane toads and succumb to toxins exuded from glands behind the cane toad's head (Woinarski et al., 2015). Although the Pilbara region and its offshore islands were once thought likely to remain free of cane toads, thereby providing a sanctuary for the northern quoll, it is now predicted that cane toads are capable of invading this region (Elith et al., 2010; Kearney et al., 2008; Tingley et al., 2013).

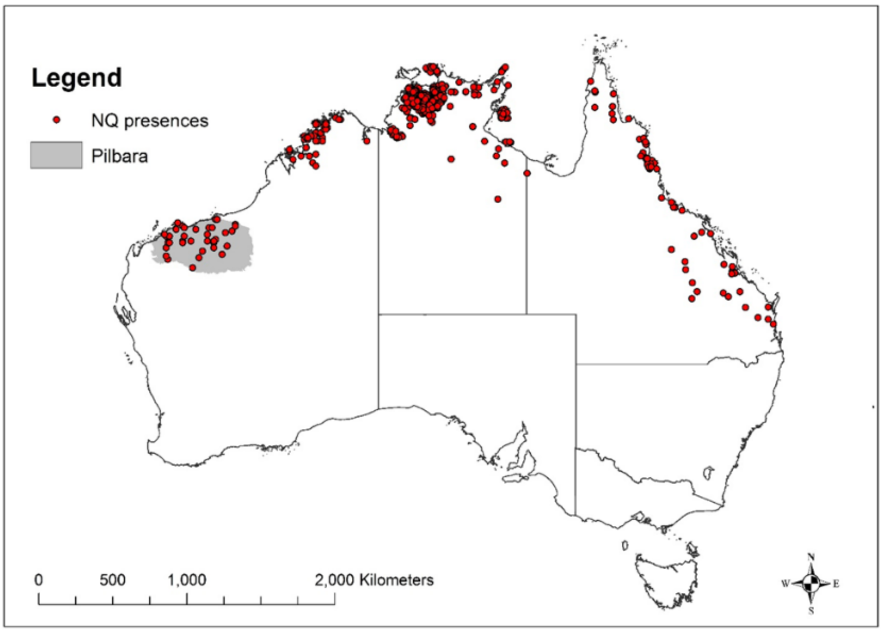


Figure 3: Northern Quoll presences with Pilbara population shaded. Presence data sourced from Atlas of Living Australia (2015).

Other impacts currently causing rapid and severe declines in northern Australia's critical weight range mammal fauna are also likely to be impacting on the northern quoll (Burbidge et al., 2009). These include: altered fire regimes, the grazing impacts of introduced herbivores, climate change and predation by introduced predators, in particular the feral cat *Felis catus*

(Burbidge & McKenzie, 1989; Cook, 2010; Woinarski et al., 2015; Woinarski et al., 2011). As a consequence of all these impacts and recent declines, the northern quoll is listed as Endangered under both the Commonwealth's *Environment Protection and Biodiversity Conservation Act 1999* (*EPBC Act 1999*) and the Western Australian *Wildlife Conservation Act 1950*.

A further activity that is likely to impact upon the northern quoll in the Pilbara is the removal or alteration of habitat through mining activities and associated infrastructure development. The northern quoll is therefore a key consideration in the majority of mining project assessments under the *EPBC Act 1999* in the Pilbara (Cramer et al., 2015). Furthermore, northern quolls have a strong habitat affiliation with rugged rocky habitat, often in close association with permanent water (Begg, 1981; Braithwaite & Griffiths, 1994; Oakwood, 1997; Pollock, 1999; Schmitt et al., 1989). In the Pilbara, this habitat affiliation aligns with ridges and mesas of channel-iron deposits and banded iron formation ranges that are often the primary focus of iron-ore extraction, while exposed granite outcrops are quarried for road and rail beds (Ramanaidou & Morris, 2010).

The main Western Australian populations of the northern quoll occur in two discrete mainland regions, the Kimberley and Pilbara, which are separated by the arid Great Sandy Desert. Both mitochondrial DNA sequences and nuclear microsatellite loci reveal clear differentiation between these two populations and a greater distinction between these populations and those in the Northern Territory and Queensland (Spencer et al., 2013). Populations on Western Australian offshore islands show and even further genetic distinction (Cardoso et al., 2009; How et al., 2009). There is also a marked variation in sexual dimorphism between the two Western Australian populations and those in the other states. These Western Australian populations also differ from those remaining in Queensland and the Northern Territory, in regard to both genetic structure and demographic parameters and represent the last intact populations in Australia that have not experienced major declines subsequent to the spread of the cane toad and consequently display the highest levels of genetic integrity (How et al., 2009; Spencer, 2010; Spencer et al., 2013). However, cane toads have now reached the Kimberley, and are rapidly spreading into the region, and are seen as a major potential impact on this northern quoll population (Doody et al., 2015).

Given that the Pilbara population of the northern quoll:

1) is genetically and demographically distinct from all other populations,

2) retains its pre-European genetic diversity,

3) is currently outside of cane toad distribution, and

4) has much of its habitat still intact,

this population has been afforded a high conservation and management priority (Cramer et al., 2015).

2 Variable selection

2.1 Species distribution models, an introduction

Species distribution models (SDMs) combine species presence or abundance data with information about environmental variables to predict species' potential distributions across landscapes (Pliscoff & Fuentes-Castillo, 2011).

Spatially explicit maps showing a predicted probability of occurrence generated by SDM tools have been used in conservation planning and for the management of habitat at finer scales. For example, models can identify critical habitats and predict how different scenarios, e.g., climate change scenarios, might alter the potential distribution (PD) of a target species or community (Elith et al., 2010; Kearney et al., 2008; Loehle & Eschenbach, 2012; Manel et al., 1999; Radosavljevic & Anderson, 2014). They do this by statistically identifying and quantifying the influence of particular environmental variables (e.g., climate and geomorphology) or management practices (e.g., fire regimes, pest control, forestry practices) on the probability that a species will occupy a given area that is, might be, may become, or cease to be, habitat for a target species or community (Reside et al., 2014).

The accuracy of the SDM depends on such factors as: the quality and appropriateness (in regard to sample size and representativeness) of the presence and/or absence data for the target species or community, the capacity of the modeller, the selection of an appropriate modelling tool (or software package), the selection of an appropriate suite of predictive/independent variables, the quality of the variable data used, and an acknowledgement of the strengths and limitations of the SDM (Elith et al., 2010).

2.2 Independent variables.

As each SDM uses different algorithms and species inputs, they also require the use of differing sets of variables in their respective analyses (Fordham et al., 2012; Guo & Liu, 2010). This requires a relatively broad suite of variables. However, to obtain optimum efficiency, minimize multicollinearity and prevent overfitting, the suite variables used should be kept compact (≤10 in number) and should be composed of group of independent variables (i.e. the target's presence, abundance or absence does not impact on the properties, or values, of that variable) which can best define the potential distribution (PD) of the target species or community (Beaumont et al., 2005; Elith et al., 2011; Hijmans, 2012; Van Gils et al., 2012). To accomplish this, we reviewed the literature for potential independent variables from the literature that may be suitable for producing an SDM for the Pilbara population of the northern quoll (Table 1) and commenced a stepwise process to select an appropriate suite of variables for this purpose.

Although most SDMs apportion contribution values to each variable, and extra variables may make a model appear statistically stronger, too many variables add “noise” to the model, i.e. there is a tendency for the model to become more reliant on coincidence and covariance rather than reflect the model’s true predictive capacity. This is called over-fitting the model (Radosavljevic & Anderson, 2014; Van der Aalst et al., 2010). This means that modellers need to undertake a balancing act to minimise the number of variables used while still maintaining a statistically strong model. Most recent modelling exercises endeavour to keep the number of variables used to preferred maximum of ten in number (Elith et al., 2010; McInerny & Purves, 2011; Van Gils et al., 2012).

2.3 Data collection

There were 53 data sets using in this modelling exercise, 44 of which were assessed as potential independent variables. These are listed in Table 1, along with the databases from which they have been sourced (dark cells). The GIS layers named in italics were created from the preceding GIS data set using tools and functions in ArcGIS 10.3. All data sets were downloaded at, or adapted to (CLIMOND data), a pixel resolution of 30 seconds (~1km^2) using the WGS 1984 datum. Data descriptions and, where available, meta-data statements can be found at the links provided in this table.

Table 1: GIS data sets used in variables assessments. Darkened cells indicate that source data base. Italics indicate derived data. Data sets marked in bold script were assessed as potential predictive variables for the northern quoll.

WorldClim http://www.worldclim.org/
BIO1 = Annual Mean Temperature
BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3 = Isothermality (BIO2/BIO7) (* 100)
BIO4 = Temperature Seasonality (standard deviation *100)
BIO5 = Max Temperature of Warmest Month
BIO6 = Min Temperature of Coldest Month
BIO7 = Temperature Annual Range (BIO5-BIO6)
BIO8 = Mean Temperature of Wettest Quarter
BIO9 = Mean Temperature of Driest Quarter
BIO10 = Mean Temperature of Warmest Quarter
BIO11 = Mean Temperature of Coldest Quarter
BIO12 = Annual Precipitation
BIO13 = Precipitation of Wettest Month
BIO14 = Precipitation of Driest Month
BIO15 = Precipitation Seasonality (Coefficient of Variation)
BIO16 = Precipitation of Wettest Quarter
BIO17 = Precipitation of Driest Quarter
BIO18 = Precipitation of Warmest Quarter
BIO19 = Precipitation of Coldest Quarter
Climond https://www.climond.org/
BIO34=Mean moisture index of warmest quarter
Climate Change in Australia (CSIRO) http://www.climatechangeinaustralia.gov.au/en/

Relative Humidity Wettest Quarter
ESRI Online Databases http://www.esri.com/software/arcgis/arcgisonline/arcgis-open-data
Background mapping, i.e. topographic imagery, boundaries and placenames
Landgate https://www2.landgate.wa.gov.au/bmvf/app/waatlas/
Western Australian Fire Frequency
Pastoral Property (vesting)
Modis https://earthdata.nasa.gov/
Fire Scar
Modis Burndate
Noramalised Digital Vegetation Index (NDVI)
Near Infrared Spectrography (NIRS)
Geoscience Australia http://www.ga.gov.au/search/index.html#/
Total Magnetic Intensity
Gravity Anomaly
Land Tenure
Digital Elevation Model
Slope
Ruggedness
Water Courses
Euclidean Distance to Water Courses
Water Bodies
Euclidean Distance to Water Bodies
Geology
Land cover
Hydrology of Australia
Soils Mapping of Australia
Naturemap http://naturemap.dpaw.wa.gov.au/
NQ Presences
CWR Terrestrial Mammal Presences
NQ Absences
Unites States Geological Survey (USGS) http://earthexplorer.usgs.gov/
Landsat Mosaic
NDVI Colourised
Department of Agriculture and Food WA (DAFWA) https://www.agric.wa.gov.au/land-use-planning/maps-and-data
Beards Vegetation Associations
Rangelands Vegetation Mapping

2.4 First cut

The purpose of the initial variable assessments took the form of a relatively rapid cut process to halve the number of variables for detailed assessment by identifying and removing those with a poor statistical relationship to northern quoll presence. To do this all data was converted to GIS raster-files and clipped using a Pilbara shapefile as a mask, then three assessments were undertaken:

1. A pairwise Pearson correlation coefficient test was run to reduce multicollinearity in the bioclimatic variables (Phillips & Dudík, 2008).

2. Stepwise univariate logistic regressions for all predictive variables using the R statistical software platform (Baayen, 2008),

3. Scalar variables were also reviewed as Generalised Additive Models (GAMs) using the GG plot package in the R statistical software platform (Wickham, 2009) (Figure 4).

To reduce multicollinearity in the 19 original bioclimatic variables, we calculated the Pearson correlation coefficient between each pair of variables using data from the location of each species occurrence (Phillips & Dudík, 2008). For each pair of highly correlated variables ($r>.80$), we selected only the single variable that was most biologically relevant for northern quoll. After this procedure, nine bioclimatic variables remained. Multicollinearity between the two vegetation association data sets was assumed to be high and a decision was made to only use the best performing one in the final data suite of variables.

Simple univariate plots were then run plotting remaining predictive variables against northern quoll presences in the R platform. In each plot the "cor()" function was then used to determine the correlation coefficient value of each plot. Variables were then ranked by this value (Baayen, 2008).

Using the R package ggplot2, we randomly selected 9,999 x ~1km^2 grid squares within the study area and created a Generalised Additive Model (GAM) output for quoll presence against all predictive variables. For the continuous variables we plotted predicted habitat suitability against each presence using a generalised additive smooth function (Wickham, 2009). Each variable was then ranked in accordance with its predictive capacity.

All remaining variables were ranked in each of the last two assessments. Rankings were then averaged and the 22 best performing variables were retained for further testing (Table 2).

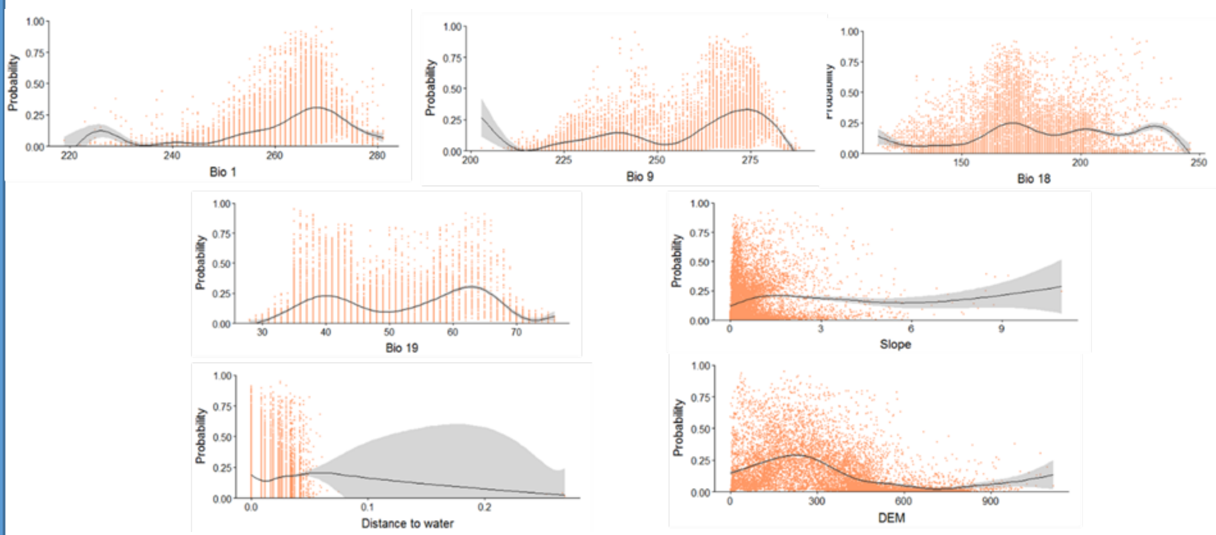


Figure 4: Relationship between habitat suitability and scalar predictive variables in logistic outputs using GGPlot. The black line is a generalised additive model curve predicting the relationship between habitat suitability and independent variables, with the grey area representing the 95% confidence interval.

Table 2: Variables by ranking, 1st cut.

Variable	Ran
Veg Rangelands Vegetation Mapping (Vegag)	1
Digital Elevation Model (DEM)	2
BIO1 = Annual Mean Temperature	3
Slope	4
Beard’s Vegetation Mapping	5
BIO18= Precipitation of Warmest Quarter	6
Water (Euclidean Distance to Water Courses)	7
BIO19= Precipitation of Coldest Quarter	8
Soils	9
BIO9 = Mean Temperature of Driest Quarter	10
Ruggedness	11
Euclidean Distance to Water Bodies	12
BIO17 = Precipitation of Driest Quarter	13
BIO14 = Precipitation of Driest Month	14
BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))	15
BIO10 = Mean Temperature of Warmest Quarter	16
BIO12 = Annual Precipitation	17
Land Tenure	18
BIO16 = Precipitation of Wettest Quarter	19
NDVI Colourised	20
BIO4 = Temperature Seasonality (standard deviation *100)	21
BIO8 = Mean Temperature of Wettest Quarter	22

2.5 Final cut

The final cut was undertaken through a step-wise elimination process in MaxEnt (Phillips et al., 2006) looking at both the contribution of each variable and the consequences of its omission. This was done by examining changes in variable contribution analysis and jack-knife tests in comparison to changes in regularised training gain, test gain and area under curve (AUC) values using. To do this, MaxEnt was run against northern quoll presence data using the 24 variables identified through the first cut process (section 2.4). The results of this SDM were then examined in light of the above tests and the process repeated with the worst performing variable removed from the model. A minimum target AUC value of 0.9 was set, indicating a suite of variables capable of delivering a very strong model (Elith et al., 2011), and this process was repeated until this value was consistently achieved. This process resulted in a final suite of nine variables. Jack-knife analyses results for the final suite of variables are given below (Figure 5) as are the contribution values and permutation importances of each selected variable (Table 3).

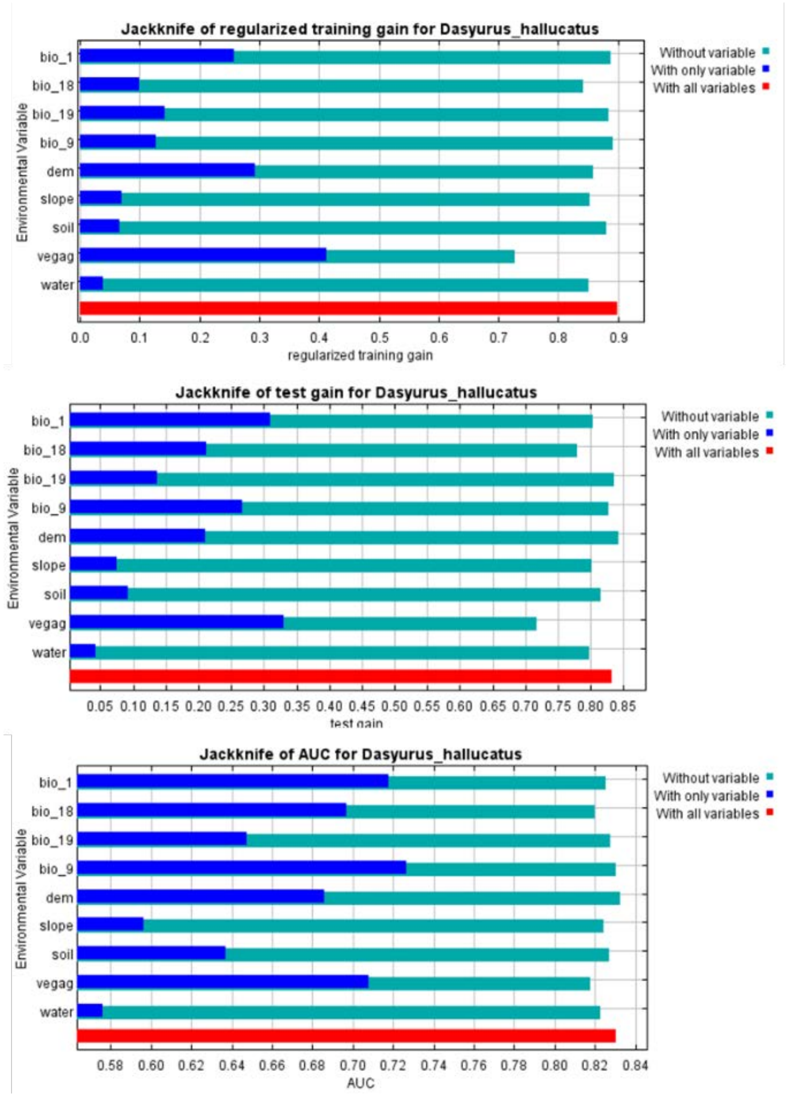


Figure 5: Logistic response of categorical variables as determined through MaxEnt.

To reduce multicollinearity in the 19 original bioclimatic variables, we calculated the Pearson correlation coefficient between each pair of variables using data from the location of each species occurrence. For each pair of highly correlated variables (r>0.75), we selected only the single variable that was most biologically relevant for spadefoot toads. After this procedure, nine bioclimatic variables remained (Table 3). This suite of variables was then used for all further distribution modelling for the Pilbara population of the northern quoll.

Table 3: Final suite of variables with % contribution and permutation importance as determined through step-wise MaxEnt analyses. All contribution and importance values reflect positive relationships to northern quoll presence.

Variable	% Contribution	Permutation Importance
Vegag (Rangelands Vegetation Mapping)	34.8	14.2

DEM (Digital Elevation Model)	16.8	35.4
BIO1 = Annual Mean Temperature	16.7	7.7
Slope	10.8	11.3
BIO18= Precipitation of Warmest Quarter	9.0	14.9
Water (Euclidean Distance to Water Courses)	3.7	5.7
BIO19= Precipitation of Coldest Quarter	3.5	4.4
Soils	2.8	4.7
BIO9 = Mean Temperature of Driest Quarter	1.9	1.6

3 Constructing the Species Distribution Model (SDM)

3.1 Previous modelling

As shown in Figure 6, one of the main reasons for undertaking this modelling exercise is because there have been previous SDM exercises conducted for the Pilbara population of the northern quoll in the past and the results of these exercises conflict markedly with each other (Biologic, 2012; Eco Logical, 2012; Van der Wal, 2014). This appears to be a consequence of methodologies using different modelling tools, independent variables, and presence data sets, and of a failure to adequately test model outputs.

A review of the Biologic (2012) and Eco Logical (2012) SDMs found that, although both examples were based on sound and proven methodologies, there were significant shortfalls in their delivery. Both SDMs were constructed as part of multiple species modelling projects within which a standard set of methods and variables were used to model a suite of species within the Pilbara. This means that, to varying degrees, both modelling exercises were generic and not totally focussed on the particular needs of the Pilbara population of the northern quoll alone. Furthermore, according to Fisher (2012), in both methodologies that are serious concerns in regard to variable selection and model bias which are not adequately addressed in their respective literature.

The CLIMAS example (Van der Wal, 2014) was accessed online from a national climate change modelling tool. Presence data came from a broad national data base modelled against a generic suite of solely bioclimatic variables. This overlooks the potential influence of a large number of geological, topographical, hydrological and biotic factors which are recognised as being influential in determining habitat for the northern quoll (Begg, 1981; Braithwaite & Griffiths, 1994; Cook, 2010; How et al., 2009; Johnson & Anderson, 2014; Meri, 2000; Oakwood, 1997; Turpin & Bamford, 2014). Consequently, other than using this tool as intended, as a broad scale indicator of the degree to which bioclimatic variables determine PD for this species, this SDM can justifiably be viewed with caution.

In light of the above, there is a strong argument for the construction of an SDM for the Pilbara population of the northern quoll independent of the above exercises. Such a model should use, an effective modelling tool, the best available data, be tailored to meet the needs of the target population alone, and should be evaluated and substantiated through a suite of proven tools and methodologies. Furthermore, we recognise that the evaluation of such a model would also benefit from a comparison between its outputs with those of its predecessors.

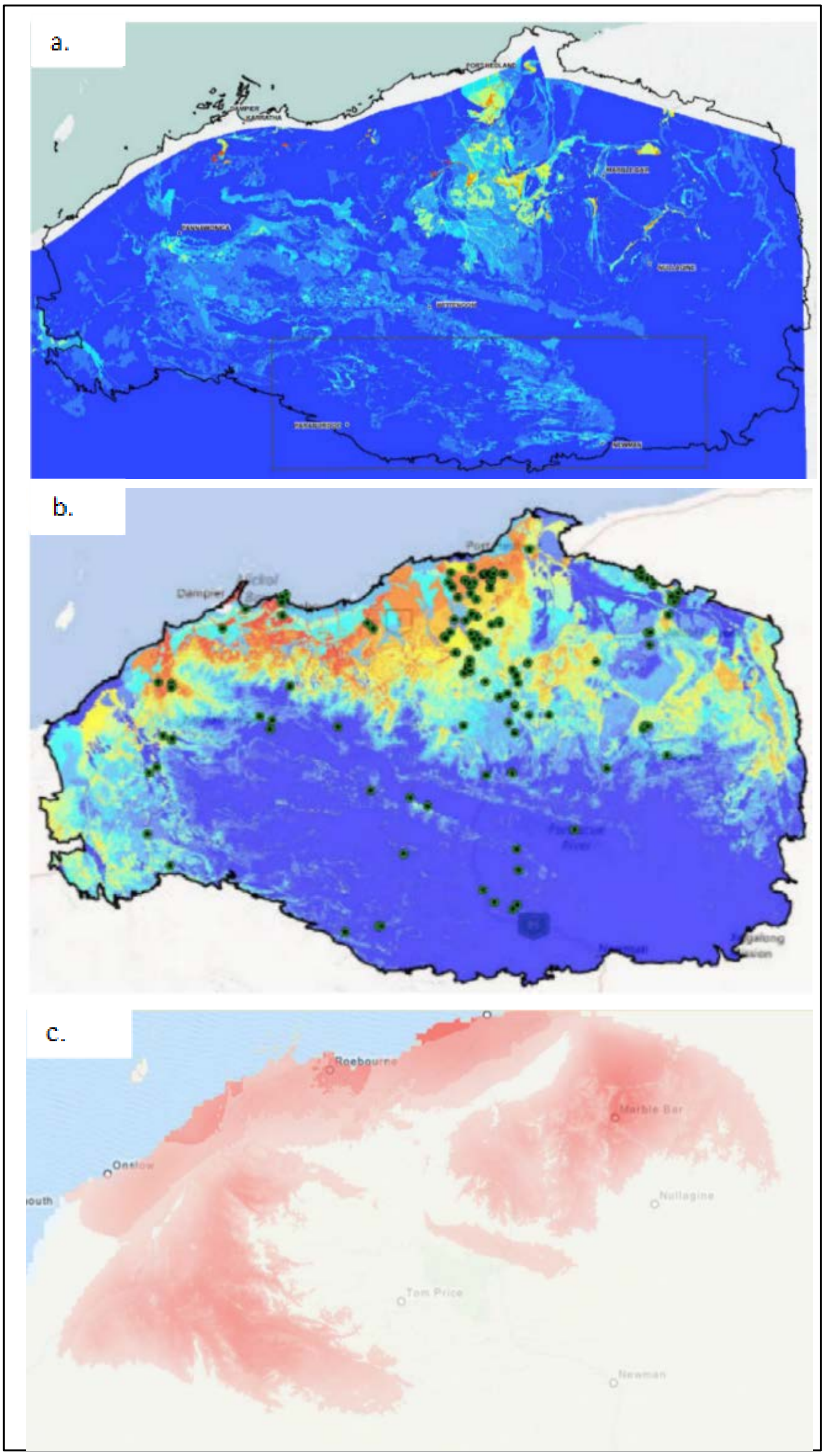


Figure 6: Northern quoll SDM for the Pilbara using: a) Maximum Entropy modelling (MaxEnt) (red-blue, highest to lowest probability of presence) (Biologic, 2012), b) Generalised Additive Model (GAM) (red-blue, highest to lowest probability of presence) (Eco Logical, 2012), c) CLIMAS climate change modelling (red-pink, highest to lowest probability of presence) (Van der Wal, 2014).

3.2 Modelling with MaxEnt

3.2.1 Creating a basic SDM

For our primary modelling tool we have chosen to use MaxEnt. MaxEnt uses a general-purpose machine learning method called maximum entropy modelling. This is a simple and precise mathematical formulation, which makes it well-suited for species distribution modelling (Phillips et al., 2006). This is a popular and effective species distribution modelling tool which has been shown to be capable of modelling PDs using both presence only and presence/absence data (Booth et al., 2014; Yackulic et al., 2013). Some limitations have been recognised with MaxEnt, notably a tendency for it to underperform where there is a biased sample, poorly chosen predictive variables or inadequate testing of results. However, where these limitations are addressed it remains a well-supported modelling tool because it is relatively easy to use and has a capacity to link fine-scale bioclimatic data to species distributions to produce accurate probability-based outputs, suitable for informing conservation management actions (Bystriakova et al., 2012; Elith et al., 2011; Kramer-Schadt et al., 2013; Syfert et al., 2013; Williams et al., 2012).

Maximum entropy modelling seeks to estimate a target probability distribution by finding the probability distribution of maximum entropy (i.e. where variable parameters are most stochastic, or closest to homogenous), subject to a set of constraints that represent the limitations of the data used. The information available about the target distribution often presents itself as a set of real-valued variables, called "features", and the constraints are that the expected value of each feature should match its empirical average (average value for a set of sample points taken from the target distribution, i.e. the training data). When MaxEnt is applied to presence-only species distribution modelling, the pixels of the study area make up the space on which the MaxEnt probability distribution is defined, pixels with known species occurrence records constitute the sample points, and the predictive variables, or features, are climatic variables, elevation, soil category, vegetation type or other environmental variables judged appropriate (Phillips et al., 2006).

MaxEnt is a very popular modelling tool, e.g. at the time of writing, a search of Google Scholar for "MaxEnt" yielded 10,600 results. Properly used and with its limitations addressed, it has been used successfully to construct SDMs which, like this exercise, combine the use of bioclimatic, abiotic and biotic predictive variables against presence only data (Adams-Hosking et al., 2012; Guerin & Lowe, 2012; Molloy et al., 2014; Prober et al., 2012; Yates et al., 2010). It is capable of being run in both R and Java platforms and can be run as part of an ensemble model in the BIOMOD2 R package (Thuiller et al., 2015). Although it has been used in the previously discussed Biologic (2012) SDM (Figure 6a), many questions pertaining to this example remain, i.e. has the model been tested for sample bias, what was the variable selection method, how was the model tested, how many repetitions were used, and what scale/resolution used and how was it selected? A failure to answer any, or all, of these questions casts doubt on the integrity of the SDM. Therefore, if we use MaxEnt to develop an SDM for the Pilbara northern quoll population, it falls to us to explain how we will address these issues. To that end we undertook the following activities:

1. **Sample bias:** Initial models were run without any compensation for bias (Figure 7). A second SDM was then constructed using a bias grid (Figure 9) constructed from pseudo-absence data (Figure 8). Furthermore, in the ensemble modelling, undertaken to test the MaxEnt SDMs (sections 3.2.4-3.4), pseudo-absence data is applied directly as a second way of compensating for potential bias. The outputs of all SDMs are then compared and the results discussed (section 3.2.3).

2. **Inappropriate variables:** A rigorous process has been undertaken to select an appropriate suite of variables, (section 2). This suite of variables has been tested throughout the modelling exercise and would have changed if it had not allowed the development of accurate and effective SDMs.

3. **Repetitions:** When using MaxEnt, we withheld a random 20% of presences for testing purposes. This means that the results of each run may vary. To compensate for this, in each SDM the software was run ten times (repetitions), and the results of all ten repetitions cross-validated to produce the final SDM.

4. **Scale:** The scale used for all modelling in this exercise is 30 second or ~1km^2 as this is both the finest resolution available for the bioclimatic variables and an effective management scale for a target landscape the size of the Pilbara due to a lack of very fine scale data for the whole of this region.

   Note: MaxEnt only recognises presence or absence once in a pixel. As nearly all samples are coming from a comparatively few ~1km^2 grid squares the number of presences used in the SDM becomes smaller than the actual number of records available. Consequently, the use of a larger scale could greatly exacerbate this problem to the point that it may impair model accuracy.

5. **Testing:** In addition to the MaxEnt testing described above (point 3), a series of other models are constructed using different modelling tools and are compared individually and as an ensemble model with the MaxEnt SDM, and the results of this comparison discussed (section 3.4).

3.2.2 MaxEnt SDM, without bias compensation

As described above, the first MaxEnt SDM was constructed in the Java platform using the full suite of nine predictive variables, without any bias compensation, with 500 iterations per run and with 20% presences withheld for testing. Ten repetitions were run and cross-validated to produce the SDM given below (Figure 7). As presences can only be recorded once in every pixel the original data set of 1984 presences is reduced to only 324, of which 260 are used for training, and 64 used for testing.

The result is statistically strong model with a training AUC value of 0.899 and an average test AUC value of 0.859. The omission plot complies strongly with expected trends. Tests statistics given on the model readout also indicate a robust model. The level of model resolution appears good with areas of a high probability of northern quoll presence not being overly generous in expanding around areas where there are recorded presences, yet there are numerous areas without presences still being given a high probability value. This indicates that this model is not simply mimicking presence data, it is actively identifying areas which meet its criteria for potential northern quoll habitat where presence records are absent. It therefore appears that this is a very good SDM.

Although this SDM appears to achieve our objectives, there is cause for concern. Much of the modelled landscape shows a very low probability value, particularly in the south, east and far west of the modelled landscape. This invites the question, does this SDM accurately reflect the potential PD of the target population or is this the result of sample bias. To that end we attempt to address the issue of sample bias through the construction and incorporation of a bias grid GIS layer.

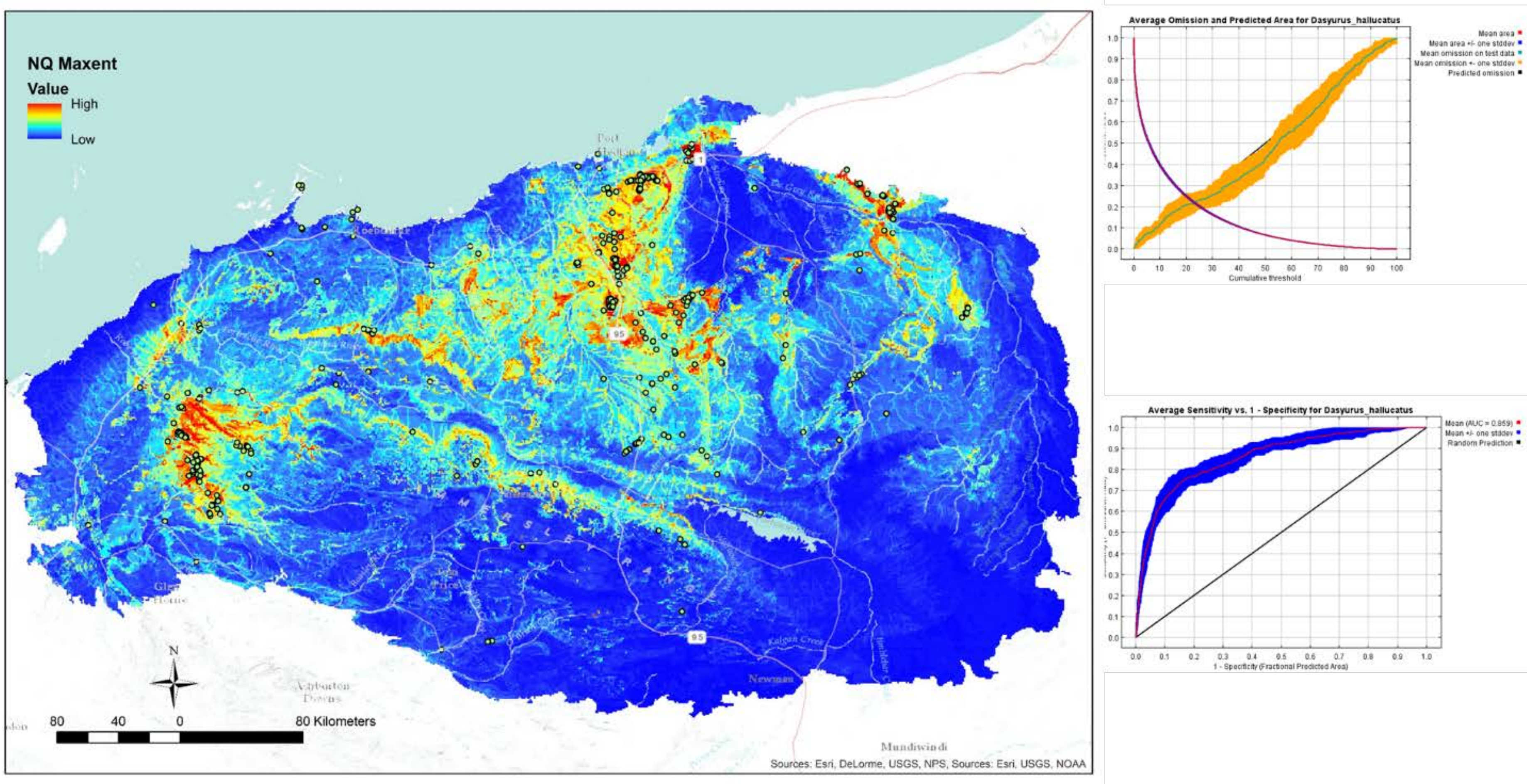


Figure 7: MaxEnt output using predictive variables developed in section 2 (Table 3). Average omission and test AUC plots inset

3.2.3 Incorporating a bias grid GIS layer.

In lieu of actual northern quoll absence data from which a bias grid could be manufactured and knowing that were many records for other non-volant critical weight range (CWR) mammals (defined by Burbidge and McKenzie (1989) as being between 35g and 4200g) obtained throughout the Pilbara, four assumptions were made:

1. Presence records reflect sampling effort.

2. Sampling for non-volant CWR mammals would probably result in northern quoll presence records (e.g., capture, sighting, tracks, scats, or other physical evidence such as remains), if indeed they were present.

3. Therefore presence records for non-volant CWR mammals may be suitable for use as pseudo-absence data.

4. A point density analysis (PDA) of non-volant CWR mammal presences for the whole of the Pilbara would indicate the degree of bias present in the northern quoll presence records and could therefore be used as a bias grid in the MaxEnt model.

To construct the bias grid, presence records for all non-volant CWR mammals (including northern quoll) in the Pilbara were gathered from the Department of Parks and Wildlife Fauna Base data base (DPaW, 2007-) and categorised into northern quoll presences and pseudo absences (Figure 8). All records were then used to conduct a PDA using the PDA function in ArcGIS 10.3 using the Pilbara shapefile as a mask and with all (Figure 9). The method for producing the SDM described in section 3.2.2 was repeated with the only change being the inclusion of this PDA as the bias grid. The results of this process are displayed in Figure 10.

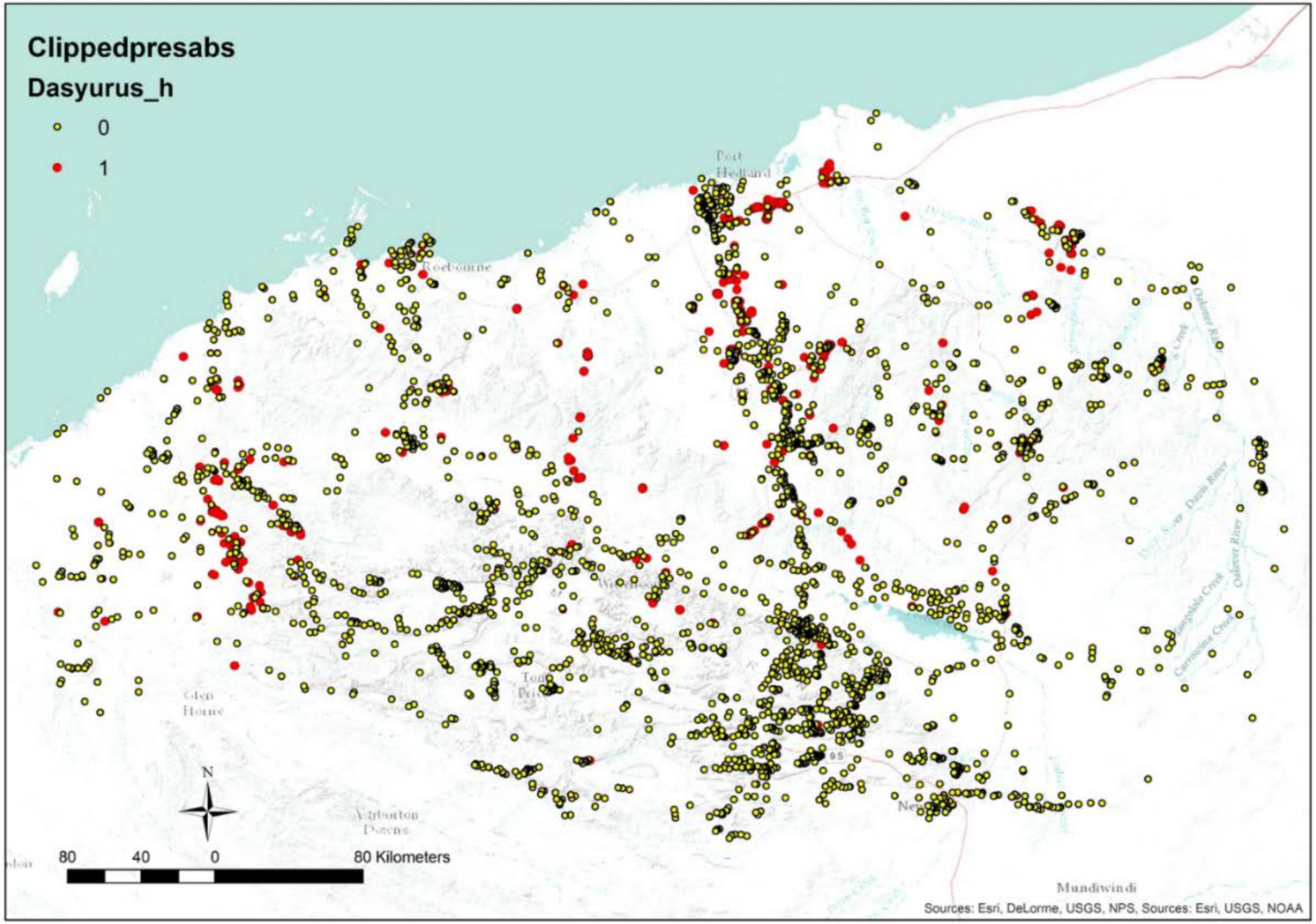


Figure 8: Northern quoll presences (1) and pseudo absences (0)

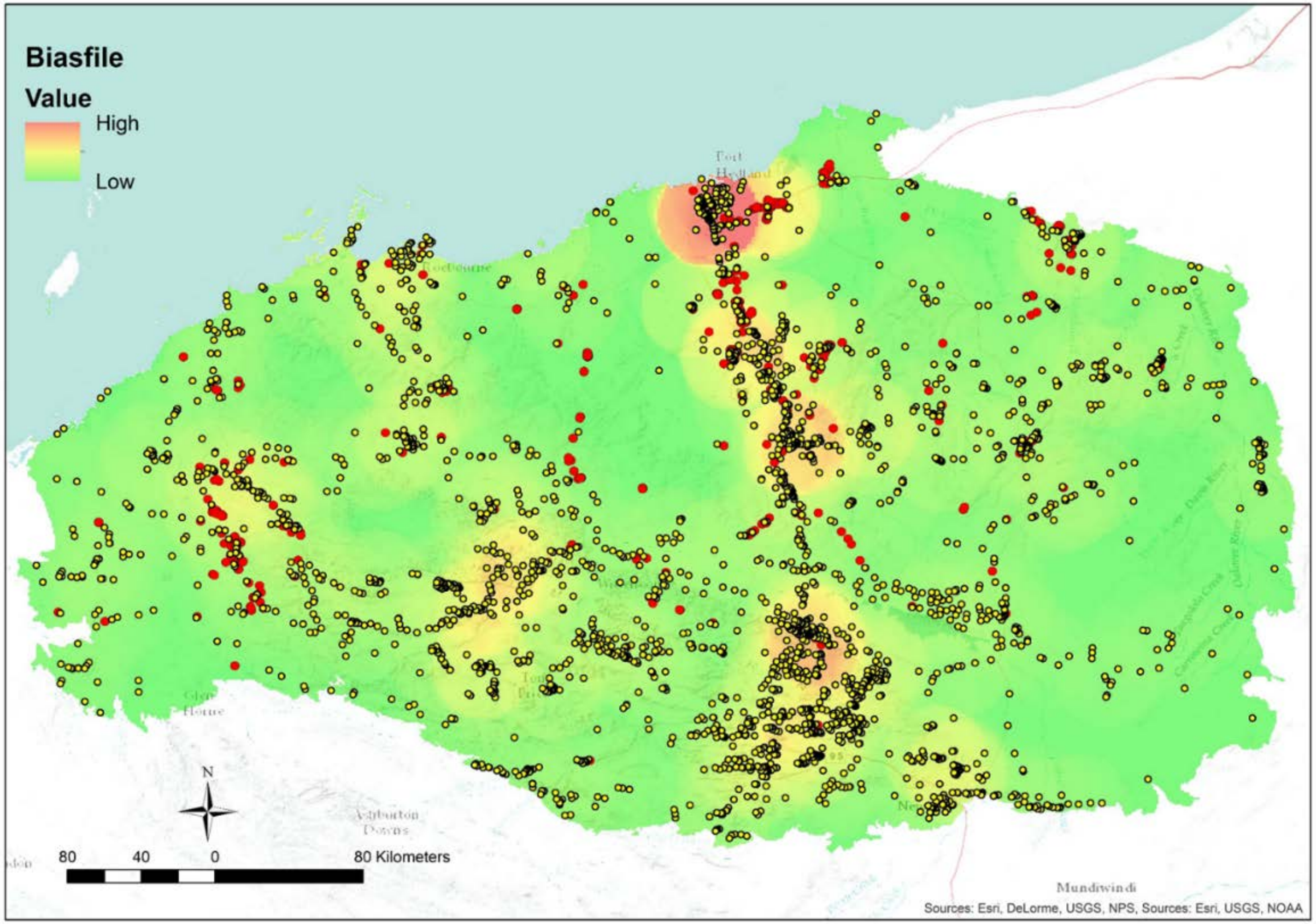


Figure 9: Bias grid GIS file created from pseudo absence data (Figure 8)

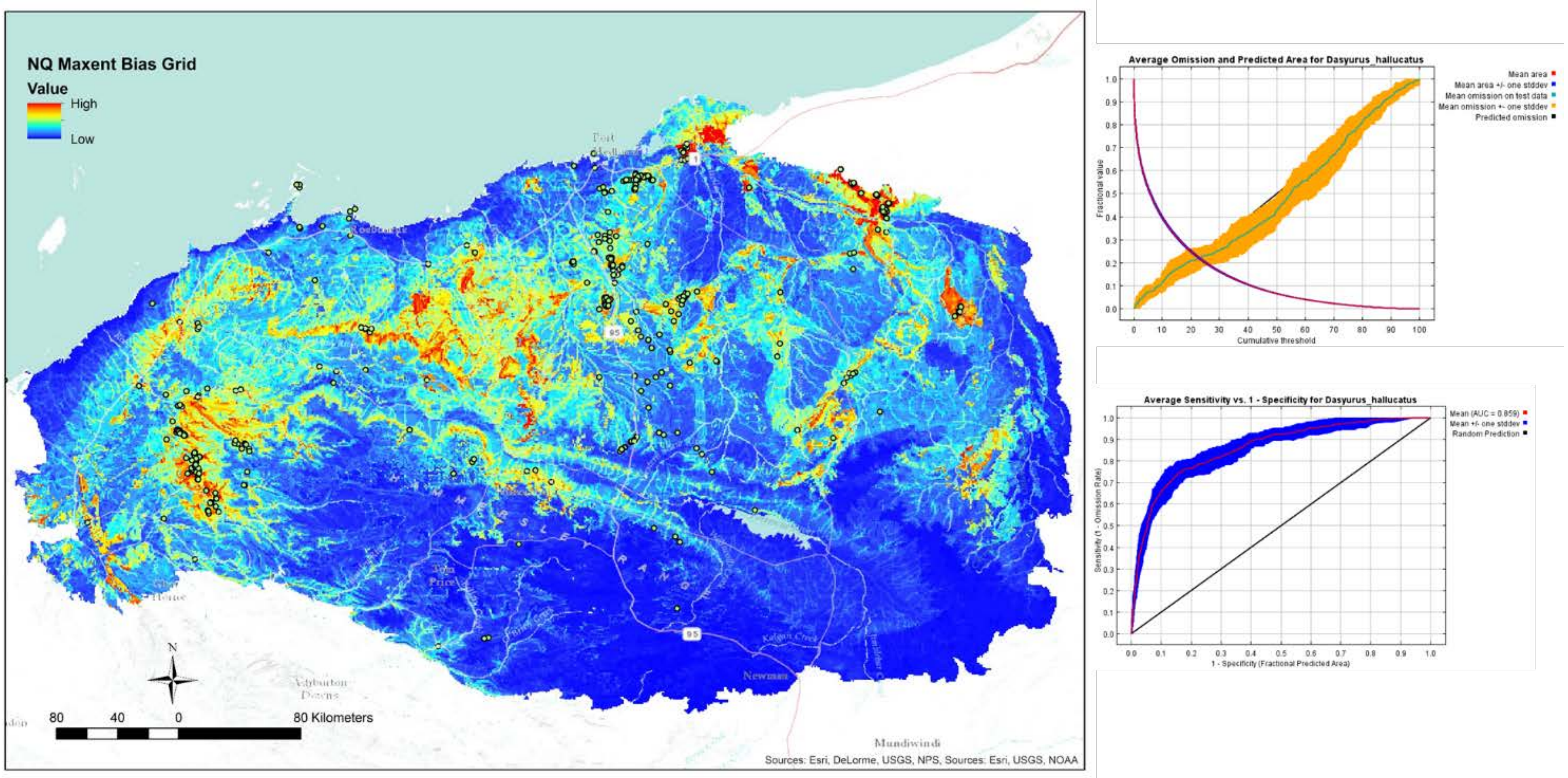


Figure 10: Preferred Model. MaxEnt output using the same settings and predictive variables used in Figure 7 and bias grid (Figure 9). Average omission and test AUC plots inset.

3.2.4 Results

In comparing the SDMs constructed with and without a bias grid, we found that with the addition of the bias grid the model remains fundamentally unchanged in the areas selected. However, there are minor changes in probability values of some areas, most notably an increase in habitat value in the eastern Pilbara, and a reduction in the average training AUC (from 90 to 88) and the test AUC (from 89 to 86). Despite this small drop, AUC values remain very high. Under these circumstances a small drop in AUC values is to be expected as the SDM previously assumed that sampling had been uniform and we have demonstrated that this assumption was false as there was a relatively small sampling bias effect. This represents a constraint in the development of the SDM. Model resolution remains very good as does the MaxEnt statistical analysis given in the model readout.

Of particular concern is the reduction in presence sample size when incorporated into the modelling process from 1984 to 324. This represents a relatively small area within the context of the Pilbara. This may result in weakness in the SDM, and may also cause a greater variation between runs because the test data becomes a random 64 presences, a small sample number and therefore one subject to potential random influences.

For the reasons mentioned above we assume the SDM incorporating the bias grid (Figure 10) to be the more accurate model. However, although this is the preferred SDM, it must be remembered that this is the output of a single modelling tool in a desktop environment. Therefore it should be substantiated and refined by the use of other modelling tools and these results, in turn, tested and enhanced through field studies on ground sampling activities.

3.3 Testing the SDM with an ensemble package

In section 3.2, MaxEnt has been used to develop a statistically, and apparently successful, preferred SDM (Figure 10). However, it should remembered that this SDM was compiled using just one modelling tool and methodology and that, as previously demonstrated (section 3.1), different tools and methodologies can yield very different, and often contradictory, results. Therefore, to test the rigour of the preferred SDM, we chose to use an ensemble modelling technique. In such a technique, a suite of different modelling tools are used to compile SDMs for a target species or community within a single platform and these SDMs combined to produce a single ensemble, or composite, SDM (Crimmins et al., 2013; Grenouillet et al., 2011). To test the preferred SDM, it was compared with individual and ensemble model outputs and differences investigated and discussed. Comparisons and observations on the modelling processes and their outputs were then discussed and conclusions drawn on the degree on the validity of the ensemble modelling process and the degree to which it supports, or conflicts with the preferred SDM.

The ensemble modelling was undertaken using the BIOMOD2 package in the R platform (Thuiller et al., 2015). This package allowed the use of the same variable, presence and pseudo absence data used to develop the preferred MaxEnt SDM. The BIOMOD2 modelling was undertaken using the following parameters:

- There were five different modelling tools available within the BIOMOD2 package which were capable of modelling accepting the model data in regard to sample sizes, categorical and scalar variables. These are described in section 3.4.

- A random 20% of presences could be withheld for testing with modelling tool, and four runs (Figure 11-14) used to add rigour to results.

- No weighting was applied in the construction of the ensemble outputs as no previous testing had indicated a need for weighting.

- All model runs and ensemble variations were set to provide graphic and statistical outputs for ease of comparison with each other and the preferred MaxEnt SDM.

- Presence and pseudo/absence species inputs are both given as simple grid data sets to compensate for bias. Bias grids were not used for any modelling tool.

- Six ensemble models were developed from all model twenty model runs (four runs for each of the five modelling tools) through different statistical and the most appropriate chosen on the basis of statistical accuracy and comparison with observations on habitat in the literature.

- All outputs are evaluated with a True Skill Statistic (TSS), Receiver Operator Characteristic (ROC) (a test comparable with the MaxEnt's AUC statistic) and a Kappa test.

- Consequently, all runs in all models applied the predictive variables differently.

3.4 The modelling packages

The following modelling packages were used for the Biomod2 ensemble:

3.4.1 Maximum entropy (MaxEnt)

MaxEnt is previously described in section 3.2.1. Although MaxEnt was previously used in a Java platform to develop the preferred SDM, the methodology for its use in the ensemble model has been altered in that:

- It is being run in the R platform, which will use TSS test to make evaluations as opposed to the AUC statistic in Java and may make marginal variations to other statistical analyses as recommended by Thuiller et al. (2015).

- Psuedo-absences are being used to account for sample bias effects rather than a bias layer.

- Multiple runs are kept independent until incorporated into the ensemble model and not averaged out.

As any of the above could have a significant impact on model outputs we considered the incorporation of MaxEnt into the ensemble model not to be a simple replication of the previous exercises.

The result of the MaxEnt runs (Figure 11) shows a variation in probability values between runs and the preferred model. However, the landscapes selected as PD remain largely unchanged.

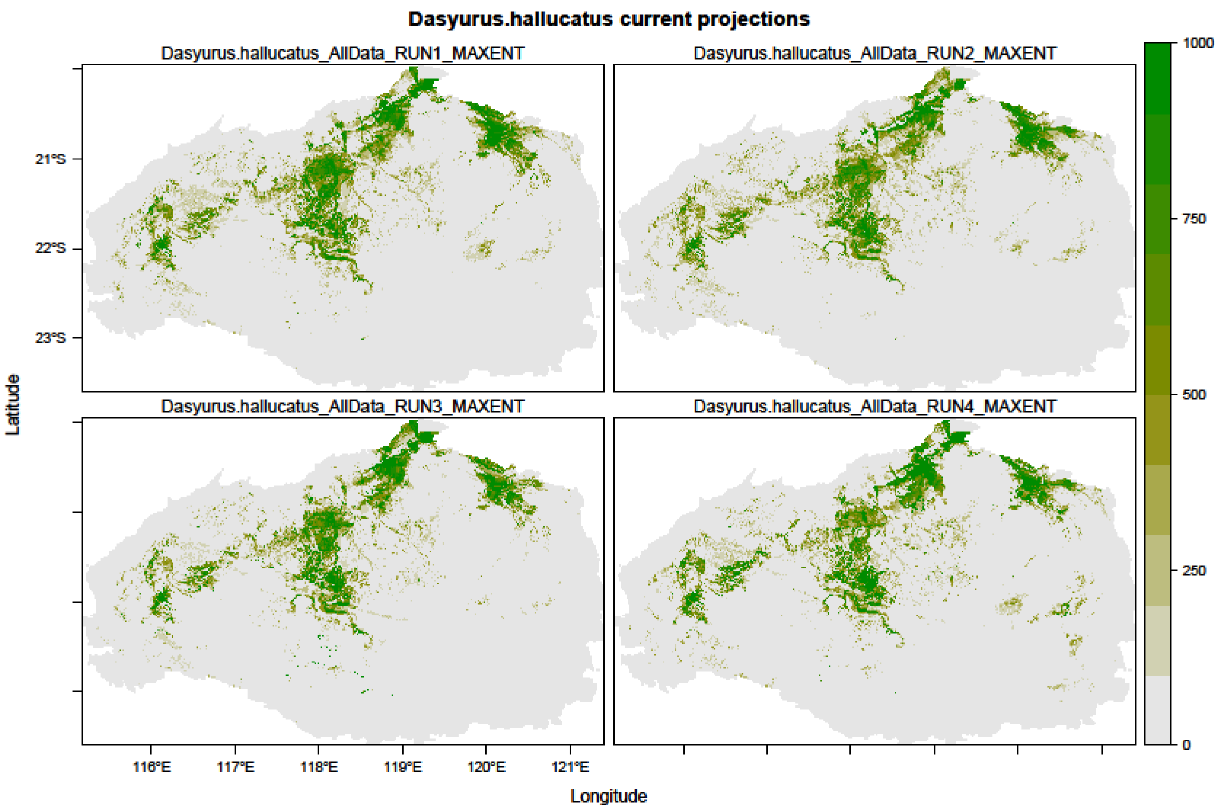


Figure 11: Predicted area outputs for all four MaxEnt runs in BIOMOD2

The test data Tables (Table 4-8) give; the Test-data (the proportion of presences included in the test data in a binary model), the Cut-off (the value applied to a probability model to make binary, i.e. areas with values below this score are not considered PD), Sensitivity (the percentage of training data absences excluded below the Cut-off value) and Specificity (the percentage of training data presences included at, or above, the Cut-off value), in all four runs. The Test data for the MaxEnt model (Table 4) shows a group of statistically strong runs which remain comparable with the outputs of the preferred SDM in regard to both Sensitivity and Specificity. Statistically, there appears to be an appreciable variation in evident model runs.

Table 4: MaxEnt test results using TSS by run

Run	Test-data	Cut-off	Sensitivity	Specificity
1	0.728	61	86.685	85.841
2	0.691	131	77.717	91.387
3	0.740	71	83.696	90.533
4	0.705	111	76.902	93.153

3.4.2 Generalised boosted model (GBM)

Whereas a Generalised Linear Model (GLM) seeks to fit the single most parsimonious model that best explains the relationship between species distribution and a set of ecological predictors, boosting methods fit a large number of relatively simple models whose predictions are then combined to give more robust estimates of the response. The algorithm used by BIOMOD2 is a boosted regression tree where each of the individual models consists of a simple classification or regression trees, i.e. a rule based classifier that consists of recursive partitions of the dimensional space defined by the predictors into groups that are as homogeneous as possible in terms of response. The tree is built by repeatedly splitting the data, defined by a simple rule based on a single explanatory variable (Elith et al., 2006).

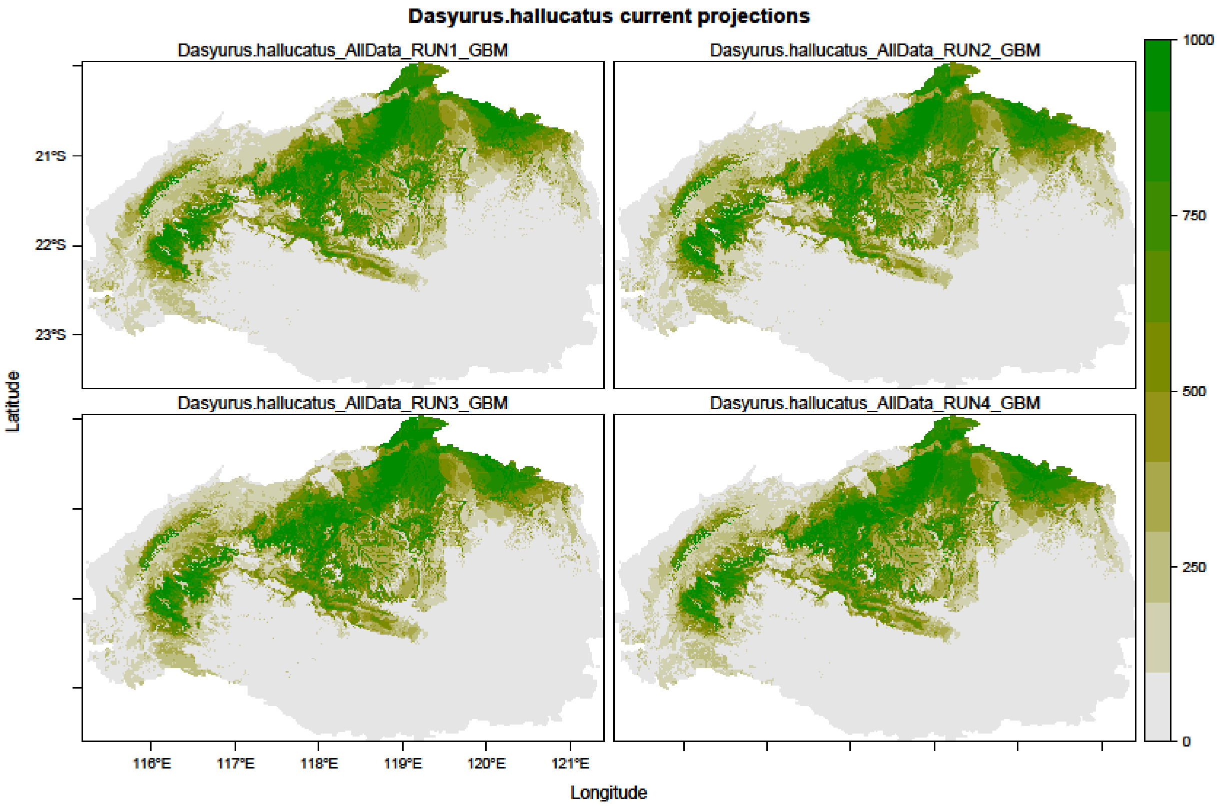


Figure 12: Predicted area outputs for all four GBM runs in BIOMOD2

In comparison to the MaxEnt SDMs, the GBM models (Figure 12) appear much courser, selecting a much greater area to produce slightly lower Sensitivity and Specificity scores and a marginally higher Test-data score (Table 5). The landscapes selected compare are generally comparable with the preferred SDM, however a much higher scores are applied across those landscapes. To that end, the GBM runs appear to support the MaxEnt outputs but seem, in this instance, unable to produce the level of resolution required. The GBM runs appear very consistent in outputs showing very little difference between model runs, both in extent and statistically.

Table 5: GBM test results using TSS by run

Run	Test-data	Cut-off	Sensitivity	Specificity
1	0.795	388	92.663	86.813
2	0.798	580	89.130	90.702
3	0.805	397	92.120	88.335
3	0.788	532	88.043	90.736

3.4.3 Generalised additive model (GAM)

Used in ecology to deal with various species response shapes to environmental variables, GAMs are designed to capitalise on the strengths of GLMs without requiring the problematic steps of postulating a response curve shape or specific parametric response function. They use a class of equations called "smoothers" that attempt to generalise data into smooth curves by local fitting to subsections of the data. GAMs are therefore useful when the relationship between the variables are expected to be of a more complex form, not easily fitted by standard linear or non-linear models, or where there is no a priori reason for using a particular model. The is to 'plot' the value of the dependent variables (occurrences) along a single environmental variable, and then to calculate a smooth curve that fits the data as closely as possible while being parsimonious (Elith et al., 2006).

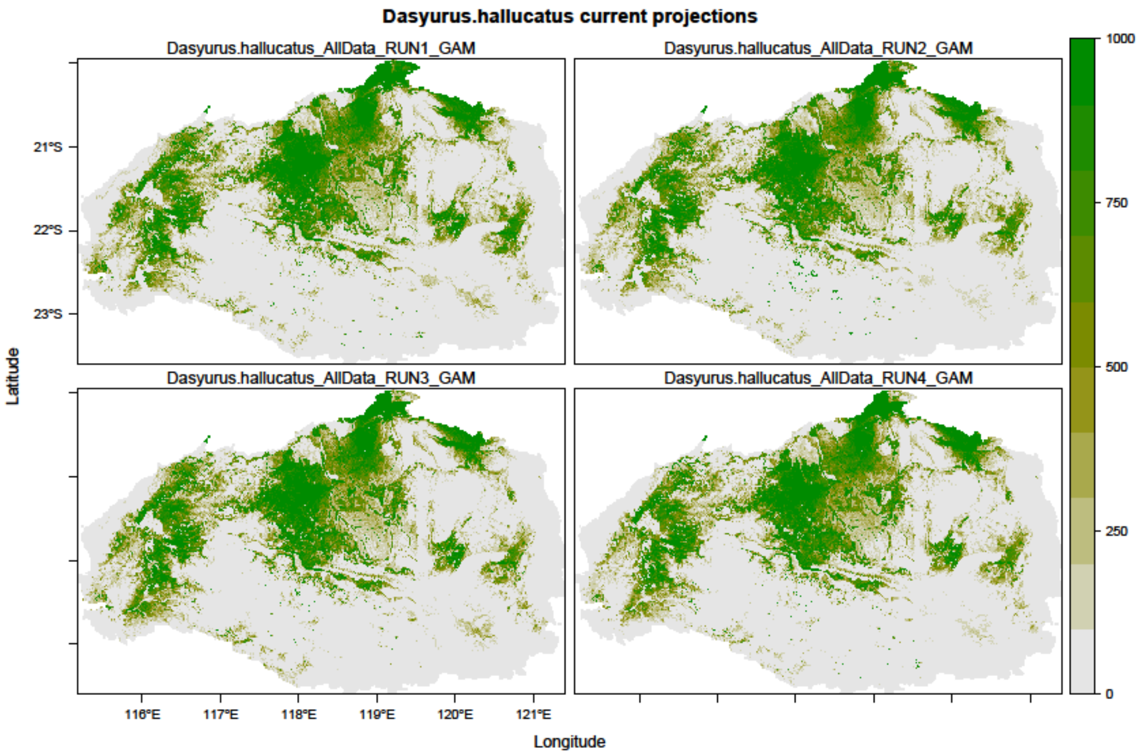


Figure 13: Predicted area outputs for all four GAM runs in BIOMOD 2

The GAM outputs (Figure 13) also identify similar landscapes to those identified in the MaxEnt and GBM runs. Like the GBM results they identify a much greater area while delivering no appreciable improvement in model performance (Table 6) in comparison to the MaxEnt outputs, although the GAM runs are statistically very consistent. The predictive power of the GAM package appears greater than that of GBM in that areas further away from known presences are identified as habitat (particularly in regard to the south and west). In those areas in the central north of the region where all three modelling tools predict the greater habitat values, the GAM package appears to give a greater level of resolution than the GBM, though not as great as that given by MaxEnt.

Table 6: GAM test results using TSS by run

Run	Test data	Cut-off	Sensitivity	Specificity
1	0.760	483	88.043	87.954
2	0.774	482	89.674	87.701
3	0.783	407	91.033	87.278
4	0.780	427	89.943	88.039

3.4.4 Flexible discriminant analysis (FDA)

FDA is a method for supervised classification based on mixture models. It is an extension of the well-known linear discriminant analysis which is closely related to analysis of variance (ANOVA) and regression analysis. However, ANOVA uses categorical independent variables and a continuous dependent variable, whereas discriminant analyses have continuous independent variables and a categorical dependent variable. FDA is an older modelling tool which has been used for multi-group classification used since the 90s. It can use a large number of predictors to identify a reduced number of discriminant coordinate functions for classification purposes and can produce a classification map that partitions the reduced space into regions that are identified with group membership, and the decision boundaries are linear (Manel et al., 1999).

In regard to the high priority areas identified, the FDA runs (Figure 14) are similar to those produced by the GAM package and are therefore largely subject to the same observations. However in comparison to all other modelling packages used it assigns a low PD value to many areas not identified by other packages. Because of this, it can be said that these differences, are largely scalar in nature. Statistically, the FDA package produces noticeably lower values than the other packages, particularly in the areas of Test-data, Sensitivity and Specificity (Table 7). This is a counterintuitive result given the comparatively large area selected by this package as being PD. Statistical variation between runs is also comparatively high.

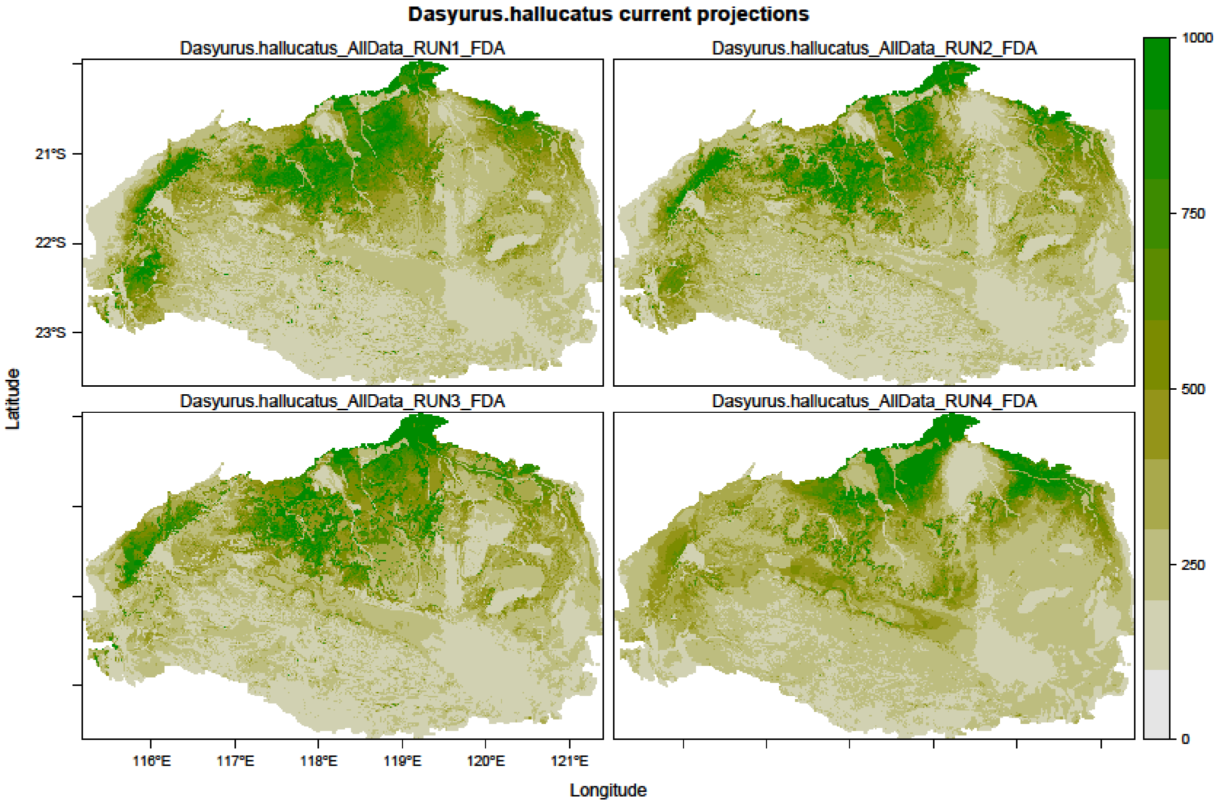


Figure 14: Predicted area outputs for all four FDA runs in BIOMOD2

Table 7: FDA test results using TSS by run

Run	Test-data	Cut-off	Sensitivity	Specificity
1	0.613	354	80.707	80.517
2	0.678	367	83.152	84.573
3	0.634	401	77.717	85.630
3	0.597	400	72.554	87.067

3.4.5 Classification tree analysis (CTA)

This method consists of recursive partitions of the dimensional space defined by the predictors into groups that are as homogeneous as possible in terms of response. The tree is built by repeatedly splitting the data, defined by a simple rule based on a single explanatory variable. At each split, the data are partitioned into two exclusive groups, each of which is as homogeneous as possible. The algorithm seeks to decrease the variance within the subset as much as possible. The heterogeneity of a node can be interpreted as a deviance of a Gaussian model (regression tree) or of a multinomial model (classification tree) (Vayssières et al., 2000).

The CTA package has produced four quite varied runs which, generally, comply well with the MaxEnt runs and the preferred. However, values for identified areas remain generally high, giving the appearance of an almost binary SDM (Figure 15). In the extent of the area selected it has produced results closer to those produced by MaxEnt than any other model, but still lacks the definition displayed in the MaxEnt runs or in the preferred model.

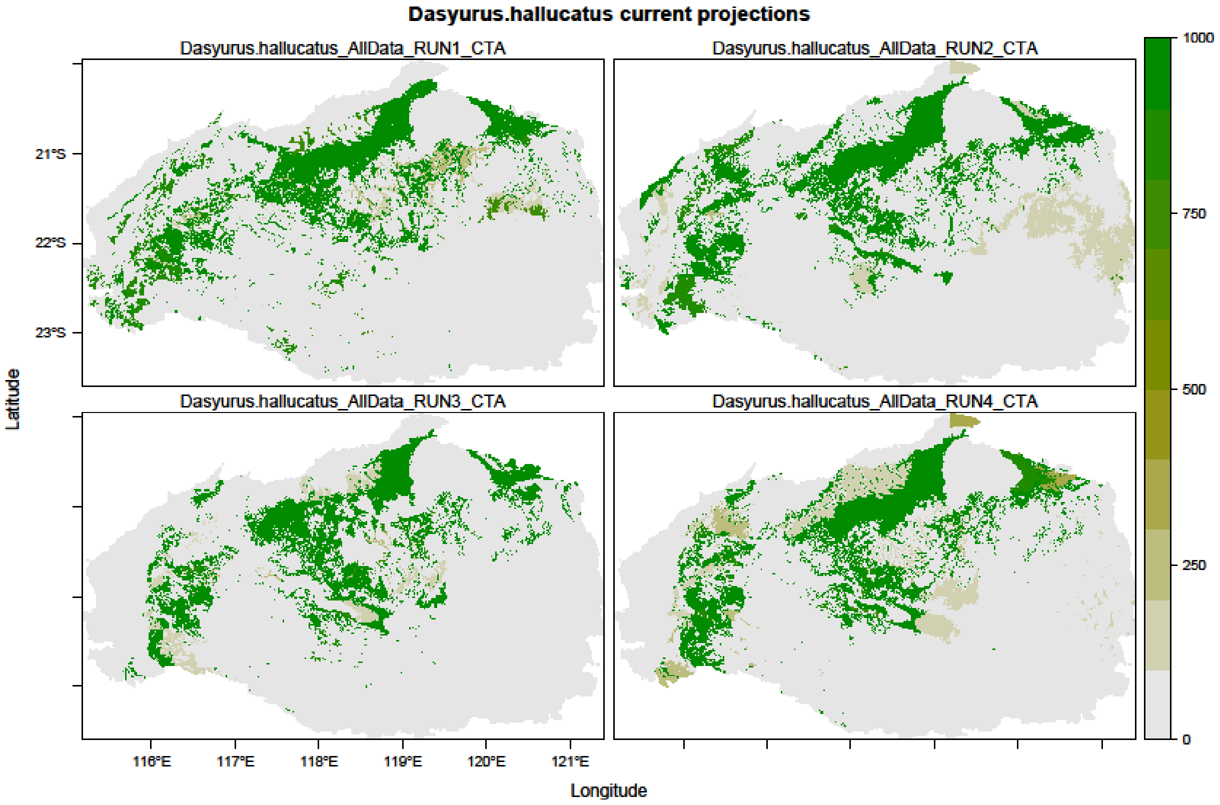


Figure 15: Predicted area outputs for all four CTA runs in BIOMOD 2

Statistically the CTA has consistently produced the highest values in re Test-data, Sensitivity and Specificity, although Cut-off values vary wildly in order to produce these results. This appears to be a characteristic of this modelling package.

Table 8: CTA test results using TSS by run

Run	Test data	Cut-off	Sensitivity	Specificity
1	0.867	477.5	93.476	93.238
2	0.841	156.0	89.986	94.167
3	0.863	795.5	91.033	95.224
4	0.822	1253	99.315	93.873

3.4.6 Ensemble model

It should be noted that, in running the five different modelling tools to create the ensemble model, predictive variable contributions altered not only for each tool, but for each tool in each run (Table 9). This demonstrates both the differences in the modelling tools and the impact of the random 20% of presences withheld for testing purposes.

Table 9: Variable contribution for each package over four runs

Run 1					
	MaxEnt	GBM	CTA	FDA	GAM
bio_1	0.07	0.076	0.525	0.401	0.146
bio_19	0.142	0.024	0.242	0.076	0.209
bio_18	0.362	0.193	0.277	0.228	0.256
bio_9	0.33	0.108	0.283	0.202	0.211
dem	0.564	0.264	0.447	1.000	0.620
slope	0.017	0.017	0.158	0.066	0.086
water	0.005	0.003	0.095	0.000	0.021
soil	0.041	0.015	0.055	0.273	0.145
vegag	0.094	0.084	0.242	0.080	0.201
Run 2					
	MaxEnt	GBM	CTA	FDA	GAM
bio_1	0.021	0.113	0.674	0.403	0.095
bio_19	0.142	0.020	0.169	0.083	0.171
bio_18	0.297	0.188	0.383	0.200	0.266
bio_9	0.281	0.118	0.248	0.174	0.207
dem	0.424	0.221	0.479	1.000	0.606
slope	0.033	0.016	0.140	0.076	0.081
water	0.006	0.004	0.050	0.000	0.020
soil	0.055	0.011	0.002	0.230	0.111
vegag	0.090	0.082	0.229	0.145	0.196
Run 3					
	MaxEnt	GBM	CTA	FDA	GAM
bio_1	0.018	0.162	0.643	0.286	0.088
bio_19	0.126	0.030	0.133	0.051	0.190
bio_18	0.313	0.171	0.412	0.185	0.263
bio_9	0.282	0.141	0.427	0.156	0.236
dem	0.363	0.154	0.444	0.999	0.601
slope	0.017	0.017	0.137	0.065	0.074
water	0.004	0.003	0.067	0.000	0.020
soil	0.042	0.013	0.063	0.263	0.129
vegag	0.135	0.087	0.207	0.216	0.208
Run 4					
	MaxEnt	GBM	CTA	FDA	GAM
bio_1	0.029	0.157	0.673	0.107	0.157
bio_19	0.179	0.022	0.110	0.165	0.171
bio_18	0.296	0.194	0.440	0.118	0.268
bio_9	0.338	0.113	0.289	0.244	0.195
dem	0.261	0.161	0.473	0.530	0.558
slope	0.015	0.017	0.159	0.083	0.074
water	0.008	0.002	0.083	0.000	0.015

soil	0.049	0.012	0.014	0.305	0.111
vegag	0.131	0.084	0.070	0.026	0.200

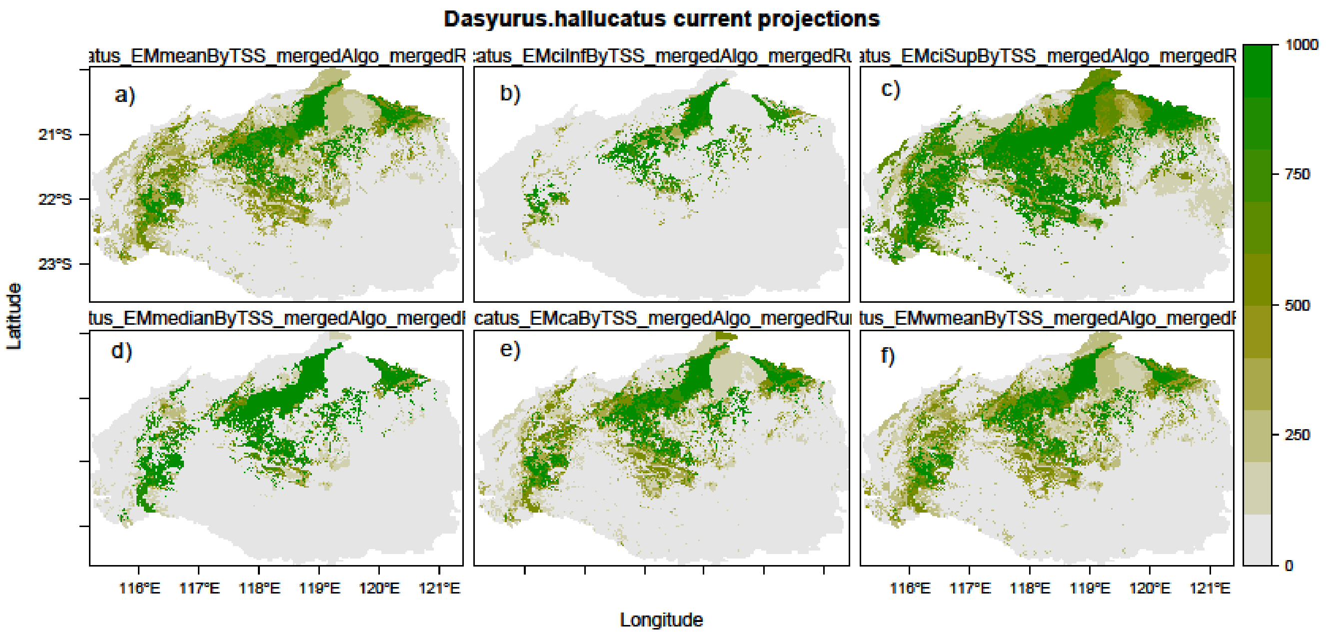


Figure 16: BIOMOD2 output. Ensemble models for the northern quoll created by: a) mean of probabilities, b) confidence interval, quantile inferior, c) confidence interval, quantile superior, d) median of probabilities, e) committee averaging, and f) weighted mean (Thuiller et al., 2015).

The outputs for the ensemble models, like those for the individual tools, show a general congruence (Figure 16). Across all six outputs there is little difference in the landscapes recognised as being northern quoll habitat. The difference again appears to be in the habitat values applied to these landscapes. To select which of the ensemble models to use for more detailed testing against the preferred model from the statistical tests given below (Table 10) for all ensemble models. Overall statistical values remain similarly high with the weighted mean ensemble model (Figure 16f) being the best performer overall in regard to all values in all tests. Consequently this SDM was chosen for further comparison with the preferred MaxEnt model.

Table 10: Statistical analyses of ensemble models

a) EM mean by TSS				
	Test data	**Cut-off**	**Sensitivity**	**Specificity**
KAPPA	0.840	803.0	88.363	97.421
TSS	0.898	363.0	95.922	93.854
ROC	0.980	363.5	95.922	93.862

b) EM cilnf by TSS				
	Test data	**Cut-off**	**Sensitivity**	**Specificity**
KAPPA	0.845	424.0	89.233	97.369
TSS	0.890	67.0	92.985	96.026
ROC	0.944	63.5	93.094	95.925

c) EM ciSup by TSS

	Test data	Cut-off	Sensitivity	Specificity
KAPPA	0.806	942.0	94.182	95.046
TSS	0.898	807.0	95.867	93.904
ROC	0.961	811.5	95.867	93.913

d) EM median by TSS				
	Test data	**Cut-off**	**Sensitivity**	**Specificity**
KAPPA	0.830	880.0	91.408	96.483
TSS	0.896	166.0	95.215	94.327
ROC	0.975	668.0	93.692	95.891

e) EM ca by TSS				
	Test data	**Cut-off**	**Sensitivity**	**Specificity**
KAPPA	0.838	899.0	88.309	97.371
TSS	0.890	500.0	94.073	94.961
ROC	0.972	500.0	94.073	94.961

f) EM wmean by TSS				
	Test data	**Cut-off**	**Sensitivity**	**Specificity**
KAPPA	0.844	776.0	89.179	97.371
TSS	0.898	354.0	96.085	93.642
ROC	0.980	403.5	93.324	94.479

3.5 Results

The mean weighted ensemble SDM (Figure 16f) is displayed as given in the BIOMOD2 readout, while the preferred MaxEnt SDM (Figure 10) is displayed in ArcGIS 10.3 with a different scale, resolution and symbology. To make an initial visual comparison possible the ensemble model must first be projected at the same settings as the preferred model (Figure 17). Having done this, a visual comparison shows a strong general similarity between the landscapes selected by both models with the differences, again, being more the habitat value of the landscapes selected rather than which areas are actually selected.

Visually, scalar model lack categorical definitions making them difficult to compare. This effect can be minimised by making models binary (i.e. pixels are given no other value than habitat of not habitat) and overlaying the results. In this comparison both models are made binary by use of a cut-off value, i.e. the score at which a pixel with a value below the cut-off is classified as not habitat (0) and a pixel with a score equal to, or above the cut-off is classified as habitat, or as part of the PD (1). Cut-off values are derived from the equal specificity/sensitivity *P* values (Figure 18) given for both model in their respective readouts. Cut-off values are 363 for ensemble SDM and 0.291 for MaxEnt preferred SDM. The results of this exercise, binary models for both SDMs and an overlay of both models is shown below (Figure 19).

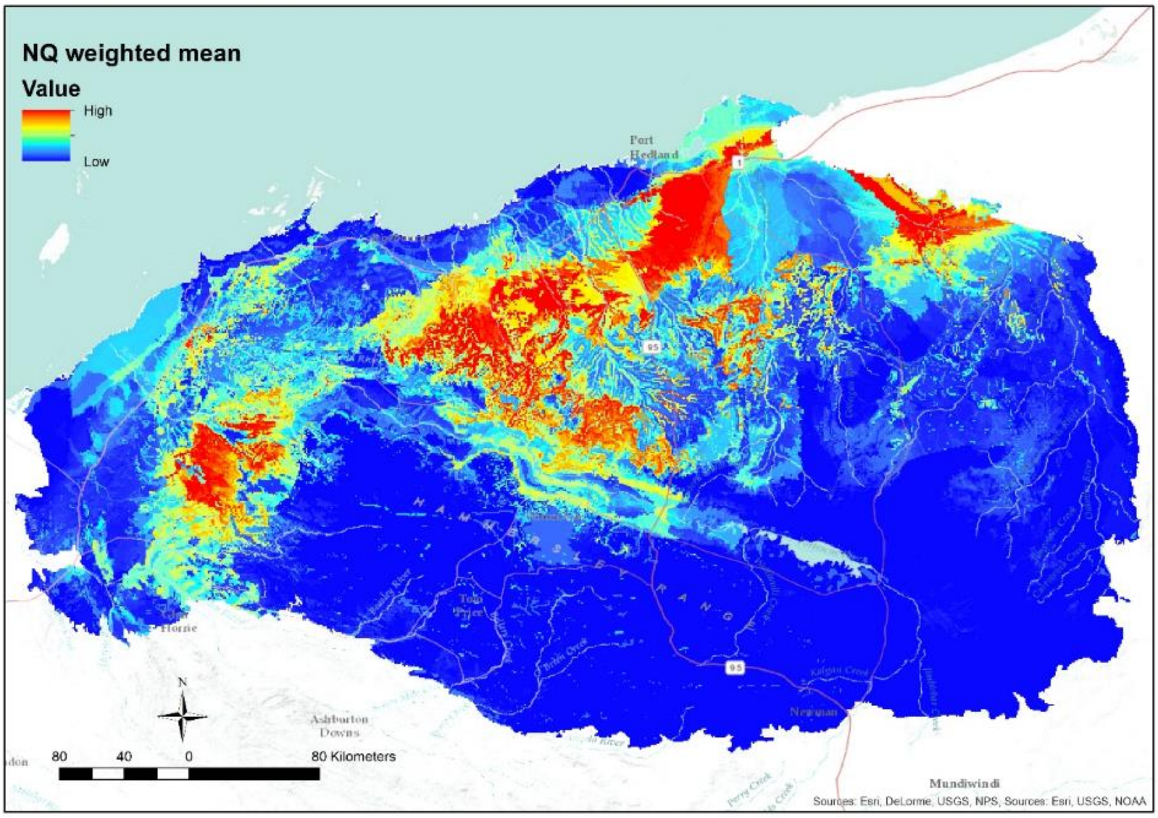


Figure 17: Weighted mean ensemble model (f) projected in ArcGIS 10.3 as per the preferred MaxEnt model (Figure 10).

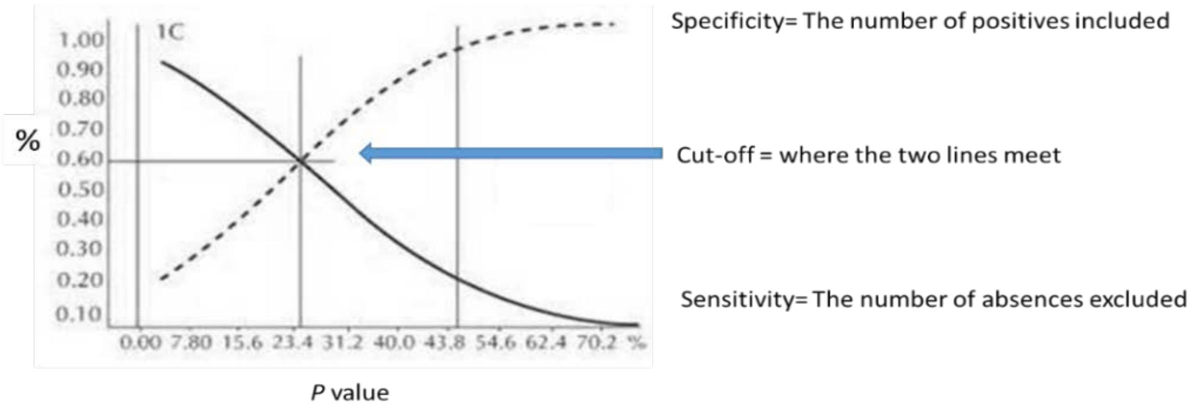


Figure 18: Threshold to convert to binary using equal sensitivity specificity cut off

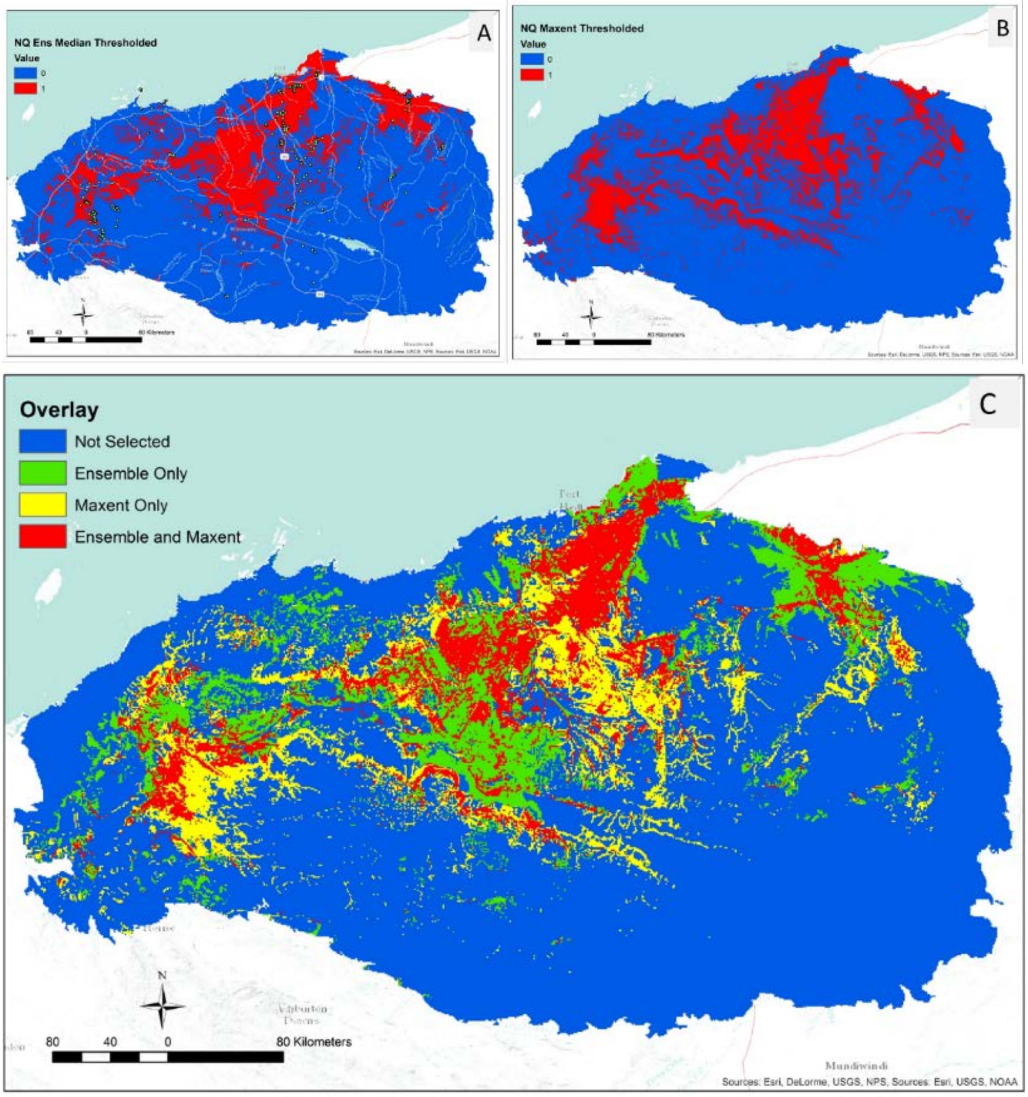


Figure 19: Binary representation of: a) ensemble median SDM, b) MaxEnt model using bias grid and c) both models overlaid.

3.6 Conclusions

The overlay (Figure 19c) shows a very strong general correlation between the preferred MaxEnt SDM and the ensemble model with conflicting predictions mostly bordering landscapes identified by both models as habitat. This supports our earlier observation that the difference between the two models is largely one of resolution rather than conflict. Given that three of the modelling tools used in the ensemble package, namely GBM, FDA and, to a lesser extent, GAM, lacked resolution, consequently overestimating PD for the northern quoll, this result is not surprising. With this in mind, we cautiously conclude that the ensemble modelling process validates our choice of the MaxEnt model with bias file as the preferred SDM. However, we reiterate that this remains a desktop process that should be validated and refined through on ground sampling and research.

4 Threats

4.1 Overview

As previously discussed (section 1.4) there are numerous threats to the Pilbara population of the northern quoll. Some of these threats have been scoped, during the variable evaluation and literature review process of this research and with no further modelling. The reasons for these decisions are discussed below (sections 4.1.1-4).

The two major threats to the Pilbara northern quoll population which do respond to species distribution modelling and further analyses are climate change (section 4.2) and cane toad invasion (section 0). These are discussed in detail below.

4.1.1 Mining

Models of northern quoll presence responded most strongly to bioclimatic, geomorphic and vegetation based independent variables. Mining activities are also strongly aligned with similar geomorphic features, and therefore the potential modification or destruction of features upon which the quoll depends. However, although we are able to nominate suitable landscapes for quoll presence, the identification of the actual geological assets which define habitat at a very fine scale (< $1km^2$) currently requires on-ground surveys by appropriately qualified personnel and an improved understanding of the biotic and abiotic variables which define habitat at this scale.

4.1.2 Fire

Although fire is recognised as a major threat to northern quoll in the literature (Cook, 2010; Meri, 2000; Woinarski, 2010), neither the use of the Modis fire scare mapping or NDVI data sets (also an indicator of previous fire impacts) showed any real predictive power for the Pilbara population of northern quoll (AUC on single variable models showed at 0.57 and 0.55 respectively and no improvement in multivariable models). That is not to say the frequency or intensity of fire does not impact on this population, it only indicates that the modelling doesn't reflect any change the probability of presence. This is not surprising as nearly all presences are recorded in land used for pastoral activities over the time frame within which (nearly all) northern quoll presences have been recorded. Hence, northern quoll presences within most of the Pilbara have only been recorded within the context of what has been a, comparatively, consistent and uniform fire and management regime (Nano et al., 2012; van Etten, 2013). Consequently, the question of how this fire regime effects the Pilbara population of the northern quoll, be it good, bad or indifferent, remains (in the absence of specific on-ground trials) beyond the scope of this project. Furthermore, it is quite possible that climate change may well impact on the intensity, frequency and seasonality of fire within the Pilbara (Edwards et al., 2015). Addressing knowledge gaps on regard to the northern quoll's response to different fire regimes will enable the Pilbara population's response to various climate change fire scenarios to be better understood and, where required, managed.

4.1.3 Pastoral activities

As previously stated, most of the area from which northern quoll records come from have historically been pastoral land (van Etten, 2013). Although this management scenario is becoming much less heterogeneous than it once was, it, like fire, remains fairly ubiquitous throughout most of the landscape from which our northern quoll presences were obtained. This does not enable us to demonstrate that there is a good, bad or indifferent link between pastoralism and quoll presence. It merely shows that the pastoral industry and northern quoll both prefer similar landscapes and vegetation associations, and that northern quolls can persist within the context of a pastoral management regime. Therefore, it is recommended that targeted research be undertaken to determine the impacts of pastoralism on the Pilbara population of the northern quoll.

4.1.4 Feral predators

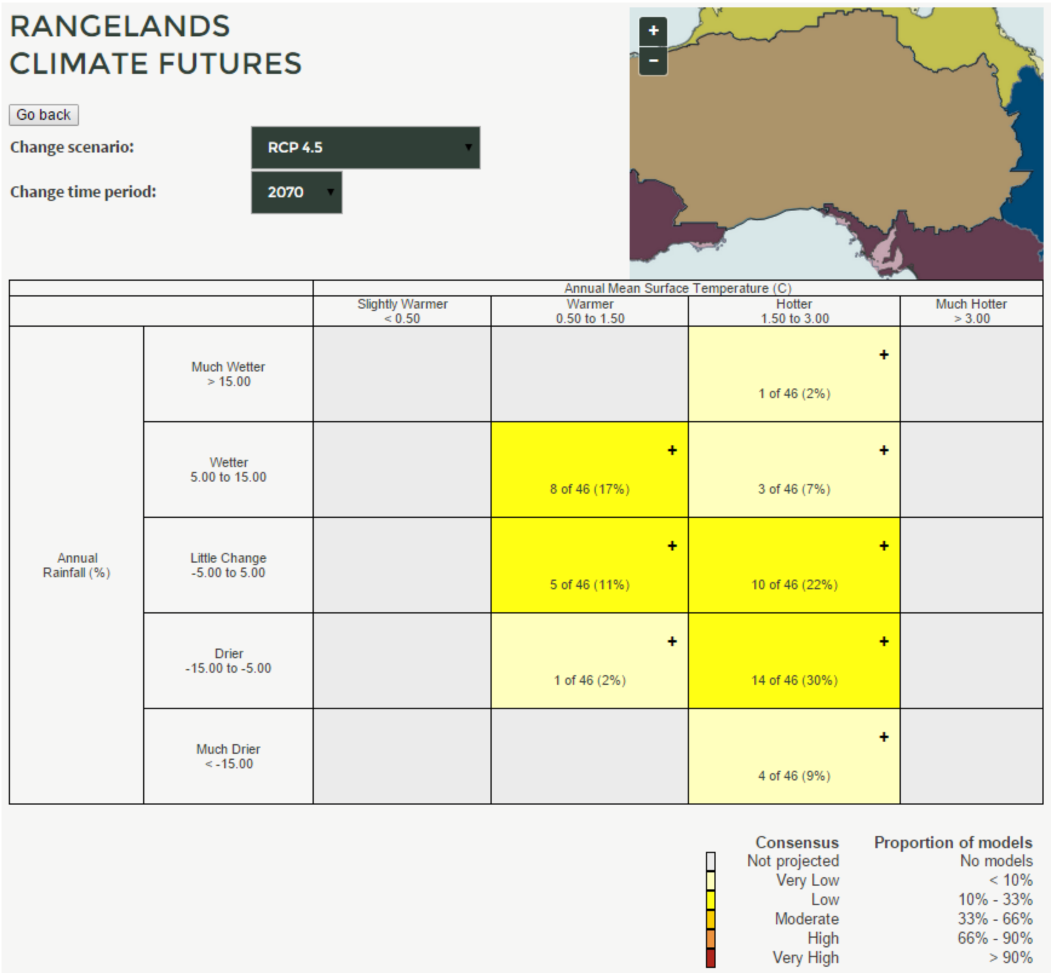
Exotic predators, in particular feral cats, dingoes and, to a lesser extent, foxes are known to predate on the northern quoll and are ubiquitous throughout the Pilbara (Burbidge & McKenzie, 1989; Pavey & Bastin, 2014). Records of feral cats in the Pilbara go back to 1959 (DPaW, 2007-). Therefore, it can be assumed that northern quoll have managed to co-exist with these predators across much of the Pilbara for over 60 years. Furthermore, despite an absence of data, there is no obvious decrease in the density or extent of the Pilbara northern quoll population. This is not to say that feral predators have had no detrimental impact on this population. It is quite possible that this population has already undergone a major reduction in number and extent due to exotic predators (Burbidge & McKenzie, 1989; Hill & Ward, 2010). We only note that this northern quoll population has persisted in spite of the presence of feral predators since at least 1959 and we have seen no evidence to suggest that, if there is no major shift in the ecology of this region, the northern quoll will not persist in the Pilbara just as they persisted in spite of exotic predators in many other regions prior to cane toad invasion, albeit with significantly reduced ranges and populations (Dickman, 1996). However, it is also possible that this capacity to persist may well be upset by either climate change, changes in land management practices or the introduction of another major threat, e.g., cane toad invasion. In light of these significant knowledge gaps on the impacts of exotic predators on the Pilbara northern quoll population, further targeted research is strongly recommended.

4.2 Climate change

4.2.1 Used climate change model/scenario

There are major conflicts between the climate change models used by the International Panel on Climate Change (IPCC) for its report to policy makers on the current status of climate change (IPCC, 2013). These conflicts are particularly evident in modelling the Rangelands biogeographical region (Figure 20) (Watterson et al., 2015). To compensate for this, we elected to use the Australian Community Climate and Earth-System Simulator (ACCESS) 1.0 coupled model, (CSIRO & BoM, 2015). The ACCESS model was chosen as it is Australia's preferred Earth System Model, and the 1.0 version chosen because it is described as being the less aspirational of the two versions and for that reason it was seen by the authors as being potentially more reliable.

The ACCESS 1.0 model has differing outputs for different resource concentration pathway (RCP) or emission scenarios and timeframes. As the literature indicates that achieving the low emission scenario is very unlikely (Schaeffer et al., 2015), we opted to model with the RCP 4.5 (medium) and 8.5 (high) emission scenarios. The timeframes selected were 2050 and 2070 as it was felt that lower timeframes would not show significant changes in PDs and timeframes beyond 2070 gave ample opportunity to create SDMs with improved tools and projections. All modelled changes are measured against baseline of 1986–2005 averages.



		Annual Mean Surface Temperature (C)			
		Slightly Warmer < 0.50	Warmer 0.50 to 1.50	Hotter 1.50 to 3.00	Much Hotter > 3.00
Annual Rainfall (%)	Much Wetter > 15.00			1 of 46 (2%)	
	Wetter 5.00 to 15.00		8 of 46 (17%)	3 of 46 (7%)	
	Little Change -5.00 to 5.00		5 of 46 (11%)	10 of 46 (22%)	
	Drier -15.00 to -5.00		1 of 46 (2%)	14 of 46 (30%)	
	Much Drier < -15.00			4 of 46 (9%)	

Figure 20: Cross evaluation of climate change models for the Rangelands by annual rainfall and annual mean temperature (CSIRO & BoM, 2015)

4.2.2 Overview of predicted climate change in the Northern Rangelands

The key messages on climate change in the Northern Rangelands (the biogeographical sub region which includes the Pilbara) as given by Watterson et al. (2015) are:

- Average temperatures will continue to increase in all seasons (very high confidence).
- More hot days and warm spells are projected with very high confidence. Fewer frosts are projected with high confidence.
- Changes to rainfall are possible but unclear.
- Increased intensity of extreme rainfall events is projected, with high confidence.
- Mean sea level will continue to rise and height of extreme sea-level events will also increase (very high confidence).
- On annual and decadal basis, natural variability in the climate system can act to either mask or enhance any long-term human induced trend, particularly in the next 20 years and for rainfall.

4.2.3 Detailed predicted changes for the Northern Rangelands

As given by CSIRO and BoM (2015):

Rainfall: Changes to summer rainfall are possible but unclear. Winter rainfall is projected to decrease in the south with high confidence. For the near future, natural variability will dominate any projected changes.

Changes to annual and summer rainfall for late in the century are possible, but the direction of change cannot be confidently projected given the spread of model results. Impact assessment in this region should consider the risk of both a drier and wetter climate.

Temperature: Average temperatures will continue to increase in all seasons (very high confidence).

There is very high confidence in continued substantial increases in projected mean, maximum and minimum temperatures in line with our understanding of the effect of further increases in greenhouse gas concentrations.

For the near future (2030), the annually averaged warming across all emission scenarios is projected to be around 0.6 to 1.4 °C above the climate of 1986–2005.

By late in the century (2090), for a high emission scenario (RCP8.5) the projected range of warming is 2.9 to 5.3 °C. Under an intermediate scenario (RCP4.5) the projected warming is 1.5 to 2.9 °C.

Extreme temperatures: More hot days and warm spells are projected with very high confidence. Fewer frosts are projected with high confidence.

Extreme temperatures are projected to increase at a similar rate to mean temperature, with a substantial increase in the temperature reached on hot days, the frequency of hot days, and the duration of warm spells (very high confidence).

Extreme rainfall: Increased intensity of extreme rainfall events is projected, with high confidence.

Understanding of the physical processes that cause extreme rainfall, coupled with modelled projections, indicate with high confidence a future increase in the intensity of extreme rainfall events, although the magnitude of the increases cannot be confidently projected.

Time spent in drought is projected, with medium confidence, to increase over the course of the century.

Marine and coast: Mean sea levels will continue to rise and height of extreme sea-level events will also increase (very high confidence).

There is very high confidence in future sea-level rise. By 2030 the projected range of sea-level rise at Port Hedland is 0.07 to 0.17 m above the 1986–2005 level, with only minor differences between emission scenarios. As the century progresses projections are sensitive to concentration pathways. By 2090, the intermediate emissions case (RCP4.5) is associated with a rise of 0.28 to 0.65 m and the high case (RCP8.5) a rise of 0.40 to 0.85 m.

Fire weather: Bushfire in the Rangelands depends highly on fuel availability, which mainly depends on rainfall. A tendency toward increased fire weather risk is expected in future, due to higher temperature and lower rainfall, but there is low confidence in the magnitude of fire weather projections.

Humidity: Little change in relative humidity is projected for the near future (2030) while later in the century a decrease is projected in winter and spring (high confidence) and in summer and autumn (medium confidence).

Solar radiation: There is little change projected for solar radiation in the near future (2030), and for later in the century, increased radiation is projected in the south in winter (medium confidence).

Evaporation: Potential evapotranspiration is projected to increase in all seasons as warming progresses (high confidence).

4.2.4 MaxEnt climate change modelling

To model climate change impacts on the Pilbara population of the northern quoll it is necessary to understand the full set of bioclimatic variables which define the PD for the species, not just for the Pilbara population. The model must be able to demonstrate how northern quoll populations may enter or leave, as well as move within, the Pilbara as a result of climate change impacts. As we have already developed a high resolution SDM for this population, and as this exercise is only being undertaken to demonstrate climate change impacts, it was decided that the SDM would only use bioclimatic independent variables in this exercise.

4.2.5 Climate change modelling, results

Bioclimatic data for the set of 19 variables at 30 second resolution was obtained the WorldClim (2015) portal clipped to Australia. Scenario's used are RCP 4.5 and 8.5 at baseline, 2050 and 2070. Nationwide presence data for the northern quoll (*n*=2,487) was obtained from Atlas of Living Australia (2015) and shown in Figure 2. MaxEnt was used to produce the SDM running at 500 iterations, averaged over ten runs, with 20% of presences withheld for testing in each run. Bioclimatic variables were reduced from 19 to a suite of eight using a stepwise reduction method as described in section 2.5 (Table 11).

Table 11: %Contribution and permutation importance for national scale MaxEnt model

Variable	% Contribution	Permutation Importance
BIO16 = Precipitation of Wettest Quarter	48.0	1.4
BIO6 = Min Temperature of Coldest Month	19.5	4.0
BIO12 = Annual Precipitation	9.8	49.8
BIO11 = Mean Temperature of Coldest Quarter	7.2	13.4
BIO15 = Precipitation Seasonality (Coefficient of Variation)	6.3	12.2
BIO18 = Precipitation of Warmest Quarter	3.8	9.0
BIO3 = Isothermality (BIO2/BIO7) (* 100)	2.8	1.8
BIO9 = Mean Temperature of Driest Quarter	2.5	8.4

This has resulted in an SDM with an exceptionally high training AUC of 0.97 and an average test AUC of 0.95 and a very good omission plot (Figure 21). However, it should be remembered that this is a national scale SDM lacking the fine species specific variables used preferred model. Therefore, these figures may be inferring a greater level of resolution at the regional (Pilbara) scale than should be expected from this SDM.

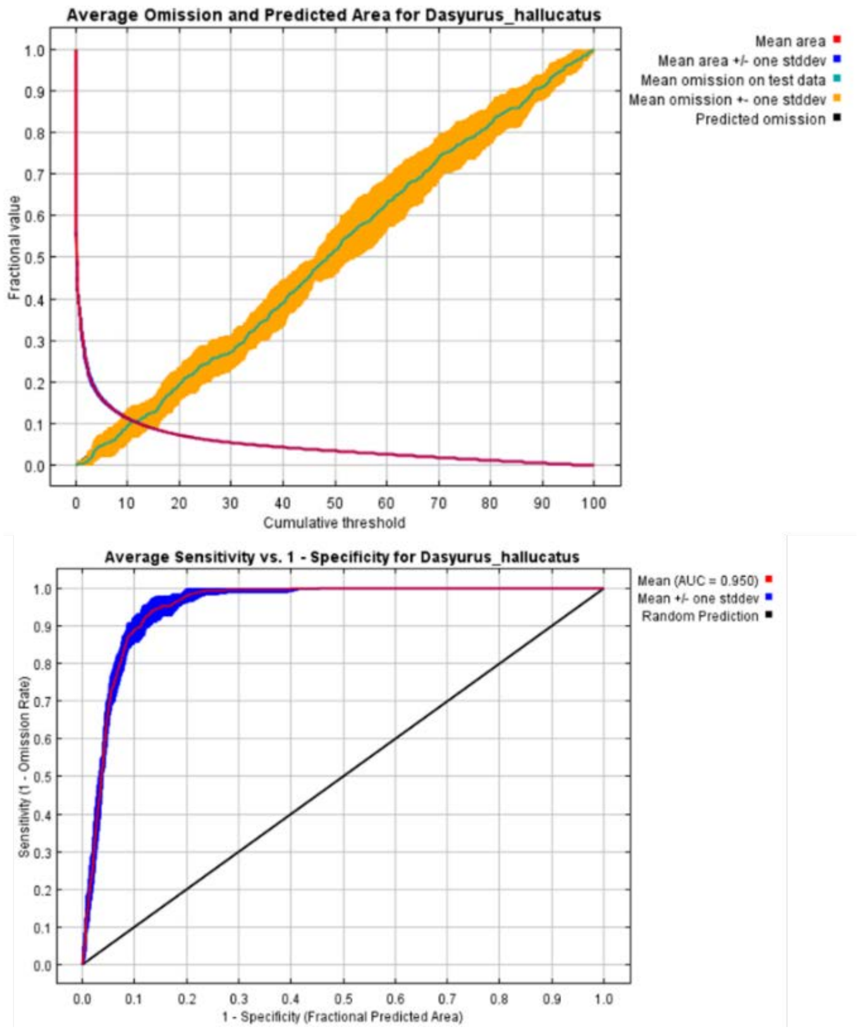


Figure 21: Omission and AUC/specificity plots for MaxEnt analysis

The baseline national model (Figure 22) shows a predictable PD for the northern quoll which complies well with other national models (Atlas of Living Australia, 2015; Van der Wal, 2014). To better demonstrate how this SDM compares with the preferred model and to allow a better comparison between predicted climate change scenarios, a binary PD has been extracted using an equal sensitivity/specificity cut off and overlaid on an outline of the Pilbara (Figure 23).

In the RCP 4.5 2050 scenario (Figure 24) there is a very small difference in the PD of the northern quoll overall, although there is a large expansion of PD into the Great Sandy Desert (the area directly north east of the Pilbara) and habitat value in the Kimberley increases. In the Pilbara overlay (Figure 25), a general expansion and small easterly movement in PD is evident. However, in this scenario very little of the baseline PD is lost.

In the RCP 4.5 2070 scenario (Figure 26) there is a little discernible difference in the PD of the northern quoll in comparison to the previous scenario with the expansion of PD into the Great Sandy Desert and Kimberley persisting. In the Pilbara overlay a general expansion and larger south-easterly movement is evident (Figure 27). Although most of the baseline PD is retained, areas of PD in the north of the Pilbara with high habitat value may be lost.

In the RCP 8.5 2050 scenario (Figure 28) there is a small discernible difference in the PD of the northern quoll in comparison to the previous scenario with the expansion into the Great Sandy Desert less evident and the expansion into the Kimberley persisting. In the Pilbara overlay the south-easterly movement in PD has increased substantially (Figure 29). Less than half of the baseline PD is retained with substantial areas of PD in the west and north of the Pilbara with high habitat value likely to be lost.

In the RCP 8.5 2070 scenario (Figure 30) the trends of the RCP 8.5 2050 scenario continue strongly. There is a discernible difference in the PD of the northern quoll in comparison to the previous scenario with the expansion into the Great Sandy Desert again comparable with that predicted in the RCP 4.5 scenarios, very high PD values for the Kimberley and a general contraction in PD in the north and east of the country. In the Pilbara overlay the south-easterly movement evident in the previous scenarios continues (Figure 31). Although most of the baseline PD in the north and west is now lost with approximately 25% retained.

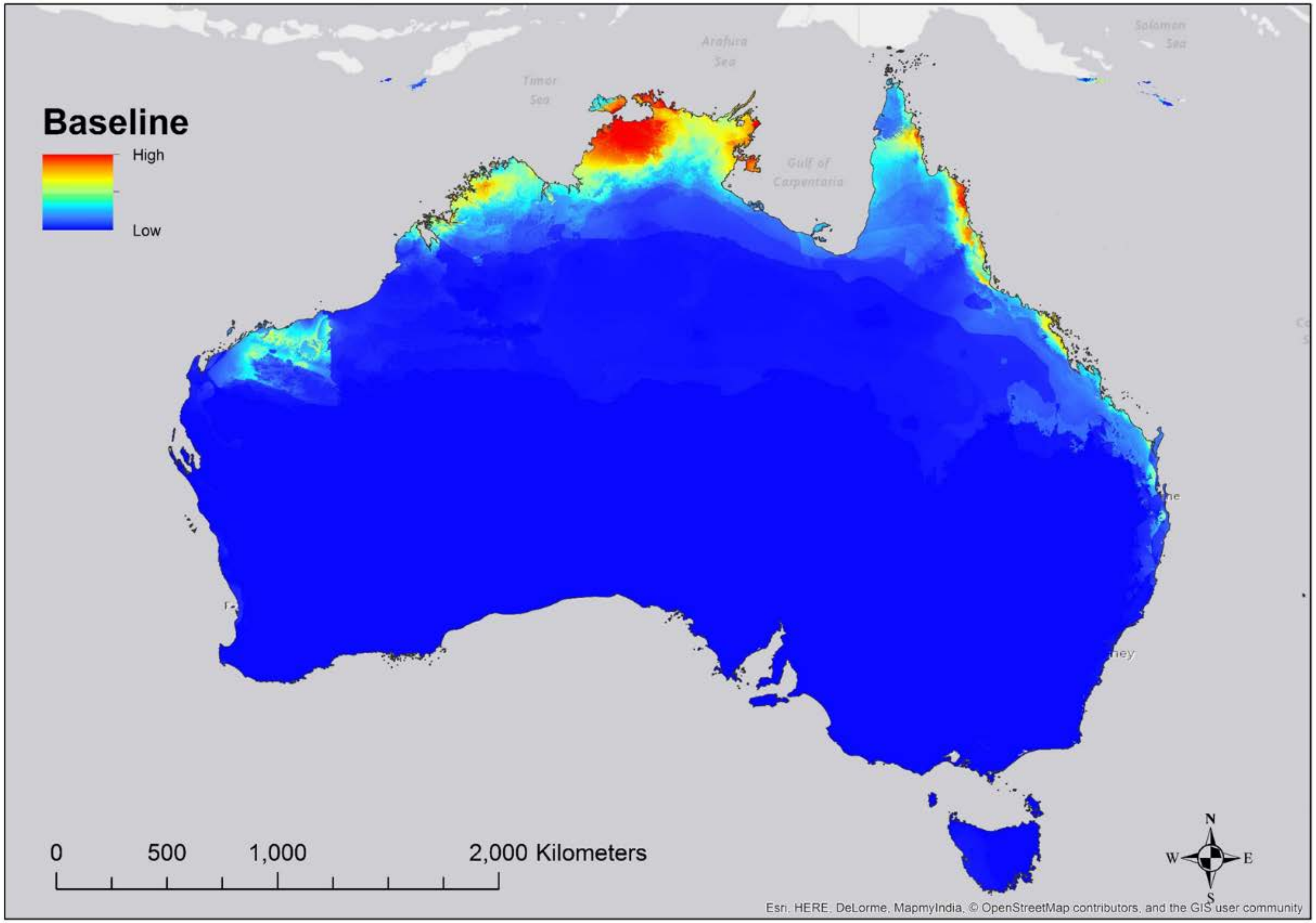


Figure 22: MaxEnt projection for the baseline scenario

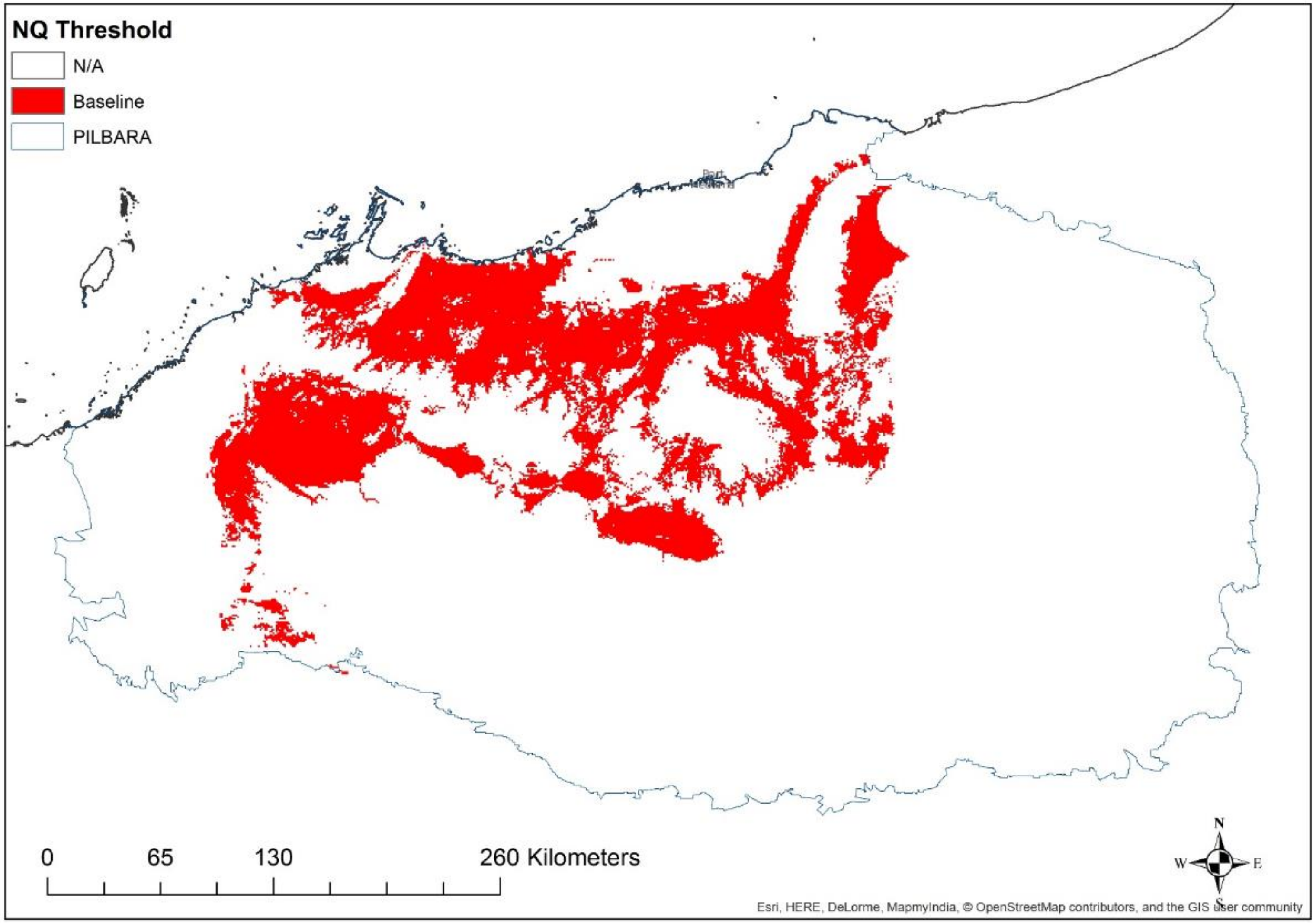


Figure 23: Pilbara baseline preferred MaxEnt SDM thresholded using equal sensitivity specificity.

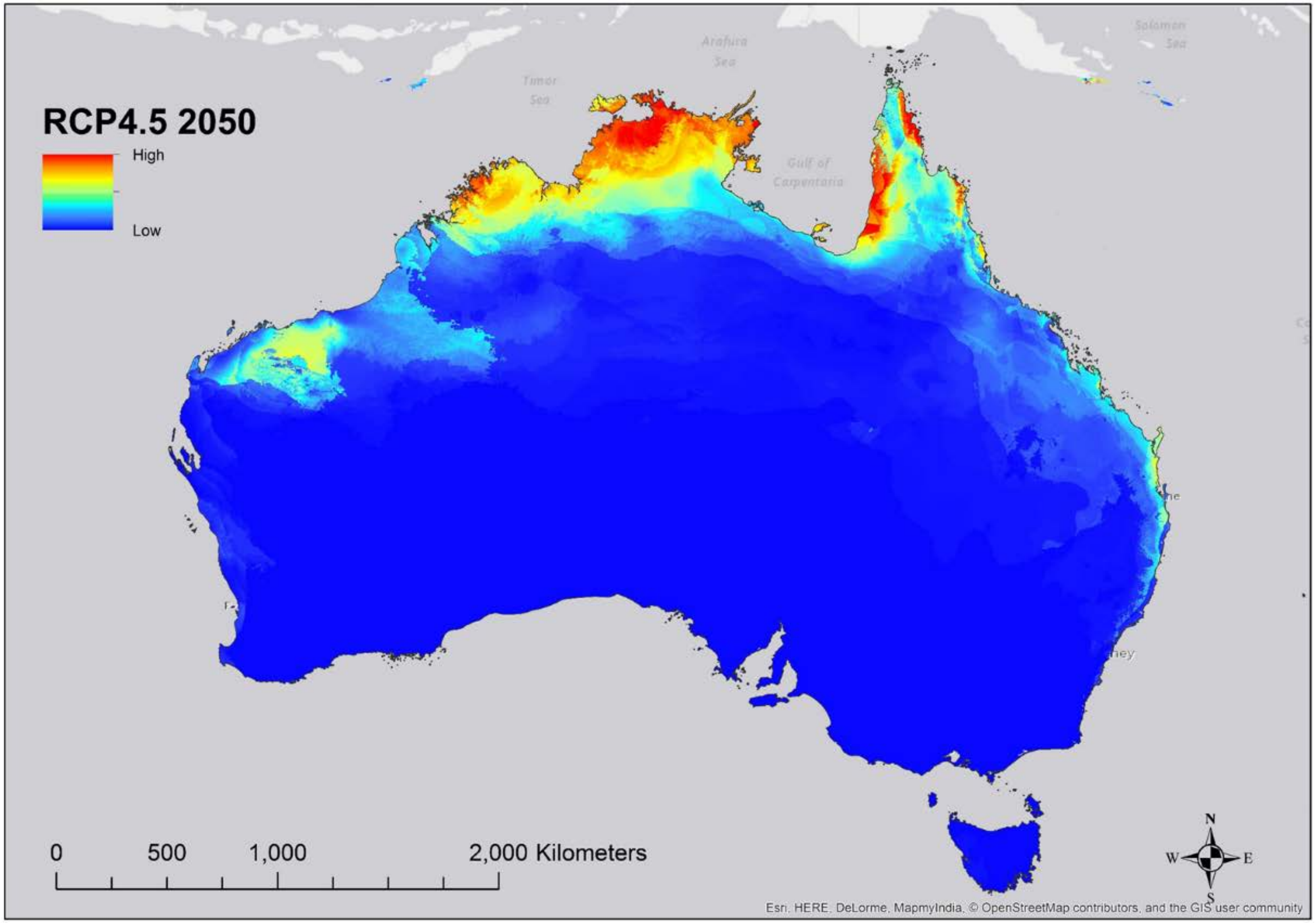


Figure 24: MaxEnt projection for the Accessm1.0 RCP 4.5 2050 scenario

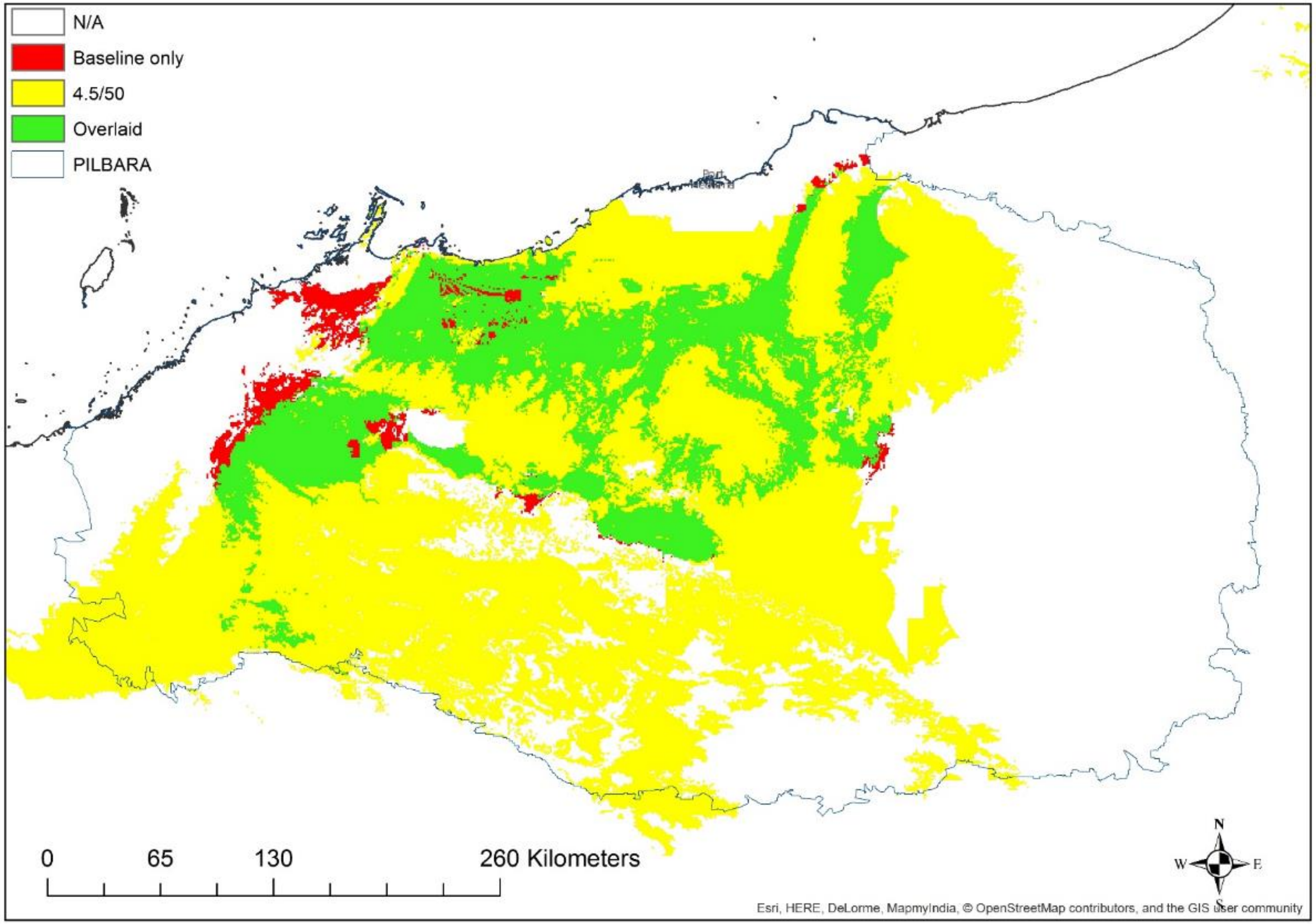


Figure 25: Pilbara baseline thresholded overlaid with Access 1.0 RCP 4.5 2050 scenario thresholded
(Green "Overlaid" areas indicate where northern quoll habitat is identified in both scenarios, i.e. areas where quolls should persist)

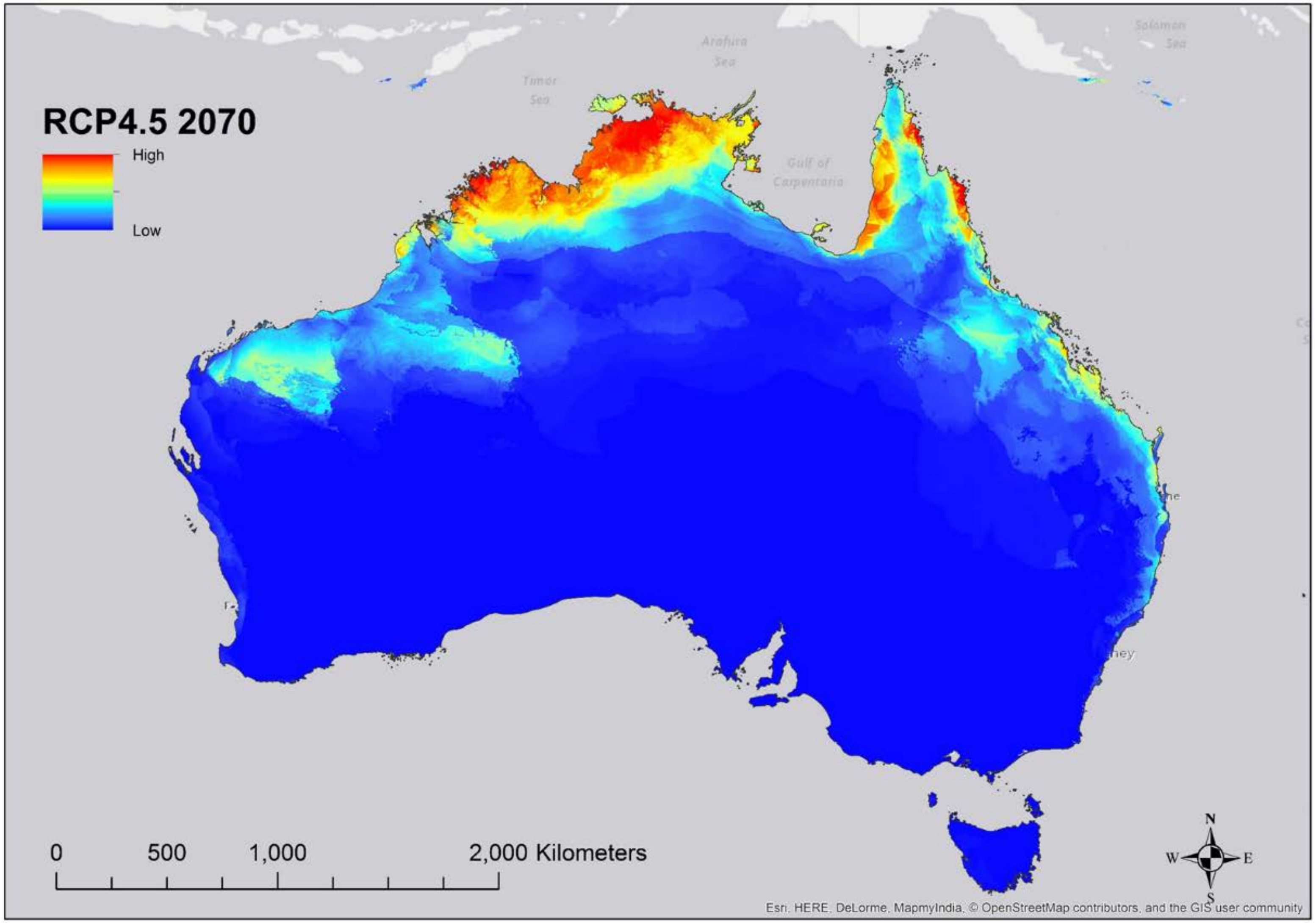


Figure 26: MaxEnt projection for the Access 1.0 RCP 4.5 2070 scenario

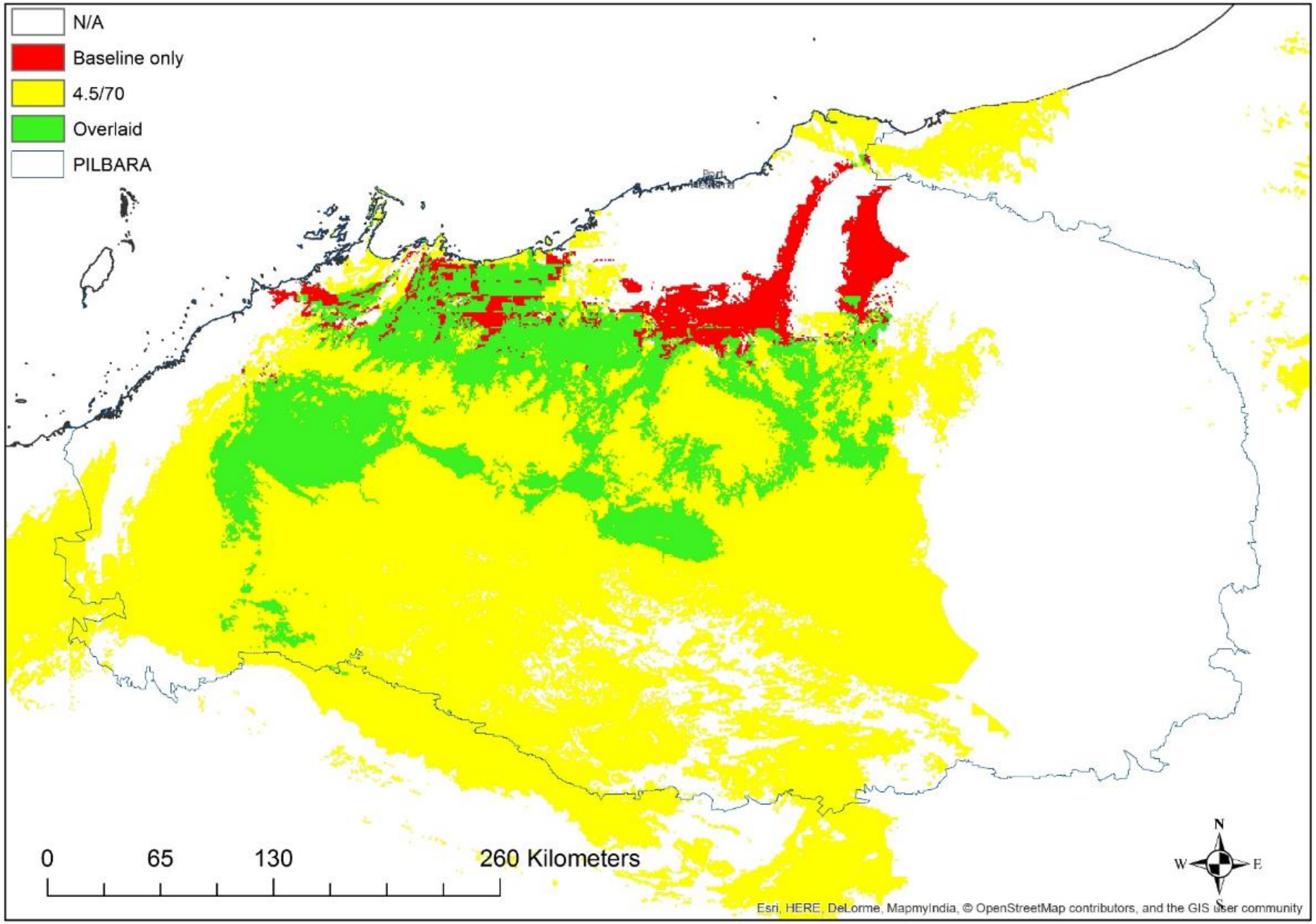


Figure 27: Pilbara baseline thresholded overlaid with Access 1.0 RCP 4.5 2070 scenario thresholded
(Green "Overlaid" areas indicate where northern quoll habitat is identified in both scenarios, i.e. areas where quolls should persist)

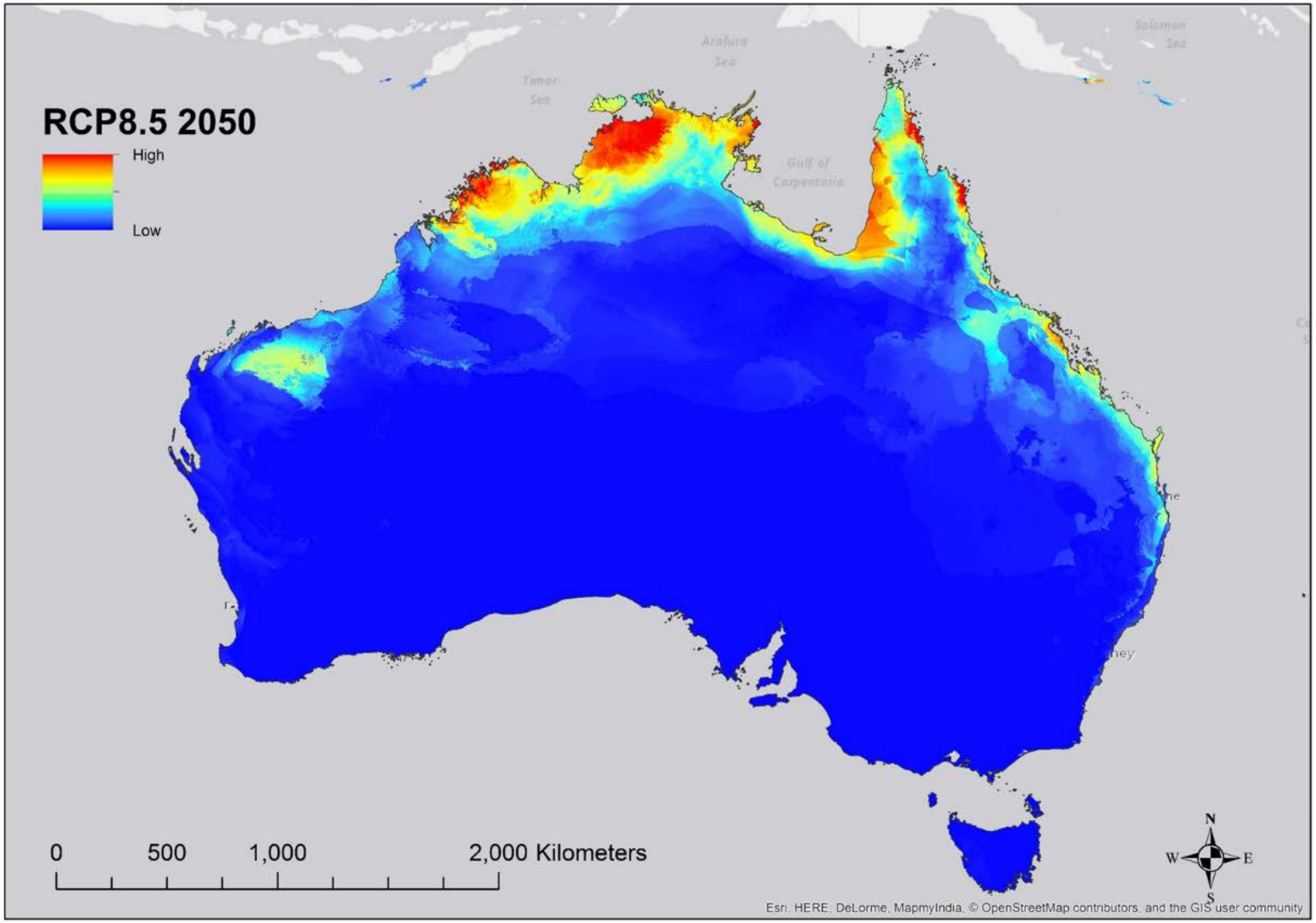


Figure 28: MaxEnt projection for the Access 1.0 RCP 8.5 2050 scenario

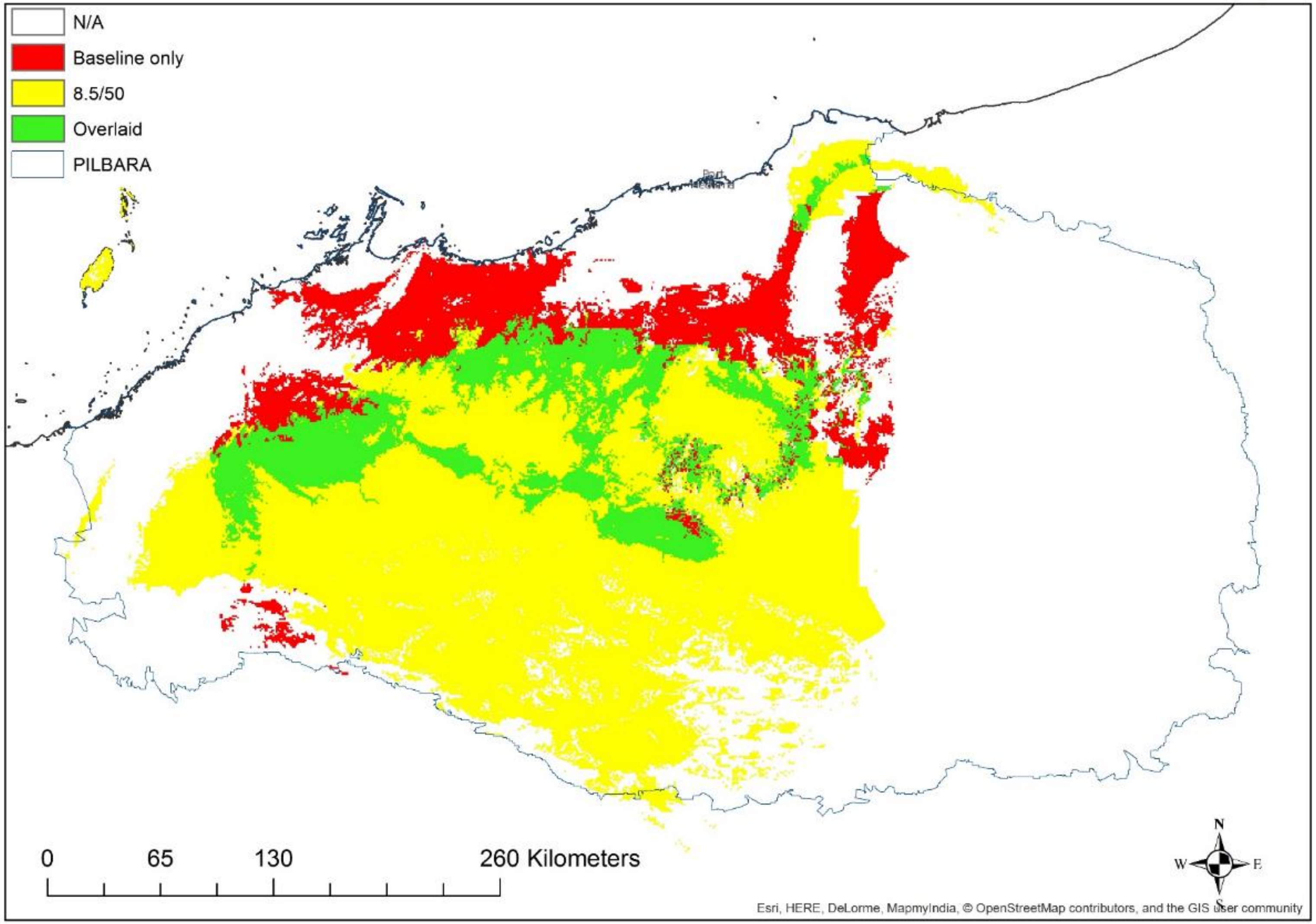


Figure 29: Pilbara baseline thresholded overlaid with Access 1.0 RCP 8.5 2050 scenario thresholded
(Green "Overlaid" areas indicate where northern quoll habitat is identified in both scenarios, i.e. areas where quolls should persist)

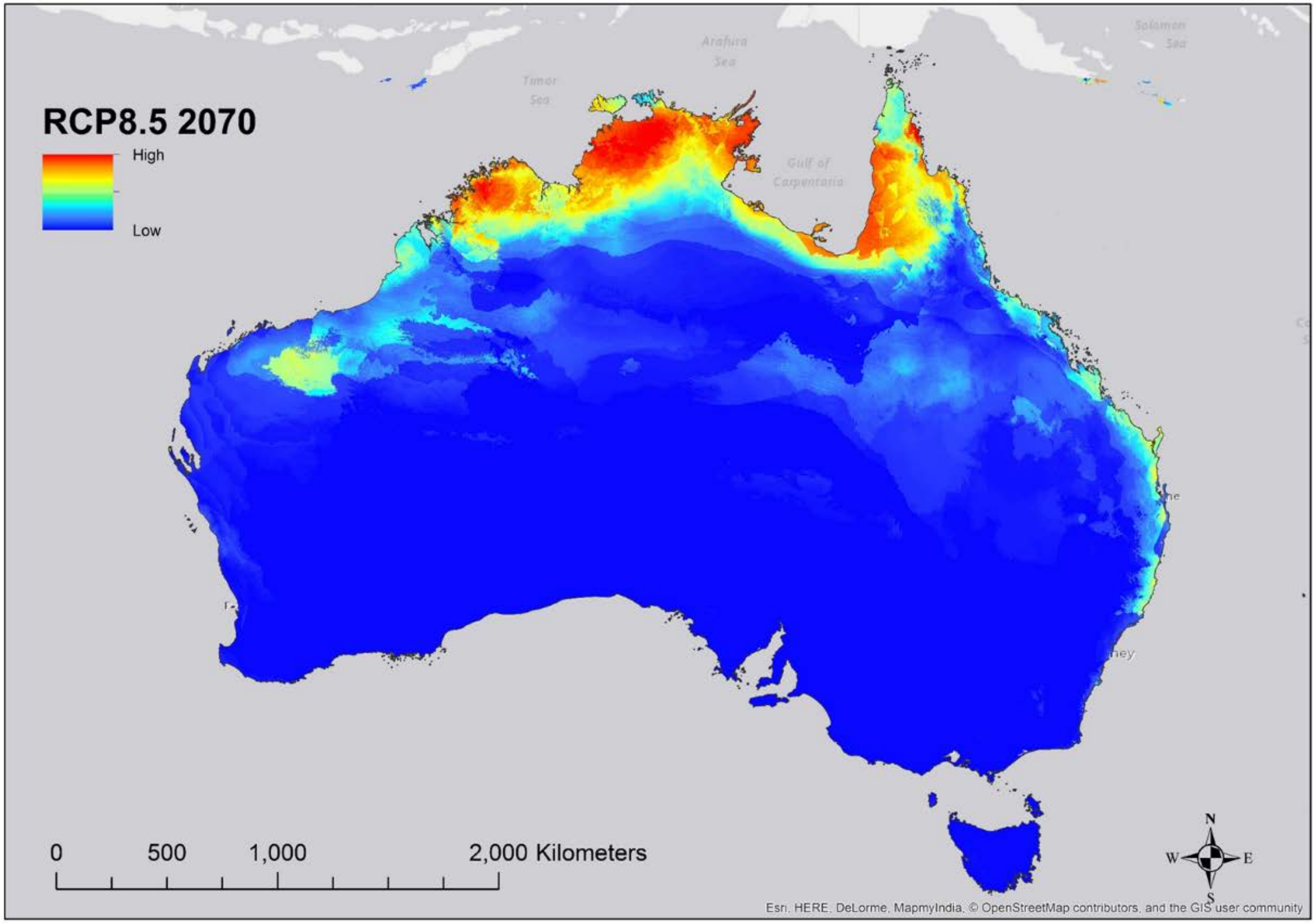


Figure 30: MaxEnt projection for the Access 1.0 RCP 8.5 2070 scenario

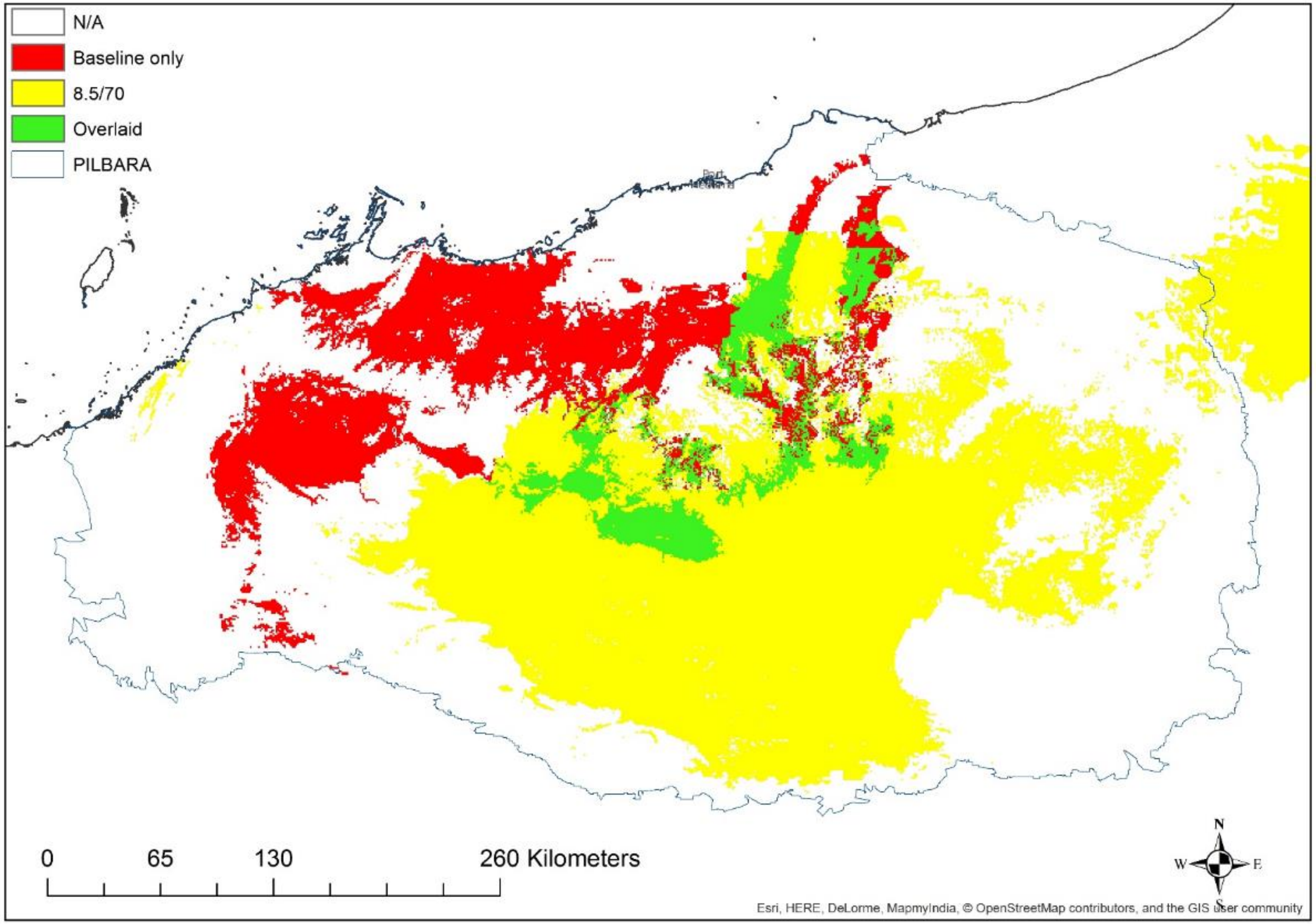


Figure 31: Pilbara baseline thresholded overlaid with Access 1.0 RCP 8.5 2070 scenario thresholded
(Green “Overlaid” areas indicate where northern quoll habitat is identified in both scenarios, i.e. areas where quolls should persist)

4.2.6 Conclusions

In making conclusions on this exercise it is necessary to consider the limitations of this exercise, i.e.:

- It has been undertaken at a national scale with a proportionately smaller presence data set. Consequently, when looking at a landscape the size of the Pilbara the model will lack the resolution of the finer scale preferred SDM.

- The influence of population specific variables such as vegetation type, soil type and topography have not been used. This too will cost the SDM resolution.

- The certainty of the climate change scenarios used for the northern Rangelands is relatively low. There is a high level of conflict in the CMIP5 models from which the Access 1.0 coupled model is derived.

- No bias compensation was used in the development of this SDM.

Having acknowledged these limitations the following conclusions can be drawn:

- The northern quoll bioclimatic envelope appears to be moving in a north-easterly direction.

- The magnitude of this movement appears to be directly influenced by magnitude of the emission scenario and time-frame.

- It represents a spread of PD into the Great Sandy Desert, where a new population have recently been found (Turpin and Bamford 2014). It should be noted that, although PD spreads into this largely sandy area, actual distribution will still rely on the availability of suitable terrain and resources within in these landscapes.

- Under the worst-case scenarios, much of the current PD in the eastern Pilbara, including many areas known to support comparatively high northern quoll densities, may no longer be able to support this species. However, other areas may become more suitable for this species.

- High emission/longer term scenarios depict the greatest disruption to northern quoll populations in the western Pilbara.

4.3 Cane toads

There have been quite a few predictive, national scale, national scale SDMs constructed to demonstrate the PD of the cane toad and how this will change with the predicted impacts of climate change (Figure 32-36). These SDMs vary greatly both in methodology and in the sophistication of their design and implementation. Therefore, it is not surprising to find that their outputs vary enormously both in current and predicted PDs. It should be noted that modelling for central Western Australia and the Pilbara is particularly conflicting.

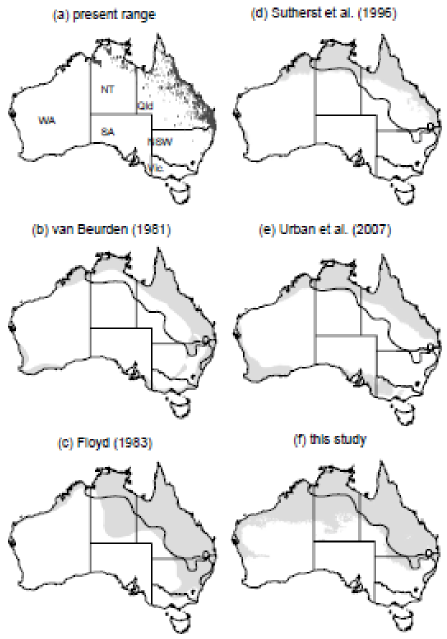


Figure 32: A comparison of Cane Toad *Rhinella marina* SDMs from Kearney et al. (2008). The 2008 distribution (a) and four predictions of its potential final distribution under average climatic conditions (b-e), and Kearney's (2008) model (f). The heavy, black line defines the approximate 2008 PD.

Figure 33: A comparison between current distribution and estimated distribution under the RCP8.5 2075 scenario from James Cook University CLIMAS data base (Van der Wal, 2014)

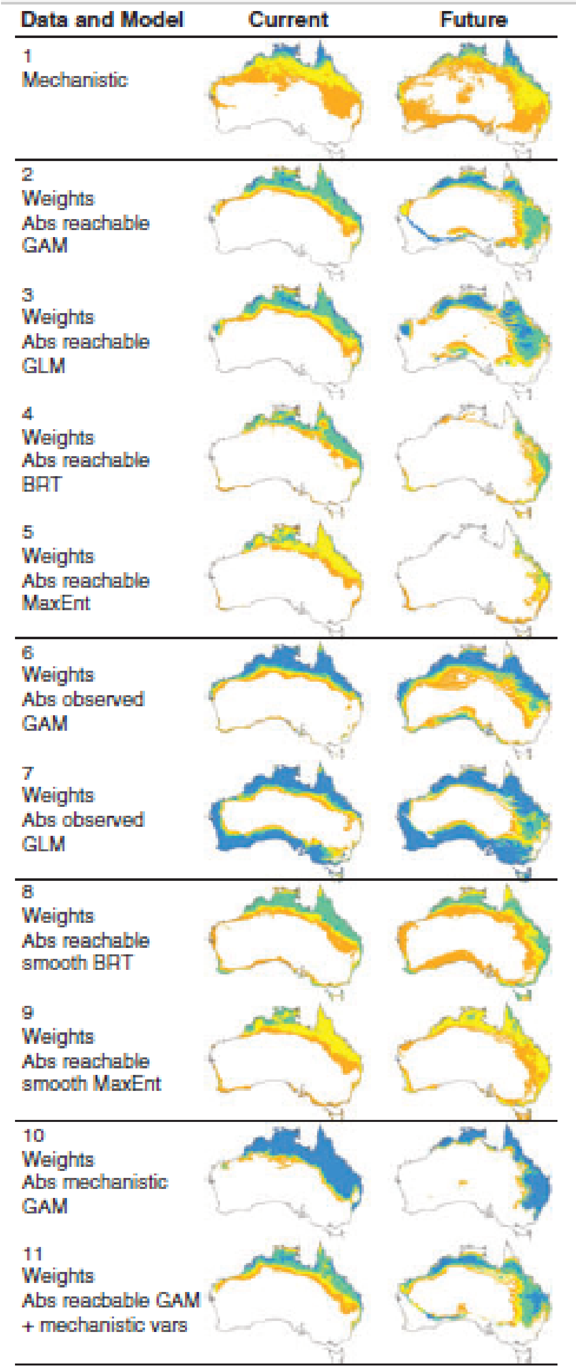


Figure 34: Multiple tool modelling undertaken by Elith et al. (2010). Current and future predictions of the distribution of the cane toad, for various model types and data treatments. Predictions are coded white (low) to orange–yellow–green–blue (high)

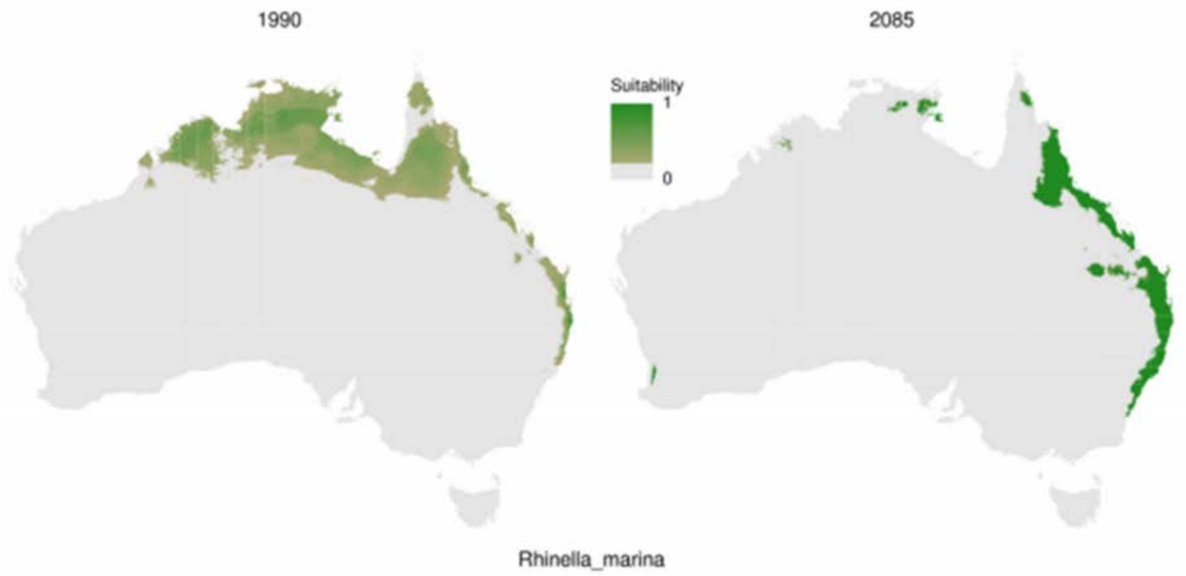


Figure 35: Cane toad habitat suitability modelling under climate change by Pavey and Bastin (2014).

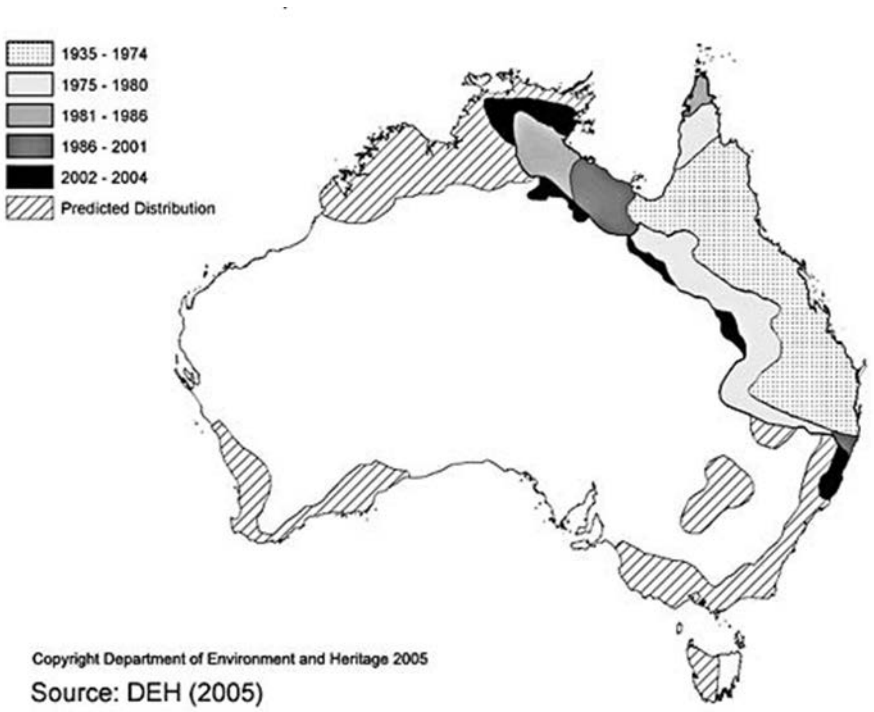


Figure 36: Cane toad predictive SDM as provided by Department of Environment and Heritage (2005)

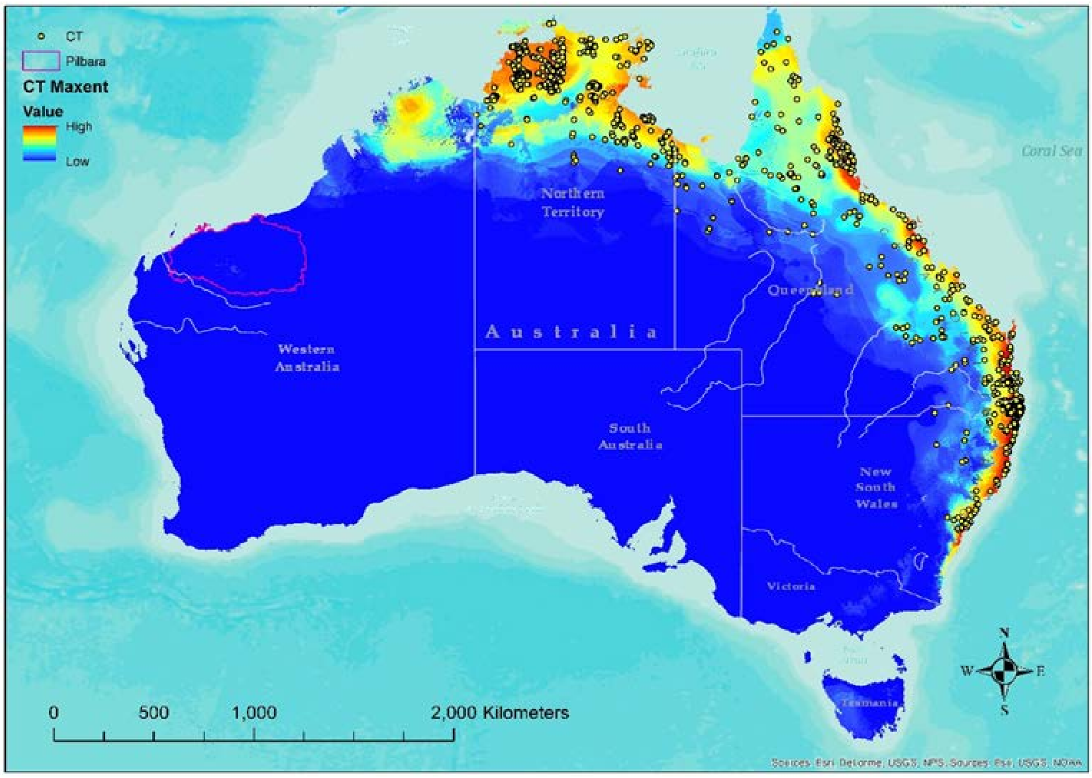


Figure 37: Test bioclimatic modelling using MaxEnt and the methodology described in section 3.2.2

A review of the cane toad SDMs leads to two questions: 1) why is modelling the cane toad so difficult, and 2) which of these SDMs is most likely to be the more accurate?

4.3.1 Why is modelling the cane toad so difficult?

When building SDMs, it should be remembered that not all subjects are equal when it comes to suitability. This is particularly so when modelling range shifting species such as the cane toad (Elith et al., 2010). In modelling the cane toad we have to account for the following limitations:

- We do not have a historical distribution of this species in this country, nor have they as yet reached their full PD. Therefore, those areas where they are present do not fully reflect their potential distribution (Elith et al., 2010). This is particularly so in Western Australia, a state into which they have only recently invaded and into which they are currently and rapidly expanding (Doody et al., 2015).

- PD for the cane toad might well be largely defined by such cryptic independent variables as humidity (Kearney et al., 2008) and non-bioclimatic variables such as access to permanent water (Tingley et al., 2013).

- This species has demonstrated a capacity to "hitch" rides on commercial and private transport, thereby enabling it to bypass barriers such are large areas of unsuitable habitat (Shukla et al., 2004).

- The Olympic Village phenomenon (i.e. Where organisms living at the edge of their range have a tendency to be phenotypically better able to adapt to their 'frontier' environment, than others of their species. Furthermore, frontier environments provide significant evolutionary incentives to individuals that demonstrate these adaptations) means that the capacity for this species to adapt to new ecological niches and its responses to changes in predictive variables are difficult to predict (Phillips et al., 2010).

- In light of the above, there are strong indications that the ecological niche of the cane toad has shifted, and that this process is continuing (Tingley et al., 2014).

- Many of the previous SDMS were constructed using outdated climate scenarios. In this exercise we are using the Access 1.0 climate model, a coupled model based on the more recent CMIP5 models (Bi et al., 2013).

In undertaking a simple MaxEnt SDM (Figure 37) these shortcomings became evident. In that this model does not expand PD much further than historical presences nor does is allow for humidity, a variable identified as intrinsic for the survival of non-burrowing amphibians as moist air buffers amphibians from temperature variation effects and helps to maintain skin moisture and respiration (Child et al., 2008; Elith et al., 2010; Kearney et al., 2008). Furthermore, one of the major factors limiting the movement of cane toads into arid areas is the lack of permanent water, which allows cane toads to breed and to persist in drought conditions. This model does not account for the fact that there are enough permanent water bodies, both natural and man-made, throughout the north-west to facilitate the persistence and movement of cane toads south, through the Pilbara and beyond (Tingley et al., 2013).

In light of the above conversation, and in recognition that many of the cane toad SDMs have been constructed through major specialist projects with resources beyond those of this exercise using current best practice methodologies, we opted to review and evaluate existing projects rather than replicate their methodologies. It was decided that to undertake such a review it should be based on variables identified through the literature, using a new methodology to gather a new insight into the PD of the cane toad and how it may respond to climate change and that the methodology should be comparatively simple to undertake and understand.

To that end it was decided to construct a sum overlay GIS SDM.

4.3.2 Constructing a sum overlay/GIS SDM

Simple sum overlay models are basic applications of logic, in that the more parameters that are met the higher the value. We chose to adopt an approach similar to that used by Lenton et al.

(2000), in that through a review of the literature a suite of ten bioclimatic variables were chosen. In this example, a suite of predictive variables are nominated and maximum and minimum values for each of these variables are identified. Where a pixel in each variable data set falls between these parameter values a score of one is give. If the value falls outside of these parameters a score of 0 is given. Once a score is given for all pixels in all data sets, the data sets are overlaid and the scores for each pixel are added up. The underlying assumption being that the more often parameters are met, the greater the likelihood that the pixel represents potential distribution. Through this process an SDM was developed was compared with existing cane toad models and conclusions drawn.

In a GIS environment a national dataset of cane toad presences were taken from the Atlas of Living Australia (2015) (*n*= 6,069). This data set was compared with each of the ten bioclimatic variable data sets gathered through a review of the literature. Parameters were defined using the geostatistical analyst tool in ArcGIS 10.3 to define a set of maximum and minimum parameters using a 95% confidence interval as a cut-off to diminish outlier effects. Variables and parameter values are given below (Table 12).

No maximum values were set for maximum temperature and moisture related variables, as both the literature and data, examined and tested during the modelling process, suggest that you can't have too much water for cane toad persistence and that very high temperatures are not a problem for cane toads where there is adequate moisture.

Table 12: Variables and parameters used in the sum overlay SDM. Blacked lines indicate data set source.

WorldClim	**Parameter values**
BIO1 = Annual Mean Temperature	>186 & <290
BIO3 = Isothermality (BIO2/BIO7) x 100	>45.2 & <62.8
BIO4 = Temperature Seasonality (standard deviation x 100)	>1847.7 & <4368.38
BIO5 = Max Temperature of Warmest Month	>238.5
BIO8 = Mean Temperature of Wettest Quarter	>201
BIO11 = Mean Temperature of Coldest Quarter	>136
BIO12 = Annual Precipitation	>675.7
BIO18 = Precipitation of Warmest Quarter	>230.4
Climond	
BIO34=Mean moisture index of warmest quarter	>34
CSIRO	
Relative Humidity Wettest Quarter	>0.424

The result of this exercise are given below and compared with the generally accepted cane toad SDMs (Figure 38). This comparison shows a high degree of similarity at the sum overlay model score of ≥seven with the models produced by Elith et al. (2010), Kearney et al. (2008) and Tingley et al. (2014). It should also be noted that in when cane toad presences (with outliers removed at a 95% confidence interval) are overlaid on this SDM, cane toads appear occur at, and above, this value. There are rare occurrences at a score of six but there are no presences below this value (Figure 39). This supports or finding, i.e. if current trends persist cane toads will probably invade the western half of Pilbara. Further, it enables us to demonstrate how changes in these variables due to climate change may impact on the PD of the cane toad in the Pilbara.

To demonstrate how climate change would impact on cane toad PD, the above method (using the same parameters) was repeated using the Access 1.0 coupled model using both the RCP4.5 and 8.5 emission scenarios over the 2050 and 2070 timeframes.

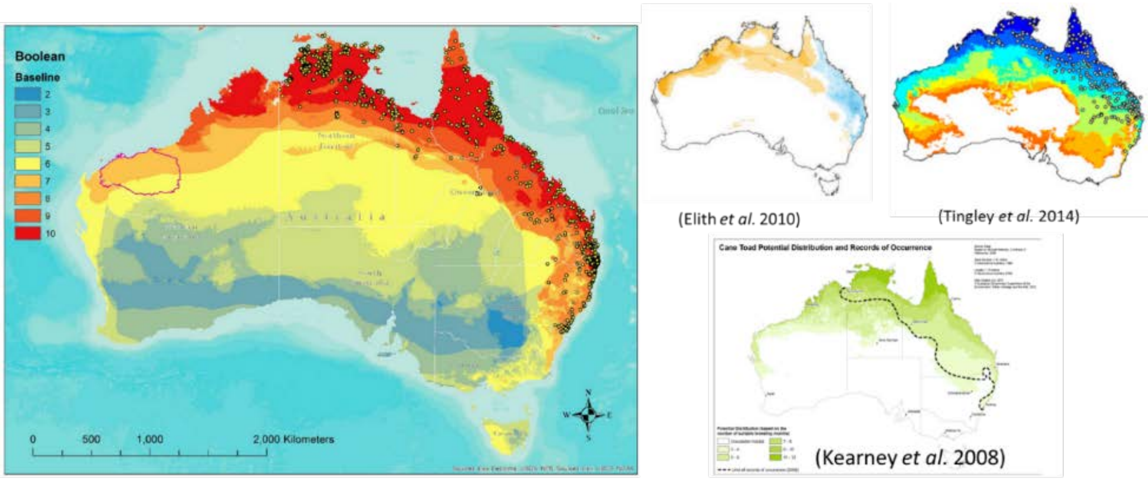


Figure 38: At a threshold of ≥7 the sum overlay model (left) complies strongly with the Elith et al. (2010), Tingley et al. (2014) and Kearney et al. (2008) models.

4.3.3 Cane toad SDM, results

A summary of all results for the risk presented by cane toad invasion comparative to the baseline northern quoll distribution given in the preferred MaxEnt model is given below (Table 13):

Table 13: Percentage of Pilbara northern quoll habitat (baseline MaxEnt preferred model, thresholded) within each cane toad invasion risk score by Access 1.0 climate change scenario.

Climate Change Scenario	Probable (Score 7)	Possible (Score 6)	Unlikely (Score 5)
Baseline	100		
RCP4.5 2050	52	48	
RCP4.5 2070	36	64	
RCP8.5 2050	38	51	11
RCP8.5 2070	32	55	13

Baseline: The national scale sum overlay baseline SDM for cane toad presence with recorded presences overlaid (with outliers removed) is given shown in Figure 39. As previously stated, this model complies with, and substantiates, the SDMs developed by Elith et al. (2010), Kearney et al. (2008) and Tingley et al. (2014). Correlating most strongly with the SDM developed by Elith et al. (2010). In Western Australia it shows that, under current bioclimatic conditions and unchanged management actions, it is probable that the cane toad has the capacity to invade an, approximately, 300km wide strip along the north-west coast, through the Pilbara, and a possibility that this invasion will spread further inland and to the south. A Pilbara scale overlay of this SDM over the thresholded preferred MaxEnt model (Figure 40) shows that nearly all of identified as baseline PD for the northern quoll will be within pixels with a score of seven in the sum overlay SDM, i.e. probably vulnerable to cane toad invasion.

RCP4.5 2050: The national scale SDM cane toad presence with for this climate change scenario (Figure 41) shows a small general contraction in cane toad PD towards wetter and coastal areas compared to the baseline model. In Western Australia it shows, under this climate scenario, a small contraction in cane toad PD towards the coast compared to the baseline SDM. The Pilbara scale overlay shows a reduction from the baseline model from 100% to 52% of northern quoll PD being probably vulnerable to cane toad invasion and the remaining 48% of quoll PD being within a pixels with a score of six, i.e. potentially vulnerable to cane toad invasion (Figure 42).

RCP4.5 2070: The national scale SDM cane toad presence with for this climate change scenario (Figure 43) shows a further small but general contraction in cane toad PD towards wetter and coastal areas in comparison to the RCP4.5 2050 model. In Western Australia it shows that, under this climate scenario, the contraction in cane toad PD compared to the baseline model observed in the previous model will continue. The Pilbara scale overlay shows a reduction in cane toad PD in comparison to that given in the RCP4.5 2050 from 52% to 36% of the northern quoll distribution probably vulnerable to cane toad invasion, and the remaining 64% of quoll PD remaining potentially vulnerable to cane toad invasion (Figure 44). Of note is an anomalous increase in cane toad PD score from six to seven in a substantial part of the Hamersley Ranges.

RCP8.5 2050: The national scale SDM cane toad presence with for this climate change scenario (Figure 45) shows that the general contraction in cane toad PD towards wetter and coastal observed in previous scenarios will continue. In Western Australia it shows that, under this climate scenario, trending contractions observed in previous models will also continue. The Pilbara scale overlay shows a small increase in probable cane toad PD, in comparison to that given in the RCP4.5 2070 scenario, from 36% to 38% of the area identified as baseline PD for the northern quoll. Approximately 51% of northern quoll baseline is potentially vulnerable to cane toad invasion and 11% of quoll PD is now within the now has a score of cane toad PD score of 5, i.e. the threat of cane toad invasion is unlikely (Figure 46). The anomaly previous noted in the Hamersley Ranges has disappeared in this scenario.

RCP8.5 2070: The national scale SDM cane toad presence with for this climate change scenario (Figure 47) shows the general contraction in cane toad PD towards wetter and coastal observed in previous scenarios will continue with a southerly movement on the east coast becoming more pronounced. In Western Australia it shows that, under this climate scenario, trending contractions observed in previous models will continue. The Pilbara scale overlay shows a decreased area subject to probable cane toad invasion, in comparison to that given in the RCP8.5 2050, from approximately 38% to 32% of northern quoll PD. Approximately 55% of quoll PD remains potentially vulnerable to cane toad invasion and 13% of quoll PD, remains unlikely to be impacted by cane toad invasion (Figure 48).

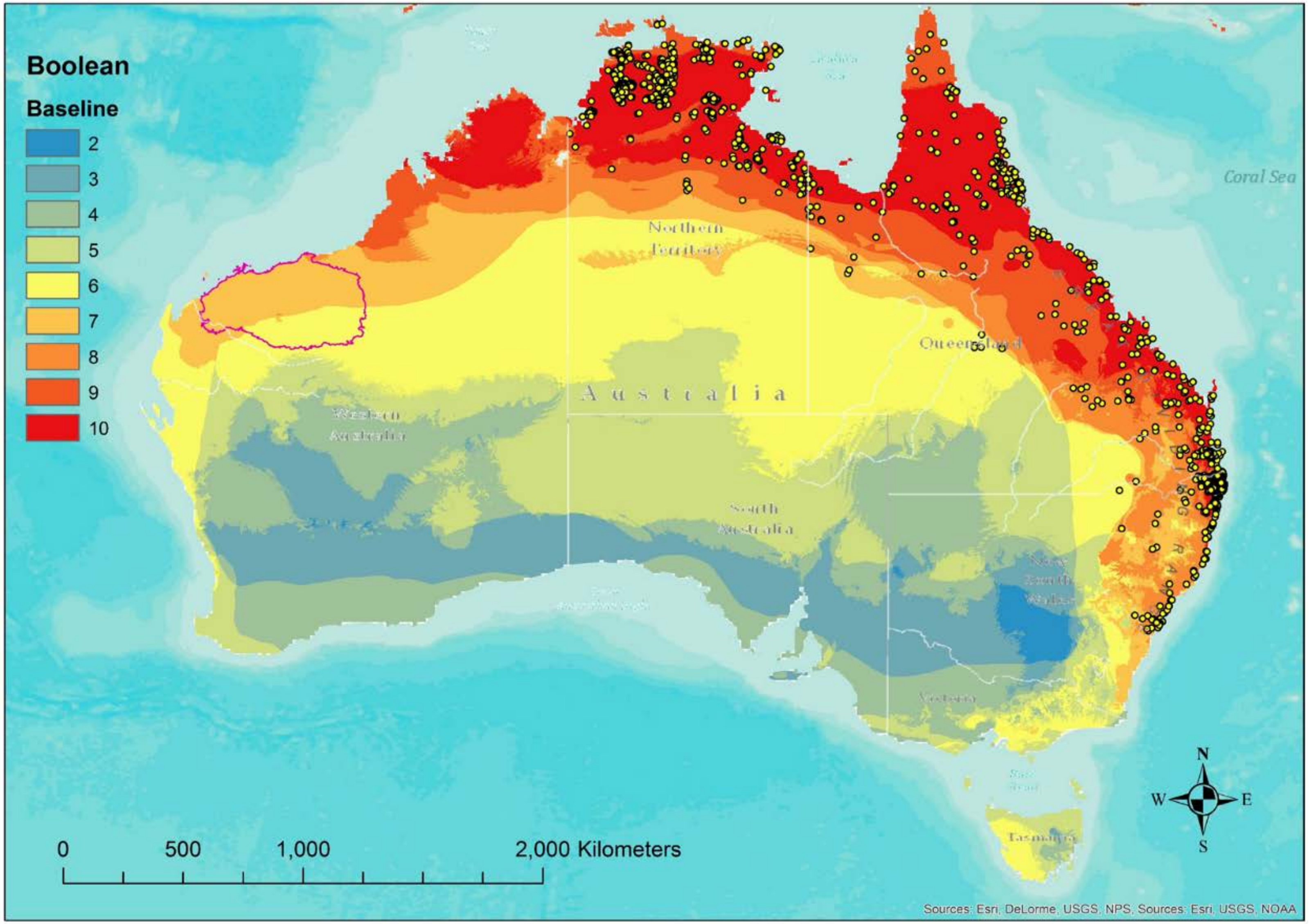


Figure 39: Sum overlay SDM baseline potential distribution, Australia wide

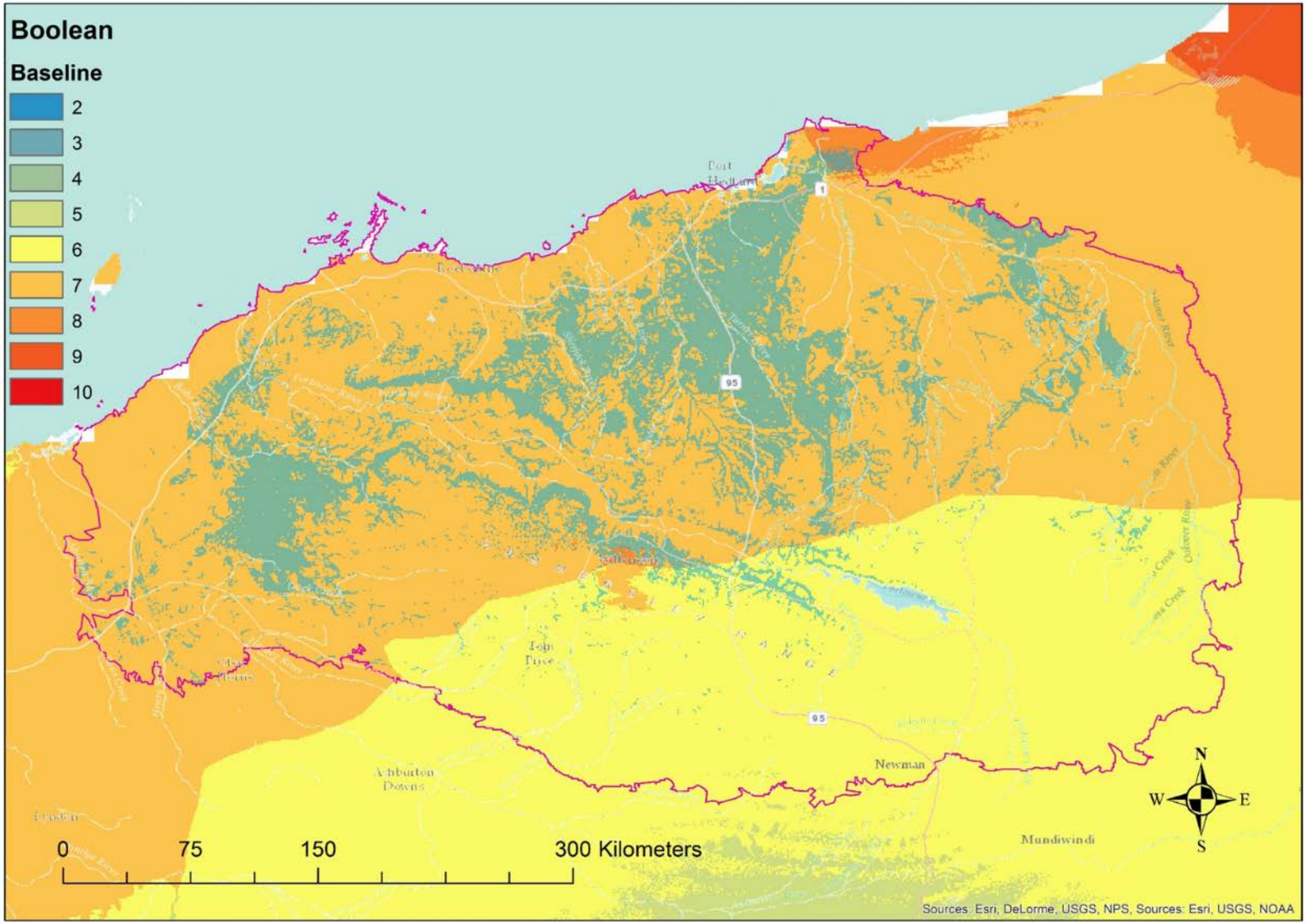


Figure 40: Sum overlay SDM baseline potential distribution for Pilbara overlaid on thresholded NQ extent (Figure 23) in blue

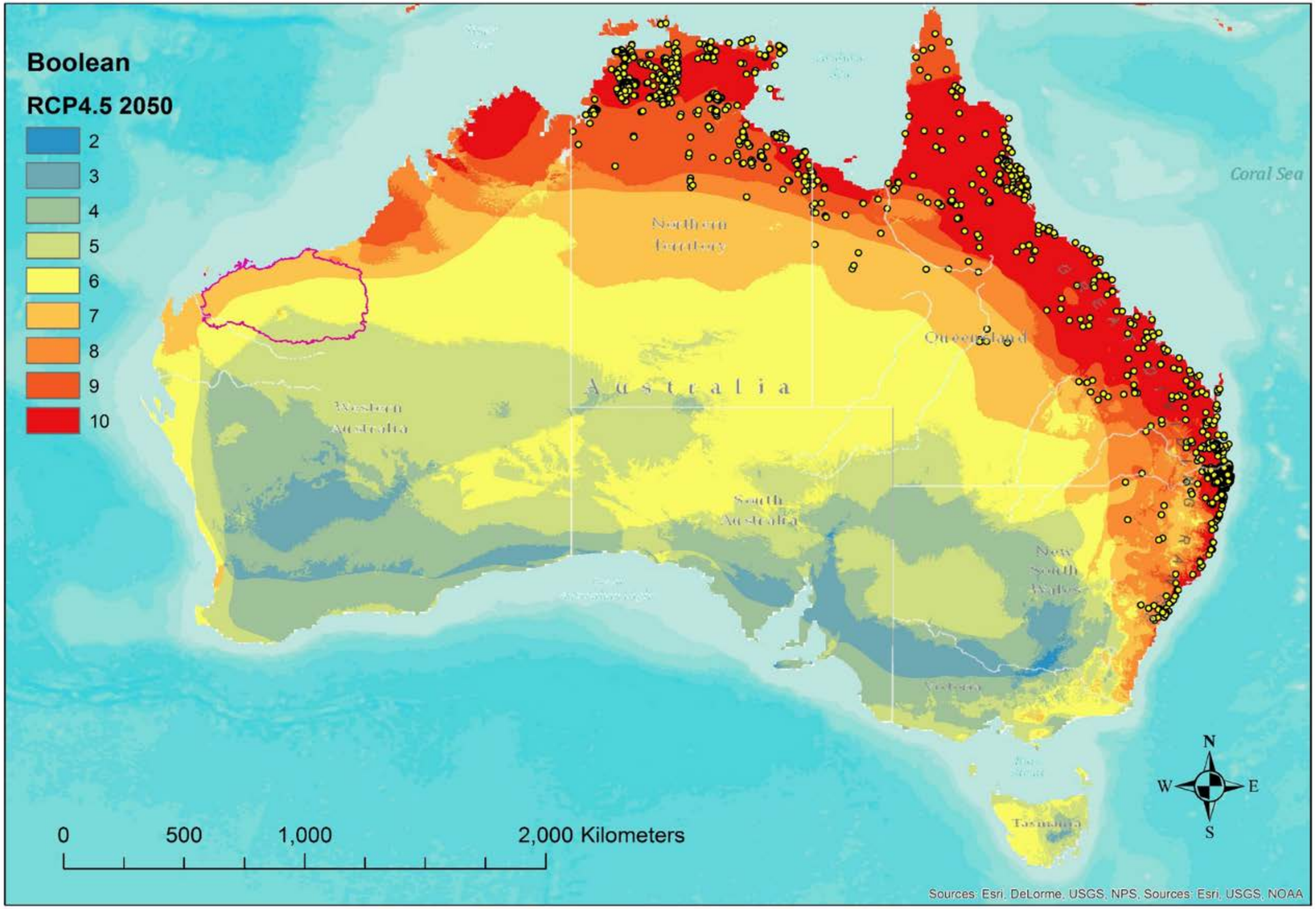


Figure 41: Sum overlay SDM Access1.0 RCP 4.5 2050 scenario potential distribution, Australia wide

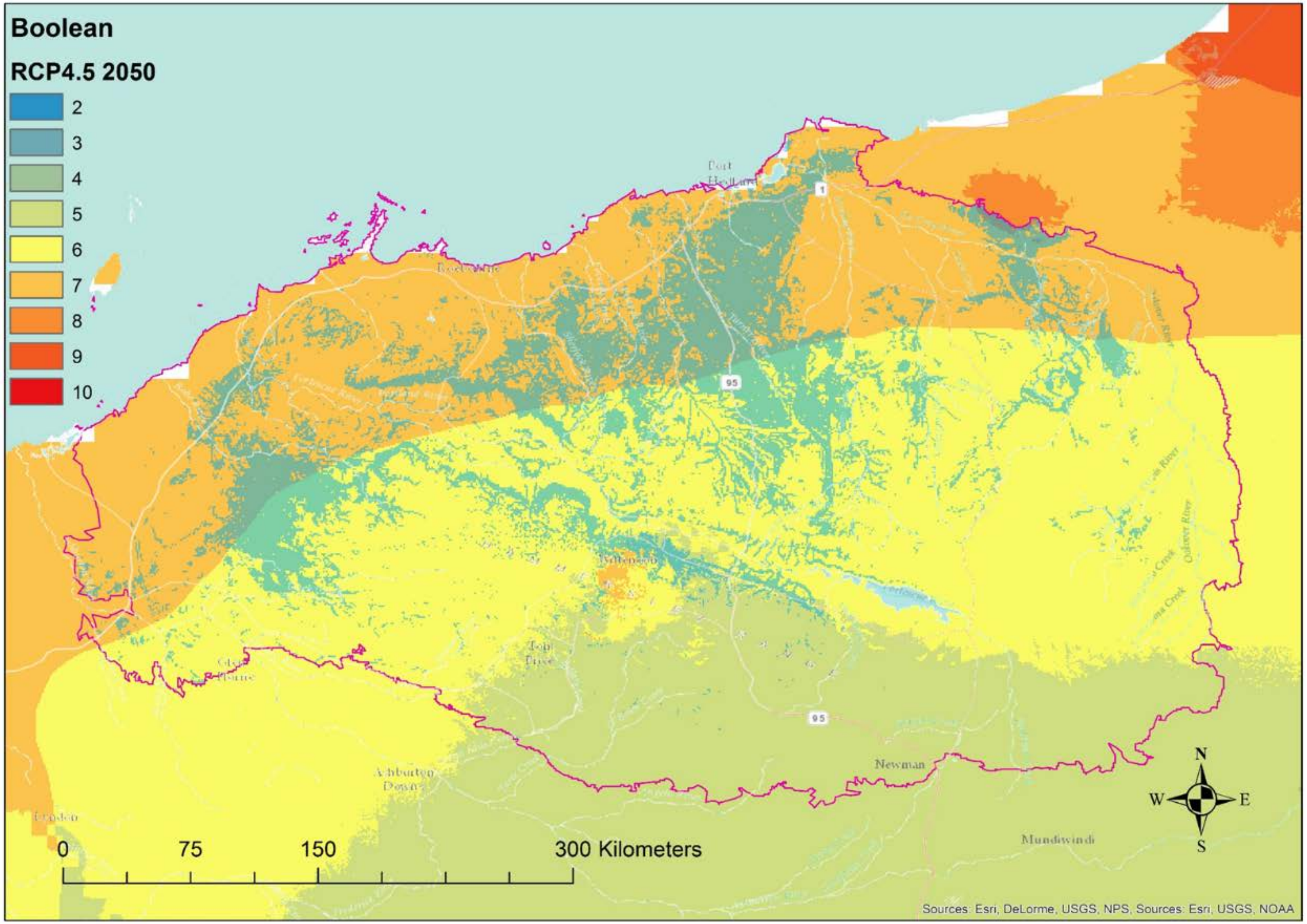


Figure 42: Sum overlay SDM Access1.0 RCP 4.5 2050 scenario potential distribution overlaid on thresholded NQ extent (Figure 23) in blue

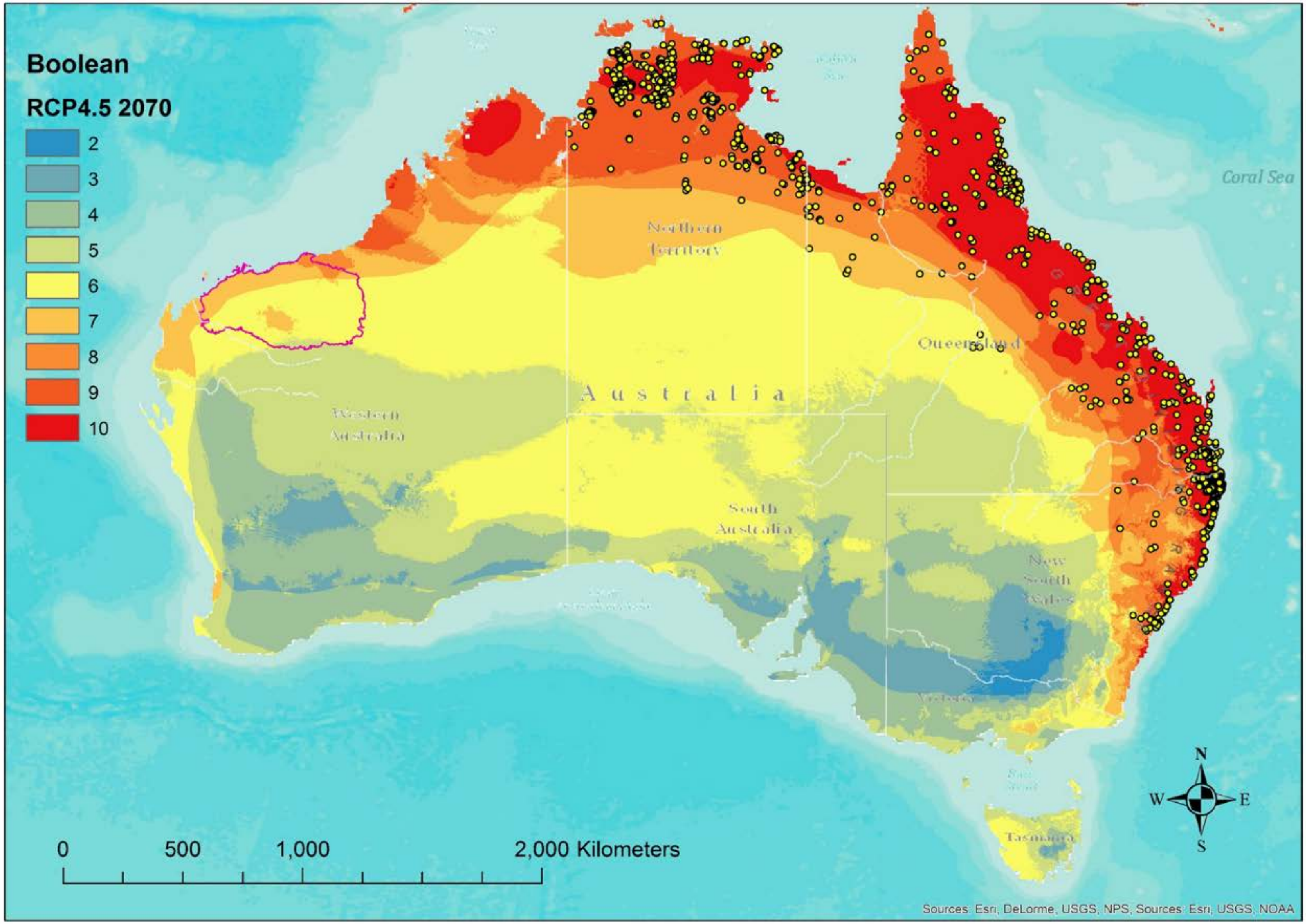


Figure 43: Sum overlay SDM Access1.0 RCP 4.5 2070 scenario potential distribution, Australia wide

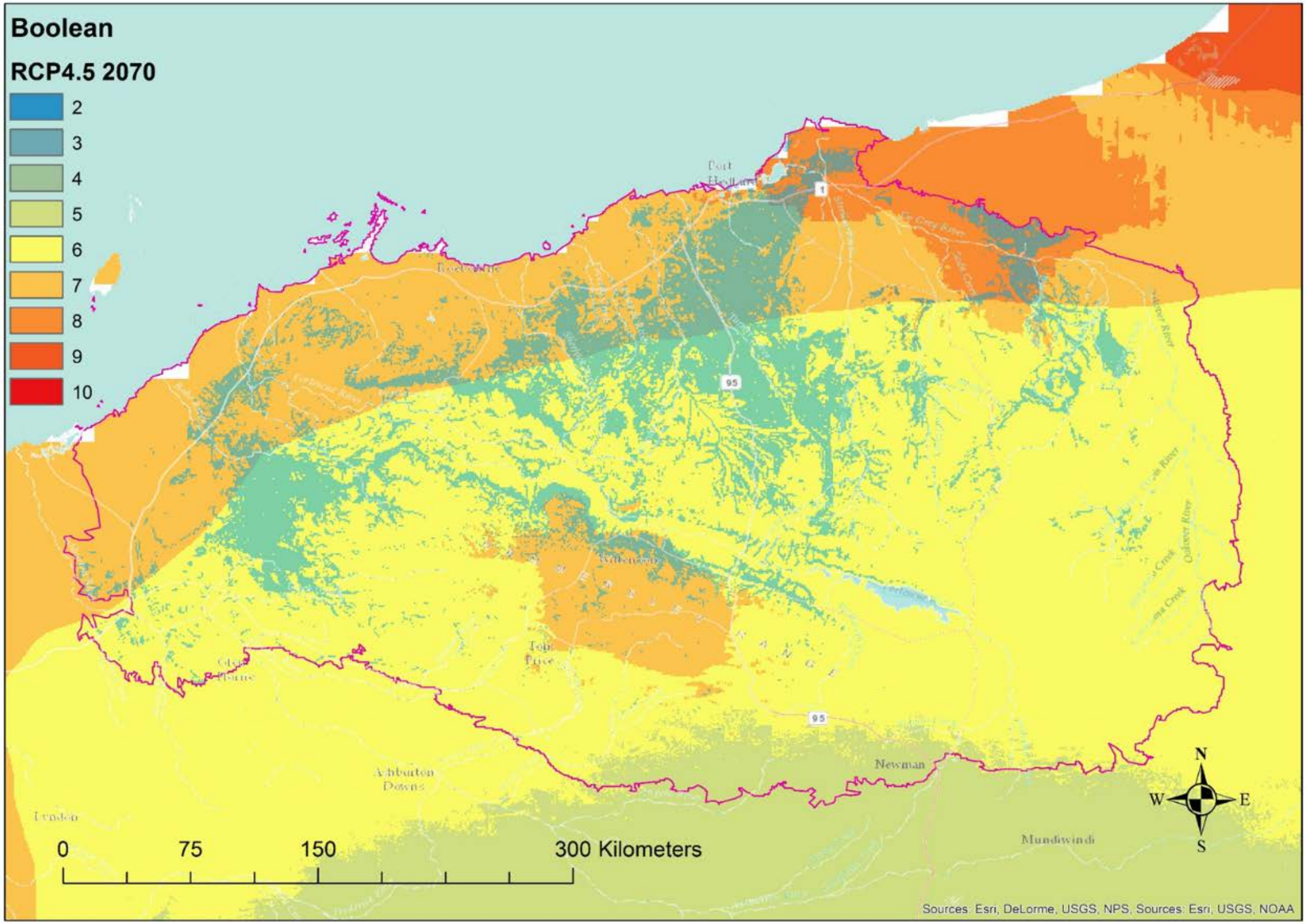


Figure 44: Sum overlay SDM Access1.0 RCP 4.5 2070 scenario potential distribution overlaid on thresholded NQ extent (Figure 23) in blue

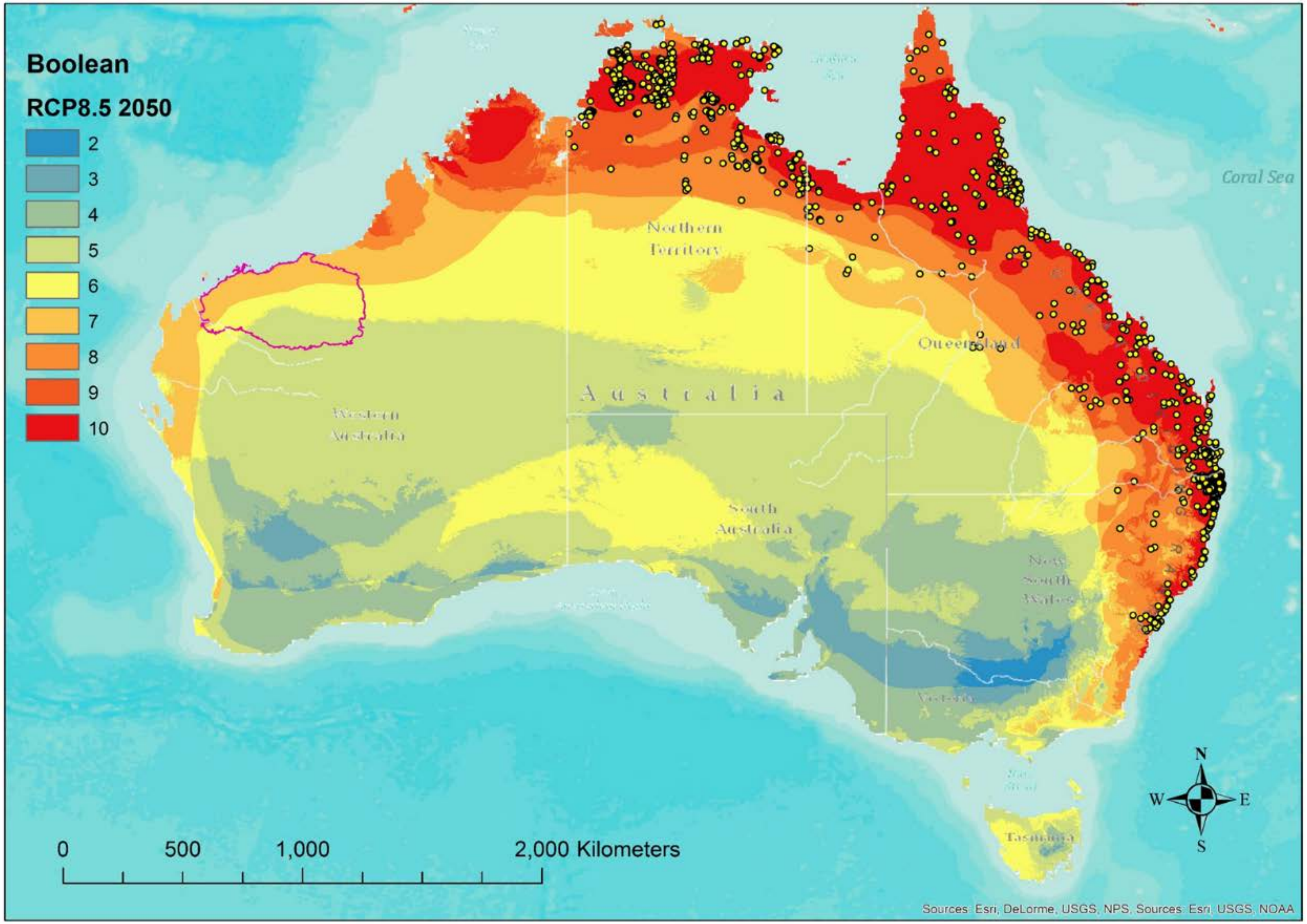


Figure 45: Sum overlay SDM Access1.0 RCP 8.5 2050 scenario potential distribution, Australia wide

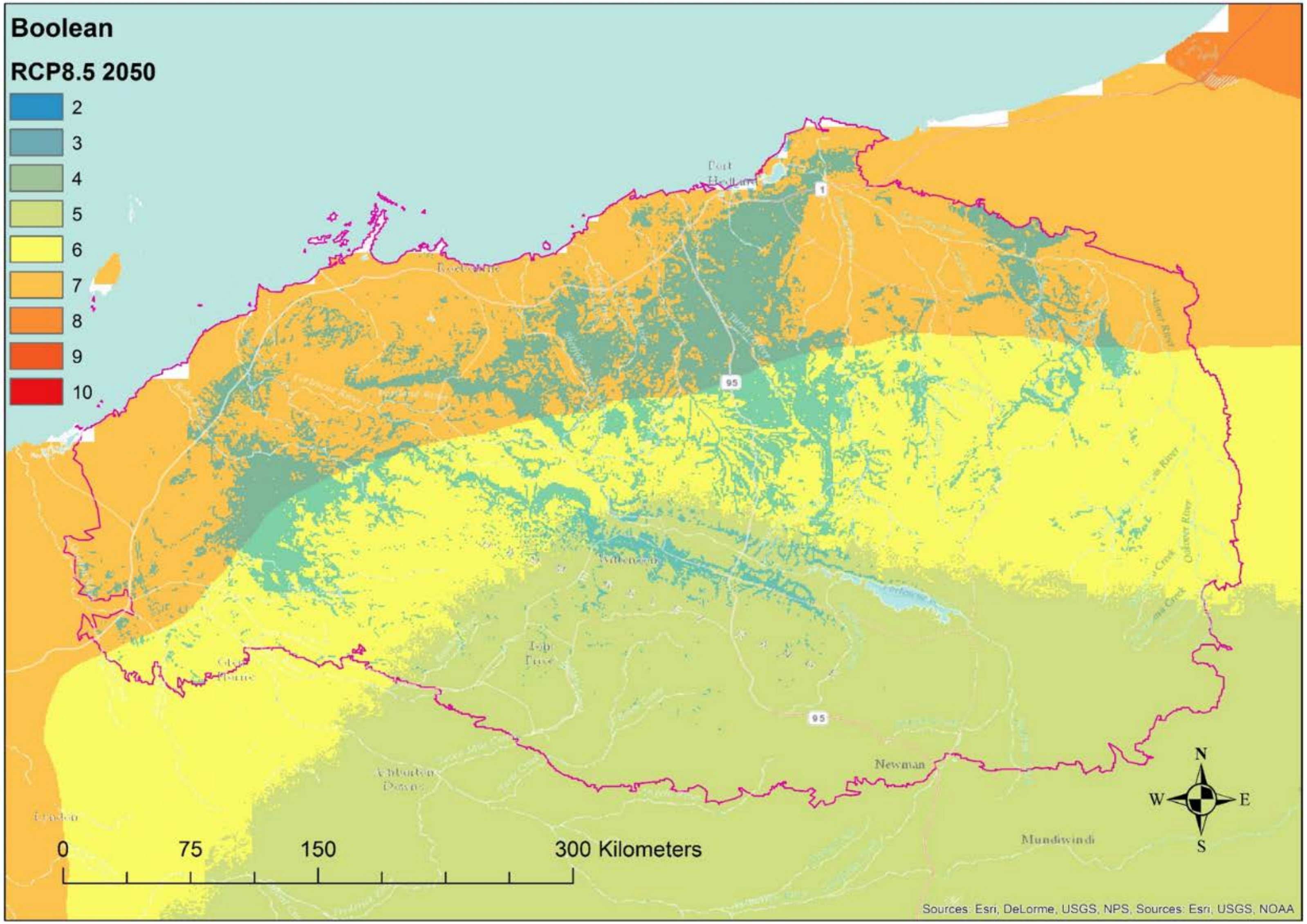


Figure 46: Sum overlay SDM Access1.0 RCP 8.5 2050 scenario potential distribution overlaid on thresholded NQ extent (Figure 23) in blue

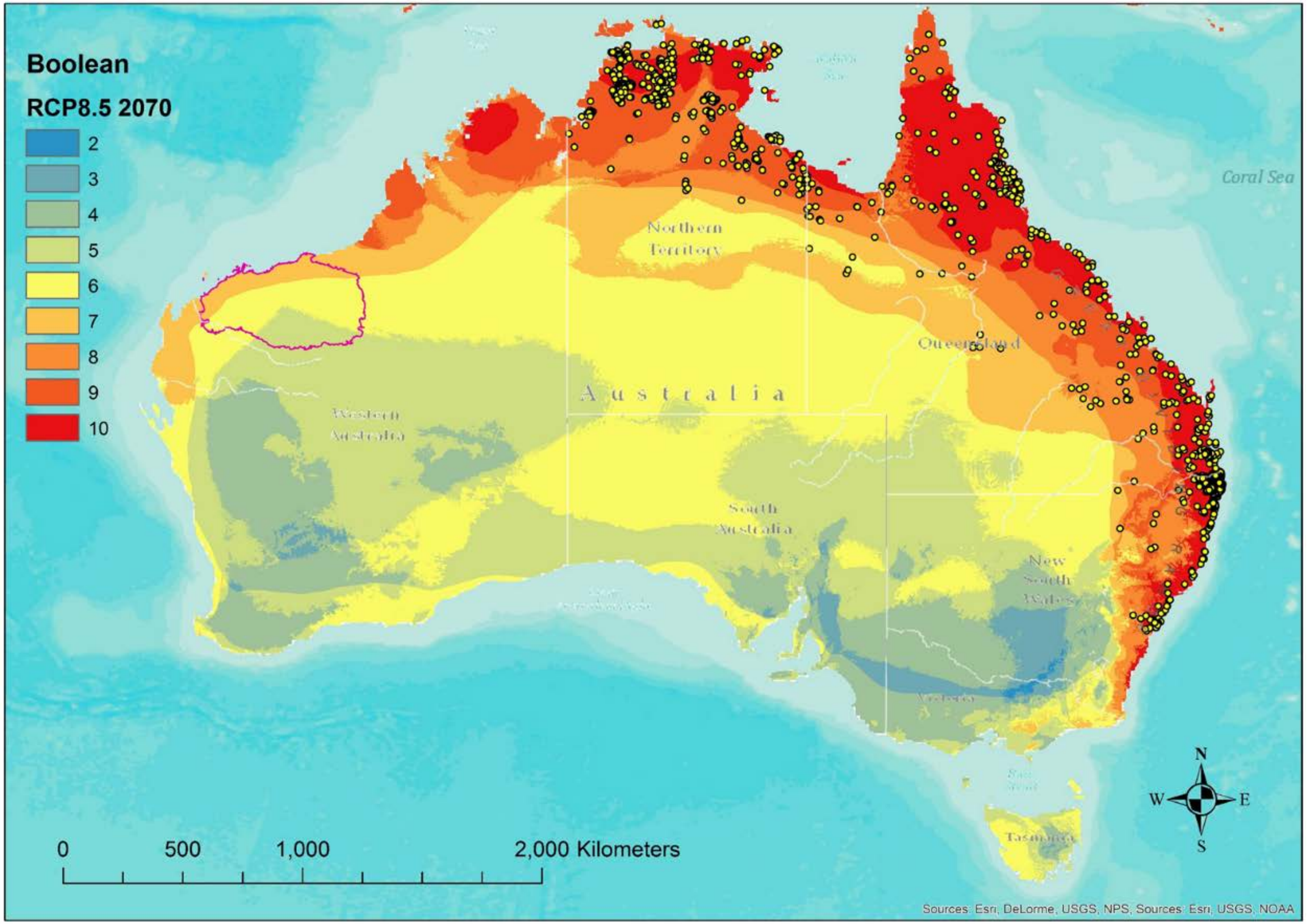


Figure 47: Sum overlay SDM Access1.0 RCP 8.5 2070 scenario potential distribution, Australia wide

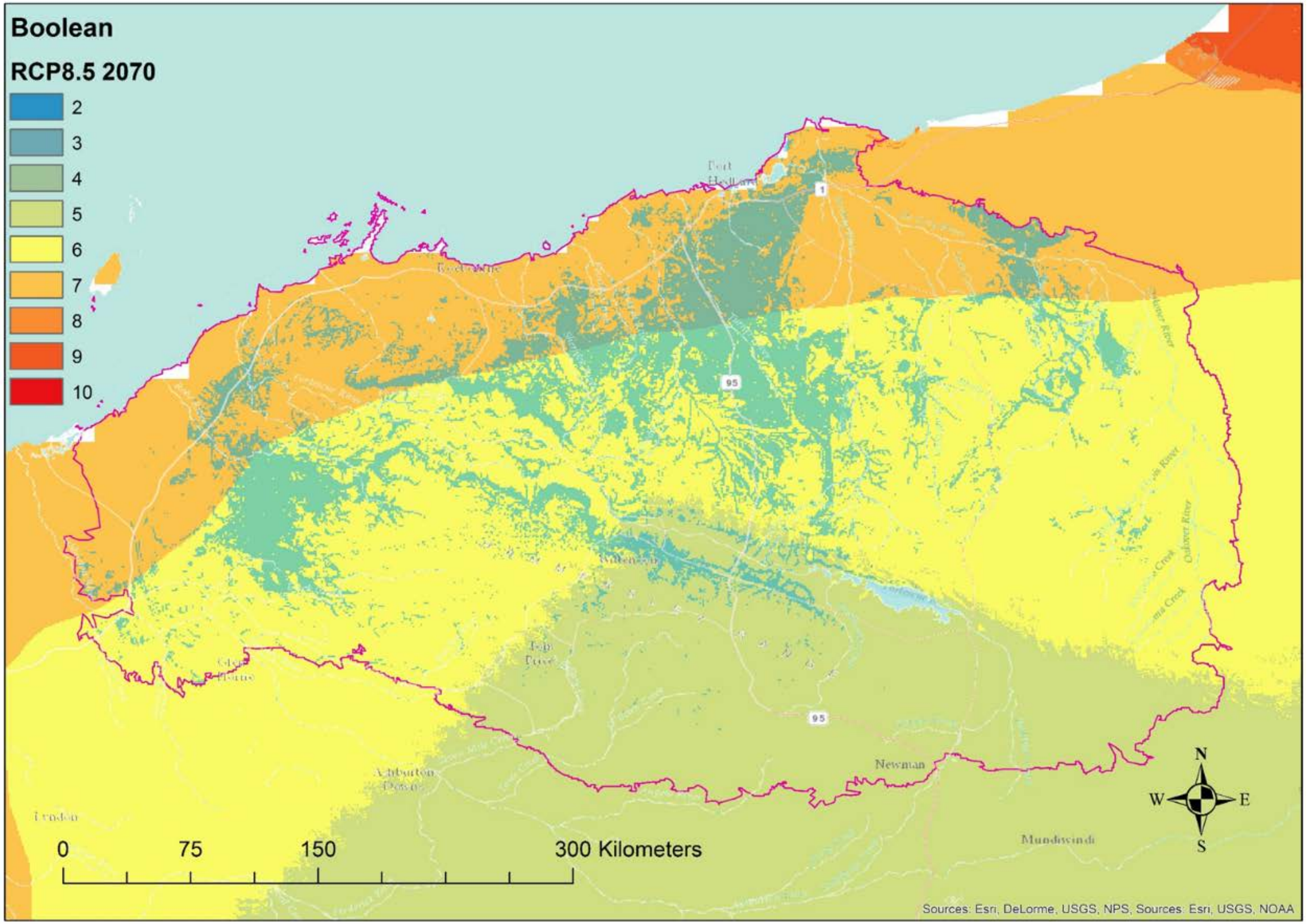


Figure 48: Sum overlay SDM Access1.0 RCP 8.5 2070 scenario potential distribution overlaid on thresholded NQ extent (Figure 23) in blue

4.3.4 Conclusions

In recognising the limitations of this exercise, i.e. that it is a broad scale modelling exercise of a range shifting species undertaken with uncertain climate modelling and using comparisons with previous modelling exercises as its main substantiation, we can still draw the following conclusions:

- Models indicate that under current climatic conditions it is probable that cane toads can invade the Pilbara and, if they do, they should be able to persist in much of the Pilbara.

- Across north-western Australia this, like other cane toad modelling exercises that we examined, shows that climate change will probably result in a westerly contraction in cane toad PD towards the coast, and that is contraction will be greater with more severe emission scenarios and greater timeframes.

4.4 Cane toad and northern quoll interaction

The models shown in section 4.3.3 demonstrate that, within the Pilbara, cane toad PD under baseline bioclimatic conditions coincides strongly with the preferred MaxEnt SDM for the PD of northern quoll. This indicates that, under current climatic conditions, interaction between these two species is also probable. Given that where these two species have interacted in the past, the impacts on northern quoll have generally been calamitous (Burnett, 1997; Oakwood, 2004; Woinarski, 2010). Such an interaction could potentially result in the extinction of the Pilbara population of the northern quoll. However, our modelling also shows that with climate change there will be a strong trend for cane toad PD to contract westerly towards the coast and that this contraction will become more pronounced given higher emission scenarios and greater timeframes. This juxtaposes our climate change modelling for the Pilbara population of the northern quoll (section 4.2.5). These SDMs indicate trending easterly movement in northern quoll PD which also become more pronounced with higher emission scenarios and greater timeframes.

To demonstrate how climate change will cause the potential distributions of these two species to diverge we have overlaid the SDM for the northern quoll RCP8.5 2070/baseline climate change comparison given in Figure 31 over the cane toad SDM for the same climate change scenario as given in Figure 48 (Figure 49). This shows that within the Pilbara and under the baseline northern quoll scenario 52% of northern quoll PD will probably be subjected to cane toad invasion, 46% of quoll PD remains potentially vulnerable to cane toad invasion and 2% of quoll PD, remains unlikely to be impacted by cane toad invasion. However, under the future climate change scenario, only 8% of future PD will probably be subject to cane toad, 56% will be potentially vulnerable to cane toad distribution and 36% will be unlikely to be effected.

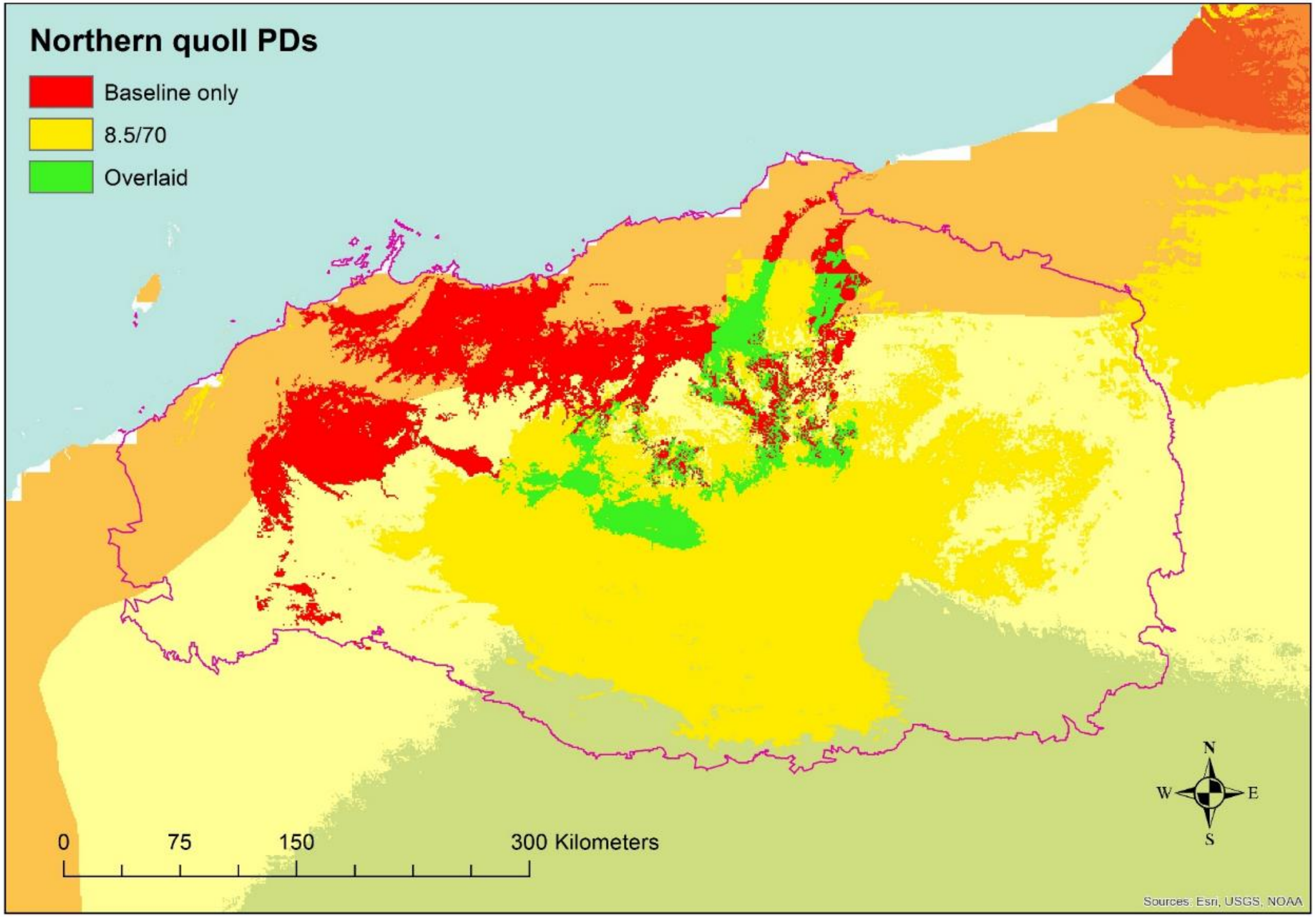


Figure 49: Cane toad SDM for RCP8.5 2070 with northern quoll baseline and RCP8.5 2070 PDs overlaid.

5 Discussion

In this report we have developed a preferred high resolution PD map for the Pilbara population of the northern quoll. To do this we have used the MaxEnt software and developed a methodology which addresses the known shortcomings of this software. This SDM is of a high quality, statistically speaking, and has been further evaluated through an ensemble model process where SDMs developed through a suite of five modelling tools were combined into an ensemble model. Our preferred model was then compared with all outputs from this process, including all individual modelling tool outputs as well as the ensemble output. Congruence between the ensemble model outputs and the preferred model remained high. Further indicating that the preferred model was accurate.

PD as identified in the climate change SDM for the northern quoll differed in minor respects to the preferred PD SDM but this was to be expected as the model was developed at a much coarser scale using bioclimatic predictive variables alone and a much larger and more diverse presence data set. However, in comparing these models it must be remembered that the purpose of the climate change modelling exercise was not to provide a fine scale SDM as had been done with the preferred model. Rather, it had been undertaken to demonstrate how climate change trends may impact on the PD for the Pilbara population of the northern quoll. This exercise indicated that PD for the northern quoll will probably contract in an easterly direction and this movement will become more pronounced with higher emission scenarios and greater timeframes.

To investigate the threat the cane toad invasion may represent to the Pilbara population of the northern quoll, a simple sum overlay model was constructed and compared with more complex and specialised SDMs undertaken to investigate the PD of this pest species. This was done because the cane toad is a highly adaptable range shifting species whose limiting parameters are not well understood hence many of the existing SDM's were highly conflicted in their predictions. To do this we constructed a sum overlay model which complied well with the more accepted SDMs for this species. Consequently, we used this SDM as a basis for determining how climate change may impact upon the PD for the cane toad in the Pilbara. This process found that cane toads probably have the capacity to invade and persist in the Pilbara under current climatic and management conditions. However, modelled climate change scenarios did indicate that, within the Pilbara, the PD for the cane toad will contract westerly towards the coast and that this trend will also increase with higher emissions scenarios and greater timeframes.

A comparison between the potential distributions of both species in the Pilbara indicated that under current conditions PD for both species is nearly totally overlapped representing a potentially threat to the persistence of the northern quoll in the Pilbara. However, apply climate change scenarios both SDM indicates that PDs for these two species will diverge and that this divergence will increase with higher emission scenarios and greater timeframes, thereby lessening the threat to this population of the northern quoll.

It must be noted that in looking at the impacts of climate change in the Pilbara, that the CMIP5 GCMs for this region have a low level of certainty in regard to many parameters which may affect both northern quoll and the cane toad PDs. We readily acknowledge these limitations and advise caution in applying the findings of this report.

6 Conclusions

In light of the previous discussion we make the following conclusions:

- Our models indicate that, under the scenarios predicted in the ACCESS 1.0 models, and over the 2050/70 timeframes, northern quoll PD will shift inland and cane toad PD will contract towards the coast, causing a divergence in the distributions of these two species.

- The outputs of this project should be tested and refined through field studies. Modelling habitat for the northern quoll at a very fine scale remains beyond the capacity of this project. Furthermore, our understanding of the cane toad's capacity to adapt remains inadequate.

- The capacity to model the effects of threats to the Pilbara population of the northern quoll in response to impacts associated with mining activities, inappropriate fire regimes, pastoral activities and feral predators, requires additional data quantifying the impacts of these threats.

- It is expected that new and improved spatial modelling tools and climate change data should also be applied to the conservation of the Pilbara population of the northern quoll as they come to hand.

- A combination of quarantine measures and blocking toad access to key bodies of permanent fresh water may prove effective in delaying their invasion of the Pilbara, thereby diminishing their impact.

7 Recommendations

It is considered axiomatic amongst modellers and statisticians that: ‘The greater the sample size and diversity, the more likely it is the sample will represent the true nature of the subject’. Therefore the larger and more diverse a sample is, the more accurate the SDM (MacCallum et al., 1996). It must be remembered that this has been a desktop modelling exercise undertaken with generic data and a relatively small (in terms of diversity) sample. Consequently the outputs of this project should be tested and refined through field studies. For example, sampling for northern quoll presences in areas identified in the SDMs as current high priority northern quoll refugia, but which have not been adequately sampled on previous occasions, whether successful or not, will provide data which can be used to refine and improve future SDMs. Conversely, finding presences in areas identified as low value northern quoll habitat will also facilitate the development of more accurate SDMs.

Modelling habitat for the northern quoll at a very fine scale (e.g. $\leq 100m^2$ (10m x 10m) pixel resolution) remains beyond the capacity of this project because of incomplete records on the habitat requirements of this species, particularly in regard to very fine scale floristic community, geomorphological and topographical preferences. This is exacerbated by an absence of similar variable data sets which record this information at such a scale for most of the Pilbara. The ability to conduct very fine scale modelling is reliant on meeting these data requirements.

Our understanding of the capacity of the cane toad to invade the Pilbara remains inadequate. Ongoing research into this area is highly recommended.

The capacity to model the effects of threats to the Pilbara population of the northern quoll in response to the threats associated with mining activities, inappropriate fire regimes, pastoral activities and feral predators, requires additional data capable of quantifying the impacts of these threats. Although some of this data could be obtained through desktop studies, a better understanding would require on-ground studies which would employ activities such as ongoing monitoring, selective sampling and treatments applied to selected populations.

There remains significant conflict between GCMs, this is particularly true in the case of the Pilbara. Advances in climate modelling continue in line with new tools, technologies and a greater understanding of the effects of anthropogenically caused global warming. As changes in climate modelling have the capacity to effect the outputs of all the exercises discussed in this report, it is recommended that these exercises be repeated and re-evaluated using the best available GCMs as the come to hand.

It is expected that new and improved spatial modelling tools and methodologies will also become available in the foreseeable future. These tools should also be applied to the conservation of the Pilbara population of the northern quoll, and their outputs evaluated for further application.

Models show that there is a reasonable probability that cane toad and northern quoll populations will diverge (spatially) as a result of climate change. As an extension of this hypothesis, given that climate change will most likely continue, it can be assumed that the longer cane toad invasion of the Pilbara is delayed, the lower its impact on the northern quoll. Therefore, finding means by which such an invasion can be delayed, if not prevented, should be considered a major priority for conserving this northern quoll population. Blocking toad access to key bodies of permanent fresh water may prove pivotal in achieving this objective.

Glossary

ACCESS 1.0: Australian Community Climate and Earth-System Simulator 1.0. A coupled climate model based on the CMIP5 suite of bioclimatic models (Bi et al., 2013).

AUC: Area Under Curve (a statistical test used in MaxEnt comparable to ROC).

Bioclimatic: Predictive variables derived from topographic, temperature and rainfall values. These are often used in ecological niche modelling.

Biomod2: Software used in the EM process.

BoM: Bureau of Meteorology.

CMIP5: Coupled Model Intercomparison Project Phase 5. The latest set of climate change models based on a standard experimental protocol for studying the output of coupled atmosphere-ocean general circulation models (Taylor et al., 2012).

CSIRO: Commonwealth Scientific and Industrial Research Organisation.

CTA: Classification Tree Analysis (a spatial modelling tool).

CWR: Critical Weight Range (the weight range of native species most vulnerable to feral predation).

Dependent variables: A value that changes in response to a change in an independent variable. It usually refers to the subject of the modelling exercise. With SDMs this refers to the *p* value or probability of presence.

DPaW: Department of Parks and Wildlife (Western Australia)

ECU: Edith Cowan University

EM: Ensemble Model (an SDM compiled from a group of related SDMs)

FDA: Flexible Discriminant Analysis (a spatial modelling tool)

GAM: Generalised Additive Model (a spatial modelling tool)

GBM: Generalised Boosted Model (a spatial modelling tool)

Independent variables: An independent, or predictive, variable is landscape feature where a change in value will indicate, but not necessarily cause, a change in the value of the dependent variable.

IPCC: Intergovernmental Panel on Climate Change,

Kappa: A statistical test used in the EM process.

MaxEnt: Maximum Entropy Modelling (a spatial modelling tool).

Parameters: Those independent variable values which define PD.

PD: Potential Distribution.

PDA: Point Density Analysis.

RCP: Representative Concentration Pathway.

ROC: Receiver Operator Characteristic (a statistical test comparable to AUC).

SDM: Species Distribution Model.

Sensitivity: The percentage of absences above the ROC/AUC curve before the cut-off value.

Specificity: The percentage of presences below the ROC/AUC curve after the cut-off value.

TSS: True Skill Statistic (a statistical test used in the EM process).

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