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Applying the principles of spatial modelling to the management of biodiversity in the fragmented landscapes of south-western Australia

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USE OF THESIS

Applying the principles of spatial modelling to the management of biodiversity in the fragmented landscapes of south-western Australia.

Shaun Molloy

Master of Wildlife Management

Diploma of Conservation and Land Management

Thesis submitted to Edith Cowan University for the degree of
Doctor of Philosophy, School of Natural Sciences,
Faculty of Health, Engineering and Science.

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For Erin, Matthew, Gwendolyn
and Emily.

Remember always, lithic truths,
Untouched by thought or question.
These axioms which forge our world,
Rare stand the light of reason.

Acknowledgments

This project would not have been possible without the assistance and support of a great number of individuals and organisations. I wish to thank my supervisors Rob Davis, Eddie van Etten and Pierre Horwitz for their unfailing and invaluable guidance, advice, wisdom and patience. There is much I have learned from each of them. In particular, I wish to acknowledge the efforts of my principal supervisor, Rob Davis, who has painstakingly reviewed all of my work, and withstood numerous tantrums, dramas and bouts of obstinacy in his quest to teach me to think and write more like an academic and less like a public servant.

To my wife Keringa, my children Erin, Matthew and Gwendolyn and my granddaughter Emily, thank you. I simply could not have done this without their love and support. For nearly four years I have been often absent, nearly always distracted and very prone to rant about things that nobody else understood or even cared about, and still they were happy to let me chase a dream.

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I would like to acknowledge the enormous contribution of all those who acted as volunteer field assistants, in particular, Jennifer Stevens and Gwendolyn Molloy. I would also like to thank the property owners, the Stallard, Ablett, and Hanran-Smith families, for allowing access to their properties, and the officers of the Cape to Cape Catchment Group, in particular Drew McKenzie, for their support and assistance throughout the fieldwork phase of this project.

All handling was done compliance with Edith Cowan University animal ethics approval 5669 and Department of Environment and Conservation licence SF007736 and SF008379.

Abstract

Biodiversity conservation throughout the world is challenged by the impacts of a changing climate on fragmented landscapes. To mitigate these threats, conservation managers require models which can demonstrate the consequences of both negative impacts and management actions. This need can be addressed through spatial modelling applications. Unfortunately, throughout much of the world, spatial modelling is forgone, being seen as requiring skills and resources beyond the means of many conservation planners and managers. This thesis seeks to address this dilemma by delivering criteria for a successful modelling application and by providing case studies which demonstrate how appropriate modelling can be undertaken without highly specialised skills or prohibitively expensive software and equipment. In this way it facilitates the delivery of better targeted and, consequently more effective, management actions.

For my case studies I have used the south-western corner of Australia as a demonstration landscape. This region is recognised internationally as a "biodiversity hotspot," not only for the biological richness and uniqueness of species but also for the level of threat to which they are subject. Like many landscapes throughout the world, much or this region's natural biota exists in fragmented, fragile and degraded patches and is therefore highly vulnerable to the anticipated impacts of anthropogenic global warming.

In this thesis I have: 1) examined the principles of spatial modelling and reviewed how spatial modelling has been applied to conservation management in this region, 2) conducted examples of different forms of spatial modelling using actual regional conservation management issues, and 3) demonstrated how these examples can be incorporated into conservation management planning.

My key findings are:

- Spatial modelling provides users with an opportunity to effectively test hypotheses, thereby informing the planning process and improving conservation outcomes. Where spatial modelling is omitted from the process, knowledge gaps are often addressed by the axiomatic and by assumption. This is contrary to the principles of effective adaptive management.

- Modelling tools are inherently more effective when selected for their capacity to meet a planning objective rather than where projects are tailored to meet a model's capacity.

- The coordinated use of multiple tools can often provide a more robust understanding of the consequences impacts and mitigating actions.

- All tools and data sets used should be utilised with a clear and acknowledged understanding of their suitability, strengths and limitations.

- A wide range of spatial modelling tools (and data sets) are freely and readily available to conservation managers. Most of these come with excellent tutorials and support services.

- Data gaps can often be addressed through targeted field observations, obtained through complimentary planning processes, or synthesised from accessible data sets.

- There is a very large body of peer reviewed literature demonstrating means by which others have applied existing modelling tools, or developed tools themselves, to meet a wide range of applications. Accessing this literature is an excellent means of building spatial modelling capacity.

- New and improved tools, methodologies and data sets are constantly being developed.

- A failure to implement effective spatial modelling is becoming increasing difficult to justify.

Publications

It has always been my intent to submit work derived from this thesis for publication in relevant scientific journals. To that end, at the time of submission, one paper, taken directly from chapter 5, has been accepted for publication (and consequently the only chapter written in the first person), i.e.:

Molloy, S.W., Davis, R.A. and van Etten, E.J. (2013). Species distribution modelling using bioclimatic variables to determine the impacts of a changing climate on the western ringtail possum (*Pseudocheirus occidentals*; Pseudocheiridae). *Environmental Conservation* (in press).

I have contributed over 95% to this chapter and 100% to all other chapters. I shall also seek to publish papers from the remaining chapters.

Caveat

It should be noted that this research project was undertaken within the context of a single landscape. Every landscape has a unique composition of pressures, biotic and abiotic components. Therefore, the specific findings of this research may not be directly transferable to other landscapes. However, through this project, it is my intention to demonstrate the application of a set of globally relevant general principles by which spatial modelling can be made a more effective tool for the management of biodiversity.

Declaration

I certify that this thesis does not, to the best of my knowledge and belief:

i. incorporate without acknowledgment any material previously submitted for a degree or diploma in any institution of higher education;

ii. contain any material previously published or written by another person except where due reference is made in the text of this thesis; or

iii. contain any defamatory material.

Signed:

Date: 24th September 2013

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1 General introduction

1.1 Introduction

Throughout the world conservation managers[1] have had to grapple with the impacts of global warming in the context of fragmented landscapes (Pearson & Dawson 2005; Fischer & Lindenmayer 2007; Benito *et al.* 2009; Yates *et al.* 2010b; Milad *et al.* 2011). Increasingly they have relied on spatial modelling techniques as a practical, affordable and cost effective means of developing effective management actions to ameliorate existing impacts and/or mitigate threatening processes (Gritti *et al.* 2006; Yates *et al.* 2010a; Adams-Hosking *et al.* 2011; Lawson *et al.* 2012). Spatial models enable this because they can be used to identify the potential impact of threatening processes and the efficacy of management actions (Ferrier & Guisan 2006). However, the effective use of spatial models relies on the selection of a model, or suite of models, appropriate for a given application and that these models are used in conjunction with the best available data and an understanding of the model's limitations and assumptions (Moore & Swihart 2005; Gontier *et al.* 2010).

In conservation management there is often a tendency for planning methodologies and tools to focus on the setting of outputs (management actions) and their post-implementation evaluation (TNC 2007).

My test landscape, south-western Australia, is internationally recognised as a biodiversity hotspot not only for the diversity and uniqueness of its biota but also for the high level of threat faced by biota (Myers *et al.* 2000; Hopper & Gioia 2004). Threatening processes include a high level of landscape fragmentation and a rapidly changing climate (Environmental Protection Authority 2007). To date, in south-western Australia, project outputs have largely been set by assumptions based on a combination of experience and

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[1] For the purposes of this document the term conservation manager refers to those people who are vested with, or assume, the responsibility of developing and/or implementing on ground projects or planning initiatives with the intention of conserving, protecting, enhancing or re-establishing populations or assemblages of native biota and the abiotic resources upon which they rely. These people may be private individuals, representatives of government or non-government organisations, or participants in relevant interest or community groups.

intuition (Lindenmayer *et al.* 2008). In appraising a situation intuitively, it is easy to assume that the immediate and most visible threat is the threat that should be addressed and that the delivery of outputs, selected intuitively or because they are the usual, or historical, response will deliver actions capable of achieving project objectives (Albert *et al.* 1998; Rodrigues & Brooks 2007; Hodgson *et al.* 2009). In this way, assumptions applied to conservation management projects through complex and apparently comprehensive planning tools can provide a potentially misleading appearance of rigour (TNC 2007; Beger *et al.* 2010; Vasconcelos *et al.* 2012). Consequently, planning tools are often used without the benefit of appropriate modelling.

In this study I have examined how spatial modelling has been applied to the fragmented landscapes of south-western Australia and demonstrated means by which it can be made more effective. To that end, I have:

1. Examined spatial modelling principles and reviewed how spatial modelling has, to date, been applied to conservation management in this region.

2. Conducted examples of different forms of spatial modelling using actual regional conservation management issues.

3. Demonstrated how these examples can be incorporated into conservation management planning processes.

In light of the above discussion I have demonstrated ways by which spatial modelling tools can be made more relevant and effective in conservation management within the context of the fragmented landscapes of south-western Australia. It was the objective of this research project to examine the principles of spatial modelling by investigating the landscape requirements of a group of endemic species and finding ways to map, or predict, these requirements. I have examined the strengths and limitations of current spatial modelling tools and investigated ways in which spatial modelling can be applied, or made more effective, in meeting the requirements of the region’s unique landscapes and species.

1.2 Research overview

This research has been undertaken in seven components: an introduction; four papers (for future publication), each of which are designed to provide a different perspective on spatial modelling applications; a demonstration exercise by which the finding of these four studies can be applied to the conservation of a species facing the dual threats of climate change and landscape fragmentation, and a discussion of the findings of this research. These are described in the following chapters:

1. **Introduction:** (this section). A review of the observations and hypotheses that lead to this research, the objectives of this research and the methodologies chosen.

2. **Spatial modelling, a review of a methodology and its applications:** Five forms of spatial modelling used in this region to date have been: realistic GIS modelling, focal species, proximity analysis, Marxan® and Conservation Action Planning (a decision support matrix often used as a substitute to spatial modelling). In this paper we develop a set of criteria for effective spatial modelling and then evaluate the five spatial modelling techniques using these criteria.

   The criteria used in evaluating spatial modelling tools are: 1) capacity to quantify barriers to movement; 2) capacity to quantify habitat; 3) capacity to accurately predict target responses; 4) capacity to demonstrate how change will happen over differing time frames; 5) effectiveness of the tool within a project's data limitations; 6) ease to which outputs are understood; 7) utility of the tool within a project's skill limitations; and 8) efficacy within a project's resource limitations.

   Reviewed methodologies focus on distance thresholds as a barrier to movement between patches of suitable habitat. These assumptions are often misleading because both habitat and barriers to movement differ for different species and thresholds are binary by nature, whereas in reality habitat and barriers to movement are viewed as probabilistic responses to predictive variables.

3. **Quantifying habitat value using existing survey data:** In the highly fragmented landscapes of south-western Australia conservation managers often simply consider patches of remnant vegetation to be habitat. In doing so they make a broad assumption which, although potentially valid for some management applications, fails to answer two major questions pertinent to conservation management: firstly, what species and communities is a site habitat for; and secondly, how can we quantify the habitat value of this area?

   Biodiversity management in south-western Australia has long been hampered by significant knowledge gaps and quantifying habitat values usually involves undertaking comprehensive research which is beyond the capacity and resources of many project managers. Under these circumstances assumption becomes the main, and often only, means of informing conservation management initiatives. In this chapter I demonstrate means and methodologies by which habitat value can be identified and quantified using readily available data.

   The objective of this exercise is to demonstrate the construction of a statistical tool which can identify and quantify the habitat values of patches of eucalypt woodland in the vicinity of the Augusta-Margaret River Shire in south-western Australia. The purpose of this exercise is to enable local conservation managers to identify and quantify habitat by determining how the probability of presence or absence of target species changes in response to landscape parameters and management regimes. This will enable regional conservation managers to quantify, model, and therefore demonstrate how target species will respond to foreseeable impacts and management actions.

   To do this, bird survey data for the target landscape has been sourced from the Birdlife Australia Atlas Database. A suite of indicator species (Caro 2010) were selected as surrogates to indicate a habitat value. These species were selected because they were sedentary, local bird species which are known to be reliant on good quality eucalypt woodland: i.e. areas within which the canopy, structure and species diversity of these floristic assemblages are largely undisturbed by anthropogenic impacts, and because they were recorded in numbers large enough to demonstrate a distribution representative, in response to these variables, of the greater population (i.e. $n > 30$) (Caro 2010; Phillips & Dudik 2008). Presence and absence of these species was then compared to a number of landscape parameters in a GIS environment and set of landscape parameters which could be effectively measured within the limitations of available GIS databases (and which directly affected the probability of presence for all of the indicator species) was determined. These parameters were area of the nearest neighbouring patch, amount of remnant vegetation in a 1 kilometer radius of the survey site, amount of remnant vegetation in a 5 kilometer radius of the survey site, and the vesting of that survey site. These parameters were calculated for all relevant survey sites in a given sample and multivariate regressions were undertaken to produce a series of coefficients which were used to produce modelling tools for all of the target species (Appendix chapter 3). Of the species tested, only those species which could be modelled with an acceptable level of accuracy were chosen for use in conservation management applications.

4. **Informing species management in a fragmented landscape; a case study of the koomal (*Trichosurus vulpecula hypoleucus*):** Climate change is predicted to have a major impact on south-western Australia. With this looming scenario, the persistence of many species will rely on their ability to survive in, and migrate through, fragmented landscapes. The purpose of this study was to investigate the ecology of a sub-species of the common brushtail possum within the context of a fragmented landscape, thereby enabling the development of more informed and effective conservation management strategies for this species in a changing climate scenario.

   The koomal is a geographically isolated sub-species of the common brushtail possum, endemic to south-western Australia. Since European settlement in this region this sub-species has undergone a significant reduction in range and population size (Jones 2004). It is currently listed as “Lower Risk” (near threatened).

A year-long trapping and radio tracking exercise was undertaken on four adjoining properties in the Margaret River region of south-western Australia. Trapped areas comprised 11 habitat patches ranging in size from 1.3 to 28.4ha, producing a total study area of 100.4ha in a landscape with 41% remnant vegetation cover. Field work comprised one thousand eight hundred and seventy two trap nights over thirty six sites and weekly tracking of eleven individuals over periods ranging from several weeks to the full study period.

5. **Species distribution modelling using bioclimatic variables to determine the impacts of a changing climate on the western ringtail possum (*Pseudocheirus occidentals*):** The ngwayir (pronounced “n-wa-ear”) or western ringtail possum is a highly arboreal species endemic to south-western Australia (de Tores 2008). The range and population of this species have both been significantly reduced through anthropogenic impacts including habitat loss, changed fire regimes and introduced predators. Consequently, this species is now classified as Vulnerable by the International Union for the Conservation of Nature (IUCN). The ngwayir is highly susceptible to extremes of temperature and reduced water intake (Jones 2004).

   The potential distribution of ngwayir was determined using three different species distribution models which used ngwayir presence records and related these to a set of nineteen bioclimatic variables derived from historical climate data. Each of these distribution models was then overlaid with three 2050 scenarios.

   MaxEnt was used to identify core habitat and to demonstrate how this habitat may be impacted. A supplementary modelling exercise was also conducted to ascertain potential impacts on tree species upon which, according to the literature, ngwayir are reliant for habitat.

6. **Incorporating the outcomes of fieldwork into species distribution and climate change modelling on the koomal (*Trichosurus vulpecula hypoleucus*).** This chapter demonstrates a means by which taxon specific observations, gathered through fieldwork, can be used to add resolution and robustness to spatial distribution models (SDMs) in defining potential

distribution (PD). This chapter demonstrates a means by which the work undertaken in previous chapters can be synthesised to inform conservation planning and management activities. To achieve this, data obtained in the field for chapter 4 has, with the aid of GIS software and statistical analyses techniques, been used to enhance the climate change modelling techniques trialled in chapter 5. This exercise demonstrates how spatial modelling can be used to model a future PD for a taxon which has been shown to be vulnerable to the impacts of landscape fragmentation, a rapidly changing climate and dieback, a virulent plant pathogen which impacts negatively on koomal habitat.

In chapter 5 the MaxEnt SDM tool used in combination with a group of proven Global Climate Models (GCMs) was effective in modelling current and future bioclimatic PD for an arboreal mammal. However, this exercise did not include variables, such as remnant vegetation extent, which limited the actual distribution of a species of taxon. In chapter 4 it was observed that home range for the koomal rarely exceeded 1 km in width, dieback *Phytophthora cinnamomi* infested areas were not occupied, and that the amount of remnant vegetation in a landscape was linked to presence. To incorporate these observations into the MaxEnt model, a perspective GIS data set was developed and tested statistically, which showed that a raster with a 1 km pixel whose value represented the percentage of remnant vegetation within that pixel and a 1 km buffer of its edges could be used to predict koomal presence. This was incorporated into a MaxEnt model within which only 5 bioclimatic variables were used (to prevent potential over-fitting). A dieback GIS data set was then overlayed onto the results of this model to exclude dieback affected areas from the PD.

The results of this exercise showed that observation data could be used to produce a more targeted PD model which removed areas which were not habitat, from the bioclimatically derived outputs.

7. **Discussion:** All previous exercises are reviewed and their findings discussed in light of their conservation management applications in landscapes subject to the combined impacts of fragmentation and a rapidly changing climate.

The emphasis of this work will be the eight criteria for a successful spatial model given in chapter 2 and the way by which the exercises undertaken over the course of this study have met those requirements.

1.3 Purpose

This study demonstrates how spatial modelling applications are particularly useful in informing the planning process. Conversely, just as planning processes can be enhanced by data obtained through spatial modelling, that data alone will not bring about change. Data can only bring about change when used to drive and inform the development of management actions. To that end, spatial modelling and project planning processes are complementary in nature. Therefore, it falls to conservation managers to recognise that these processes enhance each other and that using one process to supplant the other can have a highly detrimental impact on conservation management.

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2 Spatial modelling, a review of a methodology and its applications

2.1 Introduction

2.1.1 Overview

Spatial modelling encompasses a broad and growing suite of tools and methodologies which enable the user to compile and analyse spatial information in a realistic, implicit or explicit manner. In relation to landscape ecology, a successful spatial modelling tool has the capacity to demonstrate the potential consequences of impacts and/or management actions on spatial relationships within the context of a subject landscape, species, community or population (Collinge 2009). Spatial modelling can be particularly useful in recognising and prioritising assets within a landscape (Ferrier & Guisan 2006; Foody 2008), demonstrating metapopulation requirements (Hanski & Ovaskainen 2003) and modelling impact and management outcome scenarios at multiple spatial and temporal scales (Fischer *et al.* 2004; Ferrier & Guisan 2006). Furthermore, models are usually evaluated against inherent assumptions and the data used to construct the model. Under such circumstances, confidence in selecting the best models would be improved by evaluation of their outputs, particularly through comparisons amongst models which differ in their underlying method and assumptions (Rastetter 2003).

Habitat fragmentation is the leading cause of population decline and extinction in many terrestrial landscapes (Lindenmayer *et al.* 2008; Collinge 2009). Species and communities in fragmented landscapes are also particularly vulnerable to the impacts of anthropogenic climate change (Fitzpatrick *et al.* 2008; Greg & Andrew 2009). Consequently, spatial modelling tools and methodologies are increasingly being applied to demonstrate the consequences of climate change in fragmented landscapes (Hanski & Ovaskainen 2003; Zafra-Calvo *et al.* 2010).

It should be noted that when modelling fragmented landscapes it is important to understand that fragmentation refers to the fragmentation of habitat and that habitat is species specific in nature. For example, to a woodland species fragmentation may be brought about by a decrease in woodland extent. Conversely, as is currently the case with pastoral species in much of the European Alps where climate change is bringing about an expansion in alpine forest extent, fragmentation can be brought about by reafforestation (Brambilla *et al.* 2010; Sitzia *et al.* 2010; Tattoni *et al.* 2010; Tattoni *et al.* 2011).

In managing biodiversity in fragmented landscapes, it is generally accepted that the ecological viability and biodiversity conservation value of the whole of a patch which touches, or comes within close proximity to another patch, will probably be greater than that of a comparable patch which is isolated (Tischendorf & Fahring 2000b; Freudenberger & Brooker 2004; Watson *et al.* 2005; Lindenmayer *et al.* 2008). The application of this principle has given rise to biodiversity planning and management tools which measure and evaluate landscape connectivity through the spatial relationships which exist between patches of remnant vegetation. The purpose of these tools is to demonstrate the movement of biota within the context of fragmented landscapes, thereby allowing conservation managers to predict biotic movement between remnants under current and future landscape configurations (Belisle & Desrochers 2002; Hobbs & Yates 2003; Fischer *et al.* 2004; Ferrier & Guisan 2006; Fitzpatrick *et al.* 2008).

The diverse physical characteristics and habitat requirements of individual species imply that the use of simple spatial modelling tools may be of limited use in the management of many specific species. For example, a distance of 100 m between patches of remnant vegetation may be an insurmountable barrier to a small woodland reptile, a partial barrier to a terrestrial marsupial and no obstacle at all for a large raptor. Conversely, landscape elements or structures such as roads, watercourses, landform and vegetation structure can facilitate or impede the movement of different species in different ways. These impacts are often overlooked in simple spatial modelling applications (Holland & Bennett 2009).

In recent years, worldwide use of spatial modelling tools and methodologies in ecological connectivity projects has steadily grown in number, scale and sophistication leading to a corresponding growth in spatial modelling applications (Kindlmann & Burel 2008; Urban *et al.* 2009; Lafortezza *et al.* 2010; Saura & Rubio 2010; McLane *et al.* 2011; Schooley & Branch 2011; Luque *et al.* 2012; Šímová & Gdulová 2012). Landscape connectivity projects such as Yellowstone to Yukon and the Wildlands projects in North America (Foreman 1999), the Terai Arc project in Asia (Lumpkin & Seidensticker 2006), the STEP project in Africa (Rouget *et al.* 2006) and the Green Bridges project in Europe (Voelk *et al.* 2002) are all examples of large-scale connectivity projects aiming to improve landscape to regional-scale connectivity by incorporating a wide variety of spatial modelling tools and methodologies into their decision-making frameworks.

Effective spatial modelling also enables biodiversity managers to predict the response of biota to a variety of stochastic and deterministic impacts such as fire, changes in habitat extent or quality, climate change, the introduction of exotic species or pathogens, and/or changes to management regimes (Turner *et al.* 1995). Therefore the importance of spatial models to conservation planning and management is increasing.

In light of the above our research question is: How can spatial modelling techniques be made more effective to meet both the needs and the capacities of landscape managers who wish to undertake spatial modelling in fragmented landscapes? To this end, an example of a highly biodiverse region within which both fragmentation and climate change are recognised as significant threats to biodiversity, the south-west floristic region of Australia (Figure 1), is used as a case study. The conservation significance of this region has resulted in a number of spatial modelling approaches being used by different agencies, and this provides a unique opportunity to compare the application and effectiveness of these techniques.

2.1.2 Study area

The south-western corner of Australia is recognised internationally as a “biodiversity hotspot,” (Figure 1) not only for the biological richness and uniqueness of species but also for the level of threat faced by these species (Myers *et al.* 2000; Hopper & Gioia 2004). It is currently the only international “hotspot” recognised in Australia by the International Union for the Conservation of Nature. Rapidly increasing residential and rural-industrial development, inappropriate fire regimes, exotic species, pathogens and demands for expanded infrastructure contribute to an ongoing decline in the extent and condition of native vegetation throughout the region (Environmental Protection Authority 2007). In 2007, it was found that there was less than 22% of native vegetation remaining on the southern Swan Coastal Plain (Molloy *et al.* 2007) while the 2001 Land and Water Resources Audit (Australian Government 2001) shows that some local government areas in the Western Australian Wheatbelt have less than 5% of native vegetation remaining. This contributes to a landscape where much of the native vegetation remaining exists within small patches fragmented throughout the landscape.

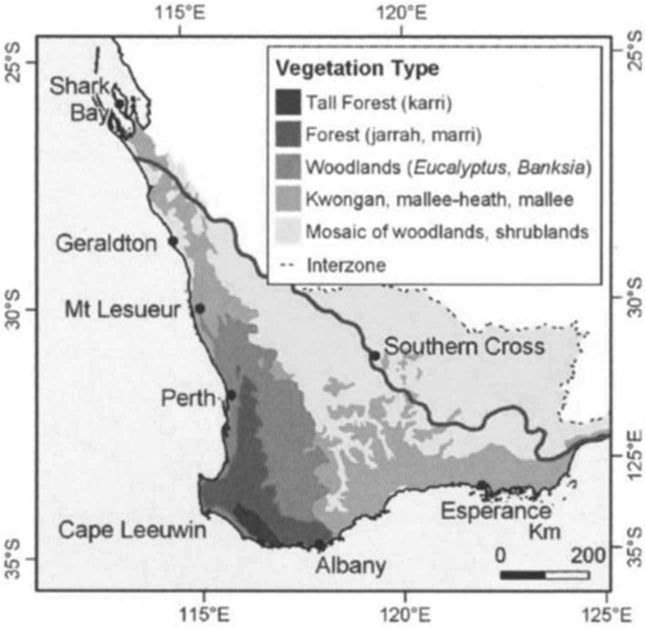


Figure 1: The south-western biodiversity hotspot. Sourced from Hopper and Gioia (2004)

Historically the management of biodiversity in Western Australia has focused on the recognition, conservation and management of individual assets, i.e. conservation estate, individual species and ecological assemblages (McKenzie & May 2003). This focus has largely been the result of Australian (ANZECC/MCFF 1997) and Western Australian Government policy which has, in turn, been largely driven by legislative requirements.

Through working within this policy and legislative framework (Table 1) the concept of maintaining and managing biodiversity at the landscape scale, and the consideration of maintaining connectivity as a major requirement for the persistence of biodiversity in a fragmented landscape, has been, until recently, largely overlooked by government authorities and natural resource management organisations. Although there has been some acknowledgement that connectivity should be considered in biodiversity planning and management (ANZECC/MCFF 1997; Environmental Protection Authority 2006) there has been no clear understanding of how this should be implemented.

Table 1: Legislation relevant to management of Biodiversity in Western Australia (Molloy et al., 2007)

Act	**Description**
	Australian Government
Environment Protection and Biodiversity Conservation Act 1999.	This Act relates to specially protected species, landscapes and communities deemed significant or important from the national perspective. This act also lists the obligations of the Australian Government in relation to international treaties and conventions.
	Western Australian Government
Wildlife Conservation Act 1950	Although out-dated, this Act is the primary State legislation responsible for the protection of native flora and fauna in Western Australia.
Conservation and Land Management Act 1984	This Act applies to State forest, timber reserves, national parks, conservation parks, nature reserves, and other land vested in the Conservation Commission created under this Act.
Environmental Protection Act 1986	This Act determines acceptable levels of impact on biodiversity are largely defined through State and Australian Government legislation and through the asset based CAR criteria (Environmental Protection Authority 2008).

Much of the revegetation undertaken in south-western Australia pays scant attention to effective ecological connectivity (Lawes & Dodd 2009), while those projects which do take ecological connectivity into consideration have, in general, been: 1) small in scale (within catchment or local government boundaries); 2) instigated as opportunistic wildlife corridor models such as the Peel Harvey Regional Ecological Linkages Project (Green Skills 2007); 3) catchment scale focal species based projects (i.e. where parameters for landscape function are drawn from the needs of a select species or group of species, such as the Wallatin Creek Project (Lambeck 1999); or 4) localised species and/or community specific connectivity projects (Brooker & Brooker 2003; Davis 2004).

It has long been recognised that properly established wildlife corridors are important for the persistence of native species in fragmented landscapes (Hobbs *et al.* 1993; Huggett 2007). However, in practice they have a tendency to be established opportunistically as thin disjunct strips of revegetation which are composed of inappropriate species or provenances (Hobbs & Saunders 1991; Wilson & Lindenmayer 1995; Smith 2008).

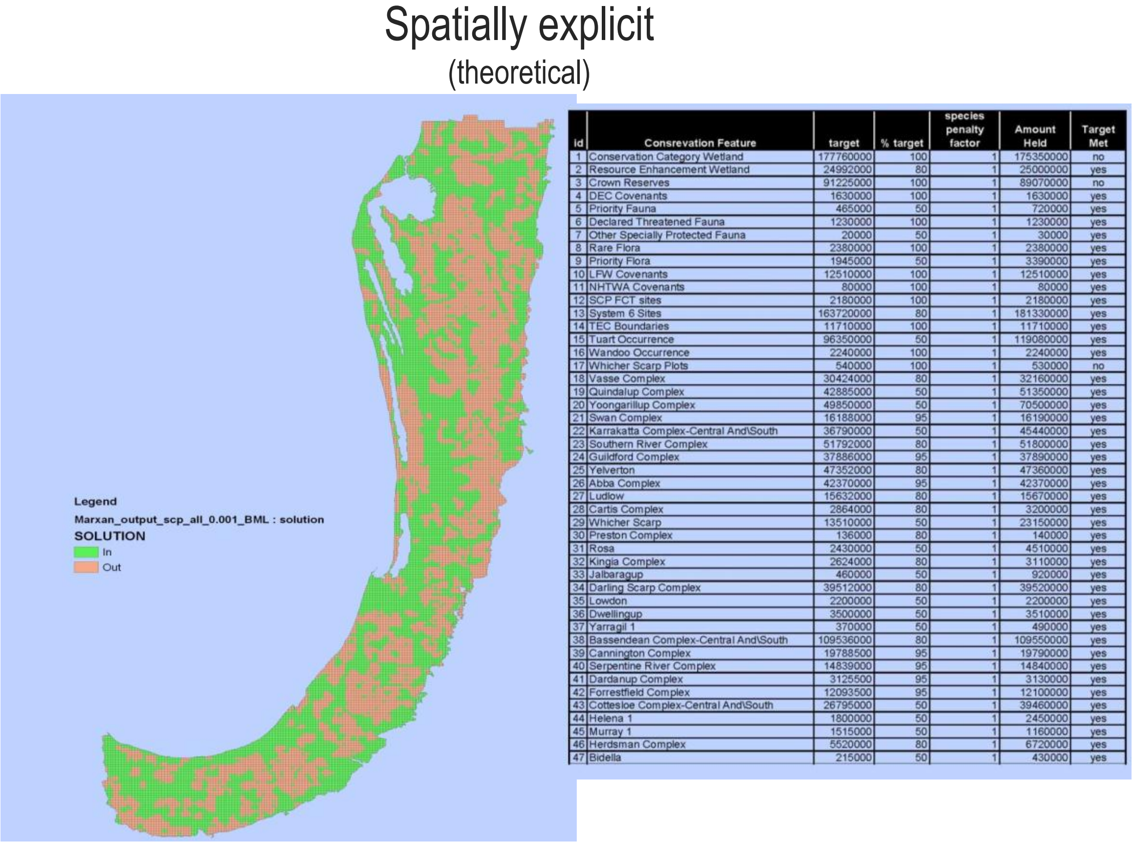
Largely as a result of the growing awareness of the potential impacts of climate change on fragmented reserve systems (Dunlop & Brown 2008; Heller & Zavaleta 2008), regional biodiversity managers have become more aware of the value of connectivity to landscape function and biodiversity management (Environmental Protection Authority 2009; National Biodiversity Strategy Review Task Group 2009). This gradual shift in management priorities from asset retention to landscape conservation has given rise in recent years to many significant and high profile connectivity-based projects. These projects include: catchment-based focal species projects (Lambeck 1999; Freudenberger & Brooker 2004; Watson *et al.* 2005; Huggett 2007); the South West Regional Ecological Linkages (SWREL) project (Environmental Protection Authority 2009; Molloy *et al.* 2009); Gondwana link (Hamish 2008); Alps to Atherton (New South Wales. Dept. of Environment and Climate Change *et al.* 2007); and similar connectivity projects in the eastern states such as Slopes to Summit (Mackey *et al.* 2010). Although these projects take a variety of forms to match a similar variety of landscapes and purposes, the planning and implementation of all of these projects is reliant on spatial modelling.

In recent years, the use of spatial modelling tools and methodologies in ecological connectivity projects has steadily grown in number, scale and sophistication. This reflects a similar growth in spatial modelling applications worldwide (Collinge 2009). Landscape connectivity projects such as Yellowstone to Yukon (Bergman 2003) and the Wildlands (Foreman 1999) projects in North America, the Terai Arc (Lumpkin & Seidensticker 2006) project in Asia, the STEP (Cowling *et al.* 2006) project in Africa and the Green Bridges (Voelk *et al.* 2002) project in Europe are all examples of large scale landscape connectivity projects which incorporate a wide variety of spatial modelling tools and methodologies into their decision making frameworks. Effective spatial modelling also enables biodiversity managers to predict the response of biota to a variety of stochastic and deterministic impacts such as fire (wildfire or used as a management tool), changes in habitat extent or quality, climate change, the introduction of exotic species or pathogens, and changes to management regimes (Turner *et al.* 1995). Therefore planning exercises based on spatial models can sometimes be assigned considerable significance. For example, internationally, spatial modelling has long been considered a fundamental tool in evaluating impacts to ecological function in environmental impact assessment processes (Wathern 1988; Cserny *et al.* 2009) and within Australia’s south west the principles of spatial modelling are now being applied by State Government agencies and relevant organisations as a formal consideration in biodiversity planning and environmental impact assessment (Environmental Protection Authority 2009).

2.1.3 Spatial modelling

Collinge (2009) gives the three most common forms of spatial modelling as:

1. **Spatially explicit models:** As demonstrated in Figure 2, these models spatially specify the locations of nominated assets and evaluate how particular spatial configurations affect ecological processes. These models often rely on grids being placed across a simulated landscape and assigned values based on landscape assets assigned to grid squares. Having done this, asset values or spatial arrangements between grids are then manipulated to provide the modeller with a series of potential outcomes that may result from impacts or changes to management activities.



id	Consrevation Feature	target	% target	species penalty factor	Amount Held	Target Met
1	Conservation Category Wetland	177760000	100	1	175350000	no
2	Resource Enhancement Wetland	24992000	80	1	25000000	yes
3	Crown Reserves	91225000	100	1	89070000	no
4	DEC Covenants	1630000	100	1	1630000	yes
5	Priority Fauna	465000	50	1	720000	yes
6	Declared Threatened Fauna	1230000	100	1	1230000	yes
7	Other Specially Protected Fauna	20000	50	1	30000	yes
8	Rare Flora	2380000	100	1	2380000	yes
9	Priority Flora	1945000	50	1	3390000	yes
10	LFW Covenants	12510000	100	1	12510000	yes
11	NHTWA Covenants	80000	100	1	80000	yes
12	SCP FCT sites	2180000	100	1	2180000	yes
13	System 6 Sites	163720000	80	1	181330000	yes
14	TEC Boundaries	11710000	100	1	11710000	yes
15	Tuart Occurrence	96350000	50	1	119080000	yes
16	Wandoo Occurrence	2240000	100	1	2240000	yes
17	Whicher Scarp Plots	540000	100	1	530000	no
18	Vasse Complex	30424000	80	1	32160000	yes
19	Quindalup Complex	42885000	50	1	51350000	yes
20	Yoongarillup Complex	49850000	50	1	70500000	yes
21	Swan Complex	16188000	95	1	16190000	yes
22	Karrakatta Complex-Central And\South	36790000	50	1	45440000	yes
23	Southern River Complex	51792000	80	1	51800000	yes
24	Guildford Complex	37886000	95	1	37890000	yes
25	Yelverton	47352000	80	1	47360000	yes
26	Abba Complex	42370000	95	1	42370000	yes
27	Ludlow	15632000	80	1	15670000	yes
28	Cartis Complex	2864000	80	1	3200000	yes
29	Whicher Scarp	13510000	50	1	23150000	yes
30	Preston Complex	136000	80	1	140000	yes
31	Rosa	2430000	50	1	4510000	yes
32	Kingia Complex	2624000	80	1	3110000	yes
33	Jalbaragup	460000	50	1	920000	yes
34	Darling Scarp Complex	39512000	80	1	39520000	yes
35	Lowdon	2200000	50	1	2200000	yes
36	Dwellingup	3500000	50	1	3510000	yes
37	Yarragil 1	370000	50	1	490000	yes
38	Bassendean Complex-Central And\South	109536000	80	1	109550000	yes
39	Cannington Complex	19788500	95	1	19790000	yes
40	Serpentine River Complex	14839000	95	1	14840000	yes
41	Dardanup Complex	3125500	95	1	3130000	yes
42	Forrestfield Complex	12093500	95	1	12100000	yes
43	Cottesloe Complex-Central And\South	26795000	50	1	39460000	yes
44	Helena 1	1800000	50	1	2450000	yes
45	Murray 1	1515000	50	1	1160000	yes
46	Herdsman Complex	5520000	80	1	6720000	yes
47	Bidella	215000	50	1	430000	yes

Figure 2: Spatially explicit modelling. In this application (Marxan®) conservation targets for vegetation types have been used to provide a scenario where the retention of assets within nominated grid squares will see all targets met.

2. **Spatially implicit models:** As demonstrated in Figure 3, these models imply spatial and interactive relationships between species and communities. This form of spatial modelling is often used in depicting metapopulation movements and as such patches are not usually considered.

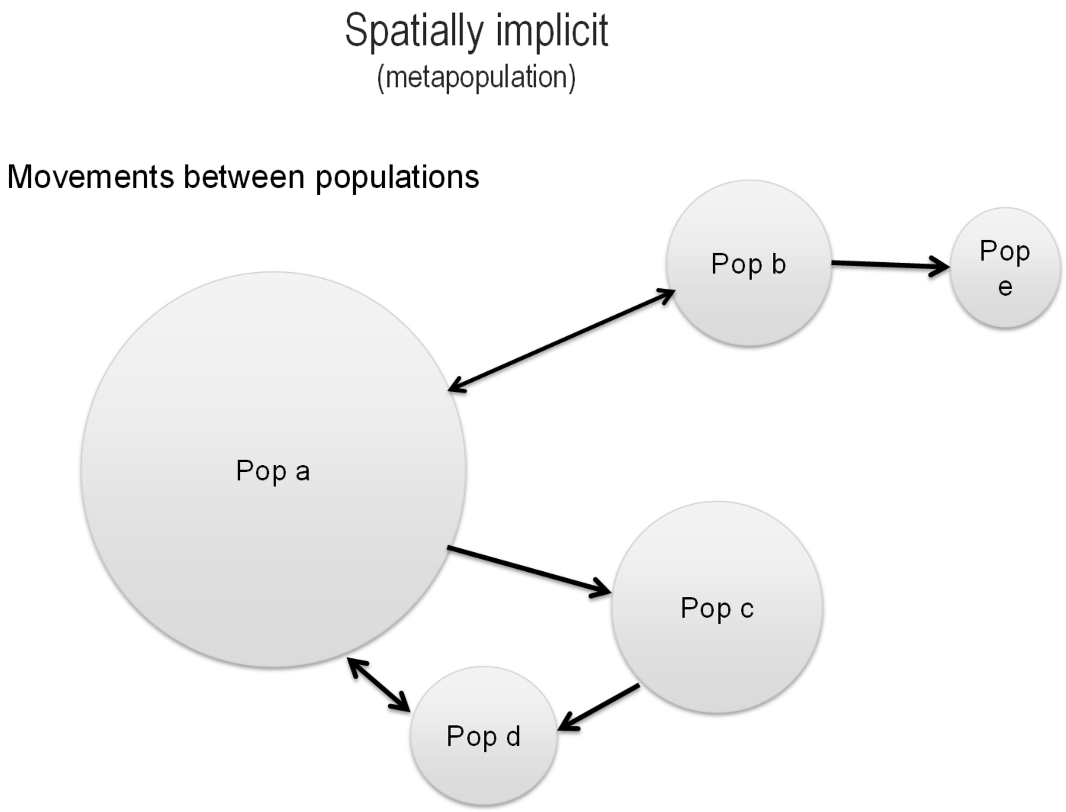


Figure 3: Spatially implicit modelling. Modelled relationships between populations are depicted in an abstract form and not directly related to habitat patches.

3. **Spatially realistic models:** As demonstrated in Figure 4, these models show a realistic (to scale) relationship between assets as they exist in a landscape. These models can be manipulated to demonstrate spatial changes to, and between, assets enabling an assessment of the impacts that disturbances or management regimes might have on a landscape. This form of modelling is most often used in basic landscape ecology.

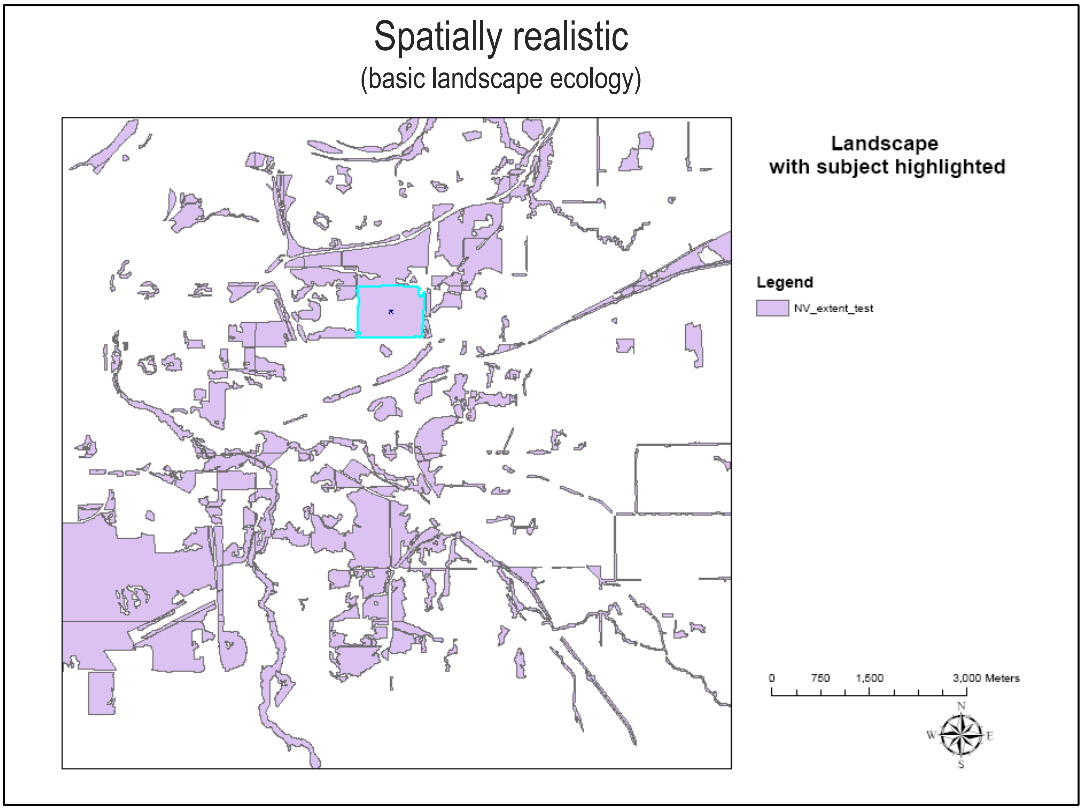


Figure 4: Spatially realistic modelling. Modelled relationships are depicted realistically and to scale.

2.2 Methods

A review of the literature was conducted to determine the principles of spatial modelling for the management of biodiversity in fragmented landscapes. To do this I reviewed all relevant, peer reviewed, post 1990 papers on Web of Science using the following separate keywords: fragmentation, habitat, spatial model, conservation management and Australia. A standardised comparison was made to determine a set of attributes common to successful spatial modelling tools and methodologies applicable to biodiversity conservation in fragmented landscapes. The intention of this exercise was to compile a list of the most useful and informative attributes for a successful spatial modelling application (i.e. one best capable of informing the formulation and delivery of effective management actions). These attributes are then given as criteria by which the efficacy of spatial modelling tools and methodologies were evaluated during the course of this thesis (Table 2).

Individual spatial modelling applications used in south-western Australia were reviewed and their individual strengths and weaknesses discussed in light of each of these criteria.

Having identified the strengths and shortfalls of spatial modelling applications used in this region to date, methods by which spatial modelling can be better used to meet the requirements of regional biodiversity conservation managers will be explored. Conclusions will then be drawn and presented based on the findings of this review.

2.2.1 Criteria for a successful spatial model

To review the effectiveness of a spatial modelling tool it is necessary to develop a set of criteria by which individual tools and methodologies can be compared and assessed (Table 2). In turn, the development of criteria begins by acknowledging the objective of the spatial modelling exercise.

For the purposes of this review it was assumed that the objective of the spatial modelling exercise was to gather relevant information to inform and, where appropriate, drive conservation planning processes, identify and prioritise effective management actions and, in turn, to deliver targeted conservation management outcomes. To that end, in setting criteria it becomes necessary to consider: firstly, the type and quality of information required by the conservation manager; secondly, the resource limitations of the conservation manager; and finally the capacity of the conservation manager to adequately comprehend and apply the outputs of the spatial modelling process through the development and delivery of effective management actions (Ferrier & Guisan 2006; Shaw *et al.* 2006; Collinge 2009; Gurrutxaga *et al.* 2010). Therefore, it is proposed that to undertake an effective spatial modelling exercise for biodiversity conservation within the context of a fragmented landscape the following criteria should be met[2]:

1. **Barriers to movement should be quantifiable**: One of the principal impacts of fragmentation is that it impairs the fulfilment of metapopulation requirements, particularly in regard to recruitment and dispersal. To manage and ameliorate this impact, biodiversity managers must be able to quantify the

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[2] For a spatial model to be effective is should also be able to engage stakeholders. However, the major barriers to stakeholder engagement (such as skill levels, comprehension, budget and resource constraints, quantifiability and efficacy Smith, A., Lambeck, R. J. & Greening Australia (W.A.). (2004) *Living landscapes : the story of a successful landcare program in Western Australia*. Fremantle, W.A.: Greening Australia (WA) Inc. are all covered in the existing criteria. Therefore, the concept of stakeholder engagement is considered to have been adequately addressed, consequently this topic (although still an important consideration) is, as a criteria in its own rite, not considered appropriate for use as a criteria in its own rite for the purposes of this review.

movement requirements of target species and the degree to which fragmentation impacts on that requirement (Lambeck 1999; Tischendorf & Fahrig 2000a; Fischer *et al.* 2004; Watson *et al.* 2005; Majka *et al.* 2008).

2. **Habitat should be quantifiable:** Not all remnant vegetation is habitat for all species. Further, habitat and resources are often found or supplemented by resources in areas that are not remnant vegetation. Therefore the management of target species relies on understanding those habitat parameters which facilitate or impede persistence (Lambeck 1999; Tischendorf & Fahrig 2000a; Fischer *et al.* 2004; Watson *et al.* 2005; Chetkiewicz *et al.* 2006; Majka *et al.* 2008).

3. **The response of species and communities to disturbance scenarios should be predictable**: Conservation management requires that the manager be able to understand how target species and communities will react to both foreseeable impacts and management actions (Turner *et al.* 1995; Tischendorf & Fahrig 2000a; Collinge 2009).

4. **Models should be able to demonstrate how change will happen over differing time frames, i.e. they have a multivariate capacity**: Effective biodiversity management requires that managers be able to model consequences of impacts and management actions beyond the present and preferably in short, medium and long term scenarios (Turner *et al.* 1995; Chetkiewicz *et al.* 2006; Heller & Zavaleta 2008; Lindenmayer *et al.* 2008; Majka *et al.* 2008; Collinge 2009; Greg & Andrew 2009). Models should also have the capacity to incorporate adaptive management methodologies, i.e. they should also be able to incorporate changes in knowledge, objectives and scenarios as they arise (Dallmeier & Comiskey 1998).

5. **Models should be able to make valid predictions based on data that is either currently held or can be obtained within a project's capacity, i.e. they can compensate for expected knowledge gaps:** A model or methodology which is reliant on data which is not available cannot fulfil its purpose and could, in turn, lead to wasted resources or misinformation. It is therefore appropriate that any spatial modelling tools selected for use be

selected with a full understanding of the type and form of data that will be available (Lambeck 1997; Ferrier & Guisan 2006; Heller & Zavaleta 2008; Lindenmayer *et al.* 2008),

6. **The outputs of the model must be easily understood by a variety of stakeholders:** If the output of a model is not properly understood it cannot be applied. If conservation managers are not able to adequately comprehend the outcomes a spatial modelling exercise or be able to convey the outcomes of that exercise to the project stakeholders the findings of the modelling process may be misapplied. For this reason there is a preference for graphic outputs from spatial models (Turner *et al.* 1995; Foody 2008; Heller & Zavaleta 2008),

7. **Skill levels required to use the model effectively are accessible**: There are a plethora of spatial modelling tools and applications available many of which require specialist skills and complex software and equipment. If an inappropriate model is selected or a model is not properly used, misinformation may result (Lambeck 1999; TNC 2007; Heller & Zavaleta 2008; Lovett *et al.* 2008; Collinge 2009), and

8. **The model should be within a project's budget and resource constraints**: When selecting a spatial modelling tool, conservation managers should be mindful that the model selected, along with the equipment, training and data required to run that model, must fit within a project's budget constraints. Conversely, when planning a conservation project the full costs of an appropriate spatial modelling exercise should be budgeted for (Simpson 1999; Freudenberger & Brooker 2004; Foody 2008; Heller & Zavaleta 2008; Lindenmayer *et al.* 2008).

2.3 Spatial modelling applications identified

Environmental planning and project officers from the Western Australian Department of Environment and Conservation, the state Environmental Protection Authority (as representatives of the primary state government agencies vested with responsibility for conservation planning and management), the South West Catchment Council and the Cape to Cape Catchments Group (as the community based Natural Resource Management organisations within the study area) were contacted in order to identify the major spatial modelling applications used in south-western Australia to date. These applications are:

2.3.1 Geographic (or geospatial) information systems (GIS).

Background: GIS is a generic term referring to a group of spatially realistic desktop software packages that enable users to manage, analyse and manipulate geospatial data. These software packages can be used to create maps, charts, reports and other statistical outputs. They can also be used to examine and portray ways by which impacts can alter landscapes (Brebbia & Pascolo 1998). Since the mid-1980s, GIS packages have become progressively more sophisticated and user friendly allowing GIS packages to be used in an increasing number of applications by an increasingly diverse user group. This, in turn, has led to a corresponding growth in the development of databases, analysis tools and training options being made available to a growing and multidisciplinary user group. In this way, both the capacity and the use of GIS in spatial modelling applications continue to grow exponentially (Kontic & Kontic 2009).

Prior to GIS becoming readily available, most spatial modelling undertaken by ecologists relied on cartographic maps as a basis for spatial modelling (Turner et al. 1995). Because cartographic maps were expensive it became common practice for modellers to draw different scenarios on sheets of Perspex overlaid on maps, thus enabling multiple scenarios and perspectives to be examined without damaging the original map. The advent of GIS enabled users to similarly overlay different data sets and scenarios over a representative landscape within a personal computer software program (Schuurman 2004). It therefore comes as no surprise that ecologists have been both quick and enthusiastic in the uptake of GIS for spatial modelling (Brebbia & Pascolo 1998; Mersey et al. 2002; Gurrutxaga et al. 2010).

Method: GIS creates a spatially defined landscape grid through a specified datum. Objects in GIS data bases are then added to this landscape to produce maps or to enable analysis. Objects are stored in GIS databases as geodatabases, shapefiles or rasterfiles. The geodatabase is the common data storage and management framework. It combines "geo" (spatial data) with "database" (data repository) to create a central data repository for spatial data storage and management. Shapefiles are comprised of drawn objects such as roads, patches of remnant vegetation, sites of interest and topographic or climatic isohyets are depicted. Rasterfiles are comprised of a matrix of cells or pixels organized into a grid where each cell contains a value representing information, such as temperature. Rasters can be digital and remotely sensed items such as aerial photographs, imagery from satellites, digital pictures, or scanned maps (ESRI Australia Pty. Ltd. 1999).

GIS enables users to link and display features and recorded values within single and multiple databases, to share and exchange values and data between databases, create new data sets (through combining, querying, or analysing data), and to alter and link databases enabling multivariate analysis. GIS is effective in the development of accurate maps, it enables a ready means of interpreting and applying remotely sensed data (Foody 2008), and it readily measures distances, areas and densities. GIS is therefore an excellent tool for mapping an actual landscape and determining how impacts may change that landscape.

Applications: Project officers for relevant agencies and natural resource management organisations report that basic GIS mapping has been, and remains, the preferred spatial modelling tool used in biodiversity conservation in south-western Australia. This is because:

- GIS portrays landscape information in a simple and easily understood format;
- it is particularly useful in displaying spatial relationships between patches of remnant vegetation and changes in vegetation extent will alter these relationships;
- it is simple to use; most conservation managers have had training in its use; and
- basic GIS software and data is relatively inexpensive and readily obtainable.

For these reasons GIS remains the sole spatial modelling tool for many of the connectivity projects in this region (Hobbs & Saunders 1991; Environmental Protection Authority. 2003; Green Skills 2007; Molloy *et al.* 2009).

Limitations: Using GIS in this manner is a simple form of spatial modelling which relies on two main assumptions: i.e., habitat is assumed to be the patch (habitat values are generally not recognised outside of the patch and habitat value is generally assumed to be uniform within the patch) and the only barrier to movement is assumed to be distance (Lindenmayer & Nix 1993; Lambeck 1999).

Comments: Effective spatial modelling for ecological viability in fragmented landscapes requires being able to quantify the impacts of change on species and communities (Bestelmeyer *et al.* 2003; Fischer *et al.* 2004; Freudenberger & Brooker 2004; Fischer & Lindenmayer 2007; Lindenmayer *et al.* 2008; Lawes & Dodd 2009; Gurrutxaga *et al.* 2010). Consequently, a means of identifying the requirements of species and communities and incorporating these requirements into a GIS modelling matrix, is required.

2.3.2 Focal species.

Background: The need to incorporate the habitat requirements of nominated species into spatial modelling applications leads to the development of the focal species approach. The focal species approach is a spatially realistic form of modelling (Department of Environment and Conservation. 2007) which rose to prominence and wide-scale application in the Western Australian Wheatbelt in the late 1990s. Although it has undergone considerable refinement, it remains this region's most commonly used biodiversity conservation planning tool (Huggett 2007).

Method: In describing this approach Lambeck (1997, p849) proposed, "a multi-species approach for defining the attributes required to meet the needs of the biota in a landscape and the management regimes that should be applied. The approach builds on the concept of umbrella species, whose habitat requirements are believed to encapsulate the needs of other species." Lambeck did this by noting landscape attributes such as patch size, and isolation, vegetation composition, structure and condition and comparing these attributes with observed presence or absence data for a suite of nominated bird species. These bird species were selected to represent dispersal and resource limited species, or were selected because a species required management as a conservation priority. By doing this, it became possible to determine which landscape attributes enabled a species, or a suite of species, to persist in a landscape and how this persistence related to threatening processes. Management activities could then be designed and implemented which would enable the persistence, recolonisation or reintroduction target bird species to the subject landscape. Birds were used as focal species because they were deemed to be effective environmental indicators and because their presence or absence in a patch could be easily determined (Lambeck 1999).

Implicit in the focal species approach is the umbrella concept. This refers to the assumption that through facilitating the persistence of a nominated suite of bird species the needs of other, more cryptic, species would be met (Lambeck 1997). This assumption has drawn criticism to the focal species approach (Lindenmayer *et al.* 2002). In spite of this, the focal species approach to spatial modelling remains widely used and is considered very effective in engaging community support as concepts easily demonstrated and understood and participation does not require specialist skills (Wallace *et al.* 1998; Lindenmayer *et al.* 2002; Freudenberger & Brooker 2004; Smith *et al*. 2004; Department of Environment and Conservation. 2007; Huggett 2007; Smith 2008).

Applications: In earlier applications of the focal species approach thresholds were set based on habitat characteristics such as minimum size, condition, vegetation type, and distance between patches. These thresholds were then used to define habitat and to demonstrate how far focal species would move from their home patch. GIS software could then be used to map patches of habitat and demonstrate gaps which would act as barriers to movement. In theory, this enabled planners to determine which patches were essential to facilitate movement of a species within the landscape and to determine revegetation sites that would enhance patch habitat values and/or link patches by acting as “stepping stones” between patches (Lambeck 1997).

Limitations: In practice, thresholds become wrongly interpreted as absolutes. For example, nominating a maximum distance threshold between patches of 100 m for species *A*, gives the impression that this species can cover a gap between habitats of up to 100 m without restriction while all movement between patches ends beyond this threshold. In a more realistic scenario we can assume that although species *A* has been assigned a distance threshold of 100 m, a 20 m gap between patches will impede dispersal less than would a 100 m gap, and a gap much greater than 100 m may not act as a total barrier to movement. Therefore, the degree to which a gap in habitat impedes movement throughout a landscape can effectively be conceptualised as a probability. That is, the probability of species *A* covering a 20 m gap in habitat will probably be much greater than the probability of the same species covering a gap of 100 m and the probability that a gap of 200 m crossed could be small to insignificant but it is still possible. Consequently, the real management question becomes what is the probability of species a crossing a gap of *x* meters or what is the probability of presence of species a with a patch size of *x* hectares. In practice probabilities become more effective than simple thresholds. To that end in later focal species projects, the impacts of factors such as patch isolation, size and condition came to be quantified as probabilities and enabling more effective modelling of the way in which landscape factors influence habitat and movement (Brooker & Brooker 2002; Freudenberger & Brooker 2004; Watson *et al.* 2005; Huggett 2007; Lindenmayer *et al.* 2008; Brouwers & Newton 2009b; Holland & Bennett 2009).

Comments: Changing the emphasis of focal species applications from thresholds to probabilities allows probabilities to be compounded over various time frames. For example, if a probability is calculated for species *A* to colonise a patch across a gap between 2 patches x^1 in a year it becomes possible to calculate the probability of that species crossing a further gap x^2 to colonise a third patch within the same or consequent years (Brooker & Brooker 2002). This greatly enhances the capacity of the focal species approach to be applied to spatial modelling over various temporal scales.

Probabilities reflecting landscape factors are largely viewed independently, whereas in practice probabilities relating to landscape factors are interrelated. For example, a probability of presence for species *Z* in a patch of 20 ha will still vary in response to factors such the condition or structure of the patch, management regimes or patch isolation. Therefore, to effectively apply focal species principles to spatial modelling applications it is necessary to understand which landscape factors most directly influence species presence and movement and to be able to use these factors as appropriately weighted covariates in the development of probabilities (Brouwers & Newton 2009a). We also need to be aware of (and compensate for) the limitations of the subject species to act as planning surrogates for non-target species (Freudenberger & Brooker 2004).

2.3.3 Proximity analysis.

Background: Proximity analysis is a generic term which refers to a suite of GIS based tools which allow users to quantify and manipulate the spatial relationships between objects or assets, thereby providing users with insights into ecological functions and their responses to variations in spatial arrangements (Ruggiero *et al.* 1994; Karanth *et al.* 2006;

Huck et al. 2008; Benitez-Lopez *et al.* 2010; Metzger *et al.* 2010; Shova & Hubacek 2011). In general, although these tools tend to be crude and simplistic in nature, they are capable of providing useful data to users providing that their strengths and weaknesses are understood and acknowledged (Tischendorf & Fahrig 2000a; Tischendorf & Fahrig 2000b).

The SWREL project was undertaken as a partnership project between the Western Australian Local Government Association and the Western Australian Department of Environment and Conservation to provide a response to the issues of fragmentation and climate change through the identification of regional scale ecological linkages. These ecological linkages were to be designed through a collaborative and consultative process involving federal and state agencies, local government authorities, and regional natural resource management organisations. The objectives of this project were to: support more effective recognition of ecological linkages in land use planning policy and processes, retain native vegetation and fauna habitat, and to maintain key ecological functions across the project area (Environmental Protection Authority 2009).

This project recognised that historically there had been a strong policy framework which required that ecological linkage be a consideration in planning frameworks (Environmental Protection Authority 2006; Environmental Protection Authority 2008). However, there were no methodologies for demonstrating, or quantifying, the impacts of development proposals or management actions on landscape connectivity that were comprehendible or applicable available to relevant planning organisations. Therefore the requirement to consider impacts on ecological linkages and consequently ecological function were generally overlooked in planning and assessment processes. In recognising this situation, project staff developed a method of proximity analysis as a means of demonstrating connectivity between patches and quantifying impacts to ecological connectivity that may arise from proposed projects or changes to management actions (Molloy *et al.* 2009).

Method: The SWREL project developed a proximity analysis tool to provide decision support data for the development of the SWREL and to provide an indication of the impacts to landscape connectivity that may arise from a proposed development. This tool was used to assign proximity values, or thresholds, to a series objects at predetermined compound distance based thresholds relevant to any nominated point of feature as spatially realistic GIS data. In determining the SWREL this tool was used to assign one of ten proximity values to patches of remnant vegetation relevant to a linkage axis line. The linkage axis line being drawn as a base point from which ecological linkage relevant to a series of patches, acting as stepping stones for biota, was measured (Molloy *et al.* 2009).

Applications: This tool enables changes in connectivity, as depicted by changes to patch proximity values, to be quantified in response to proposed changes arising from either revegetation or the clearing of native vegetation (Molloy *et al.* 2009). The proximity analysis methodology used in this project is an example of crude distance based ecological modelling with distance thresholds derived through a review of literature and broad scale ecological principles and habitat is given as binary, i.e., all patches are given as habitat of equal value and habitat values are not recognised outside of patches.

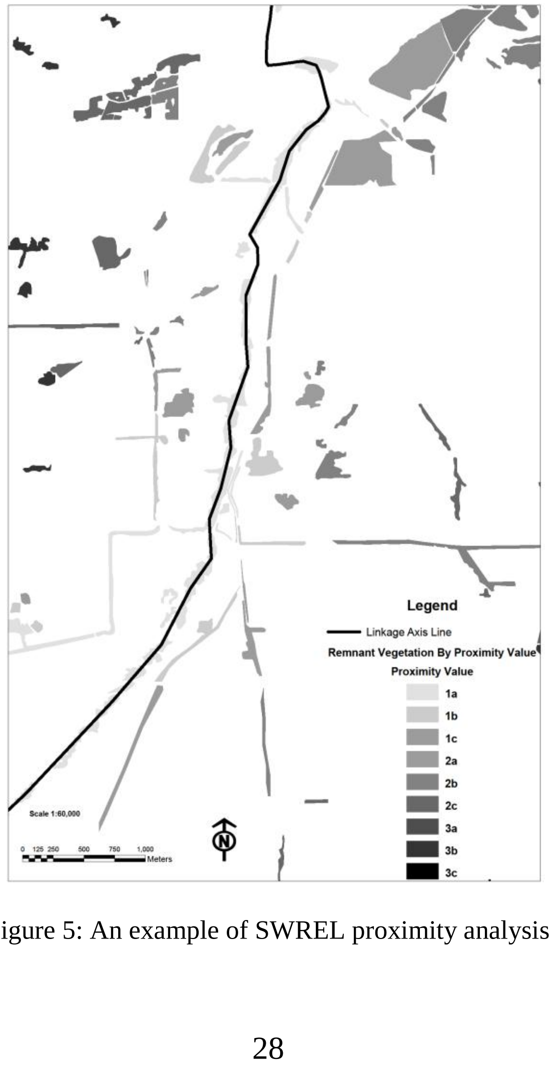

Figure 5: An example of SWREL proximity analysis

Limitations: This methodology is of limited use in the management of specific species or communities in that it relies on assumed and arbitrary definitions of barriers to movement and habitat in the absence of probability based parameters for individual species, e.g. in this habitat we have a probability of *x* that species *A* will be present and a probability of *y* that this species will cross a given gap. However, crude distance based models, such as this one, can be effective if their limitations are recognised (Tischendorf & Fahrig 2000a). Regardless of the dangers of assumptions in managing species and communities, it should be remembered that distance between patches is a barrier to movement (Belisle & Desrochers 2002; Lindenmayer *et al.* 2008; Robertson & Radford 2009) and patches of native vegetation do provide habitat for many target species (Amarasekare & Possingham 2001; Fahrig 2003; Hanski & Ovaskainen 2003).

Comments: The objective of this method of proximity analysis was to quantify the impacts of fragmentation in a manner which planners and others who are not trained in ecological principles can understand and apply and has been deemed successful in doing this (Environmental Protection Authority 2009). The proximity analysis tool makes the application of this methodology a fast, simple and automated process. It incorporates more detailed modelling processes, such as Marxan®, and expert inputs into prioritising conservation targets. Outputs are easily understood. Like basic GIS applications, it has a capacity to incorporate temporal variations through multivariate scenarios and this process enabled a comparatively quick, effective and cheap means of designing a complex ecological linkage matrix over a large and highly varied landscape mosaic.

2.3.4 Marxan®.

Background: This is a spatially explicit software package that is designed to deliver decision support for reserve system planning. The end user requirements are expressed through input targets and parameters that enable Marxan® to select a group of planning units whose retention will best reflect the user’s reserve planning priorities and constraints (Ball & Possingham 2000). Within the south-west region Marxan® has been used for decision support in the SWREL Project (Molloy *et al.* 2009), marine planning (Watts *et al.* 2009) and the South West Eco Region Initiative (Gaia Resources 2009). The Swan natural resource management organisation and Western Australian Department of

Planning and Infrastructure are currently looking at ways of incorporating Marxan® into their regional planning processes.

Method: Marxan® is primarily intended to solve a particular class of reserve design problem known as the 'minimum set problem', where the goal is to achieve some minimum representation of biodiversity features for the smallest possible cost (Ball & Possingham 2000). In minimum set problems the elements of biodiversity that you wish to conserve are entered as constraints to solutions of the problem as their retention is required in all modelled scenarios (Possingham *et al.* 1998). Given reasonably comprehensive data on species, habitats and/or other relevant biodiversity features, it aims to identify the reserve system (a combination of planning units) that will meet user-defined biodiversity targets for the minimum cost (Watts *et al.* 2009).

Applications: Although Marxan® can be used for a variety of purposes at a different stages in the systematic conservation planning process, it was designed primarily to help inform the selection of new conservation areas for minimal "cost" and facilitate the exploration of trade-offs between conservation and socio-economic objectives (Ball & Possingham 2000). Marxan® can help set priorities for conservation action by highlighting those places that are likely to be important inclusions in an efficient reserve network. Marxan® can also be employed as a tool for evaluating the representation and comprehensiveness of existing reserve networks (Watts *et al.* 2009).

Limitations: Marxan's® effectiveness in planning and designing ecological linkages is limited in that, although it can be used to effectively determine habitat given the appropriate input data, it cannot adequately quantify barriers to movement other than distance between habitat, distance to area ratios of habitat, or proportion of defined habitat within a given landscape. This results in arbitrary thresholds being used to quantify barriers to movement and the problems inherent therein (Zielinski *et al.* 2006; Huber *et al.* 2010).

Comments: Although a popular and potentially informative planning tool, Marxan® requires skilled operation, accurate and extensive input data sets, and expensive GIS software packages. Knowledge and information gaps have the potential to significantly skew results. Marxan® outputs require skilled interpretation and most Marxan®-based planning projects are undertaken by specialist consultants (Watts *et al.* 2009). For this reason Marxan® may be incorporated into planning processes by project staff that lack an adequate appreciation of the intended applications and inherent limitations of this type of software (Langford *et al.* 2009).

2.3.5 Conservation Action Planning (CAP: International)

Background: The Nature Conservancy's Conservation Action Planning (CAP) process is not by definition a spatial modelling tool, but as it has been widely used as the technical basis for planning in major connectivity projects (Lovett *et al.* 2008; Gondwana Link 2009), is the only known tool of its type used for conservation planning in this region and is a tool widely used around the world (TNC 2007) the inclusion of this process was deemed appropriate.

The CAP process is designed to help conservation projects develop strategies, take action, and measure their success and then to adapt and learn over time (TNC 2007). This planning tool has had wide application by Greening Australia and WWF and is currently being used by the Gondwana Link Project (Lovett *et al.* 2008). Adaptive management is at the heart of the CAP process. This CAP process is delivered in a spreadsheet type project management tool which uses expert opinion to set project priorities and management actions using 10 steps to project planning and management under four general headings. These headings are; defining the project, developing strategies and measures, implementing strategies and measures, and adapting and improving. This process provides scant guidance on exactly how to identify and rank assets, and managements, leaving the definition of such details to the project's experts (TNC 2007).

Method: This is a Delphi planning process based on the skills of a group of nominated experts, and as such, can be an effective way of turning the opinions and values of that group of experts into project management actions. This can be an enormous asset to a project in that it can enable high level skills and knowledge to be converted into project level management actions. However, it can also be a handicap in that management actions relate directly to the opinions, priorities, knowledge limitations, and personal dynamics of the expert group. In recognition of this potential handicap the CAP process emphasises need to appoint experts to the planning group (TNC 2007; Lovett *et al.* 2008).

Applications: The CAP process has shown itself to be an excellent way of enlisting expert opinion into a project. It is has also shown that it can be effective in bringing community values and hence support to a project and as a catalyst bringing about interaction between expert and community. This means that the process is potentially very effective in defining and prioritising targets and management actions and this can be very effective in spatial modelling.

Limitations: There is little that the CAP process brings to spatial modelling other than its capacity to apply the finding of more rigorous spatial modelling tools and applications (TNC 2007). It does not define or recognise barriers to movement or habitat values beyond the understanding of the expert group, nor does it inform the group of the impacts of management actions on these landscape attributes. Similarly the CAP process lacks a multivariate capacity. It tends to portray temporal variation as before and after in response to a limited set of management priorities and actions. It lacks the capacity to demonstrate how multiple management scenarios over differing temporal scales will impact on the resilience of a fragmented landscape.

Comments: Although not a spatial modelling application, the CAP process like other integrative or participatory approaches has the capacity to incorporate data derived from spatial modelling tools and applications into large scale conservation planning initiatives. This is because the CAP process enables project managers to facilitate the data derived through spatial modelling tools and methodologies into integral project planning processes such as the development and delivery of project priorities, target setting, works planning and monitoring and evaluation procedures. In this way the CAP process can provide a mechanism which will enable the findings of spatial modelling exercises to make the contextual “leap” from the theory and research to on-ground management action.

2.4 Comparison

Table 2 summarises the key requirements of spatial modelling applications used to date in south-western Australia. The purpose of this is to allow a quick comparison of the relative strengths and weaknesses of each methodology. In this table scores of low, medium or high are given to reflect the degree to which each of these applications meets each of the attributes which a successful spatial modelling application should possess if it is to effectively demonstrate how subject impacts affect a fragmented landscape. The scores given reflect the findings of the above discussions and are only provided for comparative purposes. The arbitrary nature of this table and its inherent limitations are therefore acknowledged.

Table 2: Comparison of reviewed methodologies relative to the stated attributes of an effective spatial modelling methodology. Comparison score is given for suitability as high (3), medium (2) and low (1).

Criteria	**Spatial Modelling Applications**				
	GIS (Basic map making)	**Focal Species**	**Proximity Analysis**	**Marxan®**	**CAP**
Defines barrier to movement. (1=low)	1 (Barriers to movement are arbitrarily defined by users.)	2 (Species requirements given as thresholds.)	2 (Species requirements given as thresholds.)	2 (Species requirements given as thresholds.)	1 (Barriers to movement are arbitrarily defined by users.).
Defines Habitat. (1=low)	1 (Habitats are defined arbitrarily by users.)	1 (Habitats are defined arbitrarily by users.)	1 (Habitats are defined arbitrarily by users.)	2 (Habitat recognition can be partially undertaken through GIS data and target setting.)	1 (Habitats are defined arbitrarily by users.)
Predicts target species/community response to impact. (1=low)	1 (Responses to impact are arbitrarily defined by users.)	2 (Crude responses can be predicted based on thresholds and basic habitat identification.)	2 (Crude responses can be predicted based on thresholds and basic habitat identification.)	1 (Responses to impact are arbitrarily defined by user.)	1 (Responses to impact are arbitrarily defined by user.)
Demonstrates multivariate scenarios. (1=low)	1 (Only functions in a single given time frame.)	2 (Can demonstrate a before and after response.)	3 (Allows instant demonstration of impacts over multiple time frames.)	3 (Allows instant demonstration of impacts over multiple time frames.)	1 (Only functions in a single given time frame.)
Input data requirement. (1=most data required)	2 (Basic mapping requires several readily available GIS data sets.)	2 (Requires several readily available GIS data sets.)	1 (Effective use requires many GIS data sets. Many of these sets may not be available or may require development.)	1 (Effective use requires many GIS data sets. Many of these sets may not be available or may require development.)	1 (Effective use requires many GIS data sets. Many of these sets may not be available or may require development.)

Outputs are easily understood (1=highest skill required)	3 (Outputs easily understood.)	3 (Outputs easily understood.)	2 (Some training required to fully understand outputs.)	1 (Comprehension of products requires extensive training.)	2 (Some training required to fully understand outputs.)
Skill level required to implement. (1=highest skill required)	3 (Basic operation of most software requires minimal training.)	2 (Basic GIS operation skills plus additional training in this methodology.)	2 (Basic GIS operation skills plus additional training in this methodology.)	1 (Moderate to high level GIS skills required plus extensive training required for this methodology.)	2 (Basic GIS operation skills plus additional training required for this methodology.)
Cost (resource requirements). (1=highest cost)	2 (Basic GIS software, data sets and personal computer equipped with Microsoft Office® required.)	2 (Basic GIS software, data sets and personal computer equipped with Microsoft Office® required.)	2 (Basic GIS software, data sets and personal computer equipped with Microsoft Office® required.)	1 (Advanced GIS software, high level data sets and personal computer equipped with Microsoft Office® required).	3 (PC equipped with Microsoft Office® required.)
Total	14	16	15	12	11

2.5 Discussion

In any form of management, it is generally considered more cost effective and efficient to prevent disaster rather than to reverse it. Therefore, effective conservation management is preventative in nature (Lindenmayer *et al.* 2008). Preventative conservation management in fragmented landscapes requires that managers are able to predict how species, communities and ecological processes will be affected by an impact or management action and the degree to which they will be affected; and they will rely on spatial modelling to give them this information. To that end, effective spatial models will be those with the capacity to use the individual and collective habitat requirements of a broad suite of species to define and quantify: a) what is a barrier to movement; b) what is habitat; and c) how these quantifiable values will change, in relation to a modelled impacts or management actions (Lambeck 1997; Lambeck 1999; Watson *et al.* 2001; Freudenberger & Brooker 2004; Watson *et al.* 2005; Huggett 2007; Lindenmayer *et al.* 2008) Conversely, where spatial modelling is undertaken in situations and there are limited resources and large knowledge gaps, spatial modelling becomes reliant on assumptions (often of an anthropocentric perspective) and the use of insufficient, inadequate or inappropriate surrogates (Tischendorf & Fahring 2000b; Watson *et al.* 2001; TNC 2007; Lovett *et al.* 2008; Caro 2010).

GIS represents an anthropogenic perspective of habitat which may differ significantly from those parameters which actually define the habitat of subject species. This appears to be a consequence of significant knowledge gaps regarding the habitat requirements of many species, and an apparent abundance of available GIS data which has largely been compiled for purposes other than conservation managment (Landgate 2011). Furthermore, GIS tools and data are readily available to a wide range of users of varying skill levels. For these reasons many of the GIS modelling applications seen to date in south-western Australia have not been as effective as they might have been.

Marxan® and Proximity Analysis deliver decision support information through the formulaic analyses of GIS data. As such they are representative of a diverse and rapidly growing group of planning tools with widely varying degrees of sophistication (Collinge 2009). However, the application of such tools in south-western Australia shares the same anthropogenic perspectives as discussed above in relation to GIS and is therefore subject to the same criticisms. In comparison to the other modelling approaches discussed, these tools tend to require considerably greater resources in regard to hardware and software to operate, and require similarly high skill levels to use (Ball & Possingham 2000). This can lead to a situation where the limitations and suitability of these tools is not fully understood by project planners. Furthermore, the ouputs of these modelling tools are also much more difficult to understand and are therefore liable to be misunderstood or misapplied in the development of conservation managment activities. The CAP process helps to develop managment actions through a Delphi process (Klenk & Hickey 2011), i.e. a process which aims to develop consensus between a group of experts over several rounds of deliberation on the assumption that combining the expertise of several individuals through these structured discussions will provide more reliable results than consulting one or two experts individually. The CAP process does not provide information as to how subject landscapes, communities or species will react to impacts or managment actions. This form of tool is highly palatable as it requires few resources and is easy to use and understand and is effective in enlisting community support. It is also very useful in situations where there is little published data available on target species or landscapes. However, as in any Delphi process, the quality of the outcome relies on the quality of the expert input and this is likely to bias the outcomes since it is inevitably influenced by the perceptions, misconceptions, values and beliefs of those whose expert opinion is sought. In south-western Australia to date, the only spatial modelling tools used by biodiversity conservation managers which attempt to demonstrate how biota may react to impacts or management actions, are applications of the Focal Species approach to conservation management. However, Focal Species applications used in this region have focussed on the use of a few birds species, used simplistic single factorial regressions as predictors of presence/absence, and have used relatively simplistic definitions of habitat (Freudenberger & Brooker 2004; Huggett 2007; Fahrig & Triantis 2013). Although the use of "focal," "indicator" or "surrogate" species has long been common practice in the conservation management of fragmented landscapes, their effective use requires a number of assumptions. Firstly, the habitat needs of the "focal" species should be well enough understood to be quantifiable; and secondly, the suite of "focal" species selected should represent a range of habitat requirements diverse enough to enable that suite of species to provide a meaningful insight into the way management actions will affect the entire biota of the modelled landscape (Lambeck 1997; Watson *et al.* 2001; Freudenberger & Brooker 2004; Huggett 2007).

In the application of all spatial modelling tools there is a need to incorporate the knowledge of relevant experts. This usually gives rise in an expert consultation or Delphi approach to the designation of project objectives, targets and priorities (Collinge 2009). The inherent problem with this is that, at some time during the planning process, expert knowledge must be applied with an understanding of the strengths, weaknesses and appropriate applications of the selected spatial modelling tools. The operation of more complex spatial modelling tools requires highly skilled and specialised operators. Consequently, the potential for conflicts and misunderstandings between modellers and other technical specialists representing different disciplines and perspectives increases where more sophisticated spatial modelling tools are utilised. Therefore, when using complex spatial modelling tools, effective project planning and implementation becomes increasingly reliant on assigning tasks and responsibilities to team members in accordance with the expertise of the indivual and on maintaining frank and effective communication between all paticipants (Klenk & Hickey 2011).

In light of the above, this review supports a general consensus amongst ecologists that, when it comes to selecting a spatial modelling application, there is no “one size fits all” (Caro 2010). Therefore, successful spatial modelling relies on the careful selection and application of an appropriate suite of modelling tools or applications. None of the spatial modelling applications reviewed can adequately consider the many ecological and social processes influencing the viability of a landscape (Tischendorf & Fahrig 2000b; Ferrier & Guisan 2006; Huggett 2007; Lovett *et al.* 2008).

As demonstrated (Table 2), when comparing these spatial modelling applications against the attributes of a successful spatial modelling methodology, all of the reviewed applications have different strengths, weaknesses and resource requirements. This reflects the varied intentions and perspectives of model designers and those who have, for various reasons, opted for their use. However, a combination of these applications can be used to meet all of the listed criteria, and by adapting certain aspects of some of these applications to directly meet our criteria, the development of a spatial modelling methodology capable of better meeting the needs and circumstances of both regional biodiversity and conservation planners can be developed. For example, a Focal Species approach that incorporates data from terrestrial and arboreal surrogate species to enhance the bird data currently used can improve our understanding of how distance and landscape attributes act as barriers to movement. This data can be used to develop probabilistic decision support tools, for example, Bayesian Belief Networks (Smith *et al.* 2007) which can quantify barriers to movement as species specific probabilities which can be used to replace arbitrary thresholds in proximity analysis. Therefore, a study of the habitat requirements of an appropriate group of surrogate species can be used to define probabilities for presence absence based on landscape attributes which can be used as a basis for project planning as demonstrated (Figure 6). These attributes can be modelled using Marxan® to identify, rank and prioritise habitat zones, while all stages of the planning process can be checked by an appropriate group of experts through a CAP like Delphi process. It is also possible to incorporate all of these proposed spatial modelling activities into a GIS format as GIS remains the most effective way of displaying spatial data in an easily comprehensible manner.

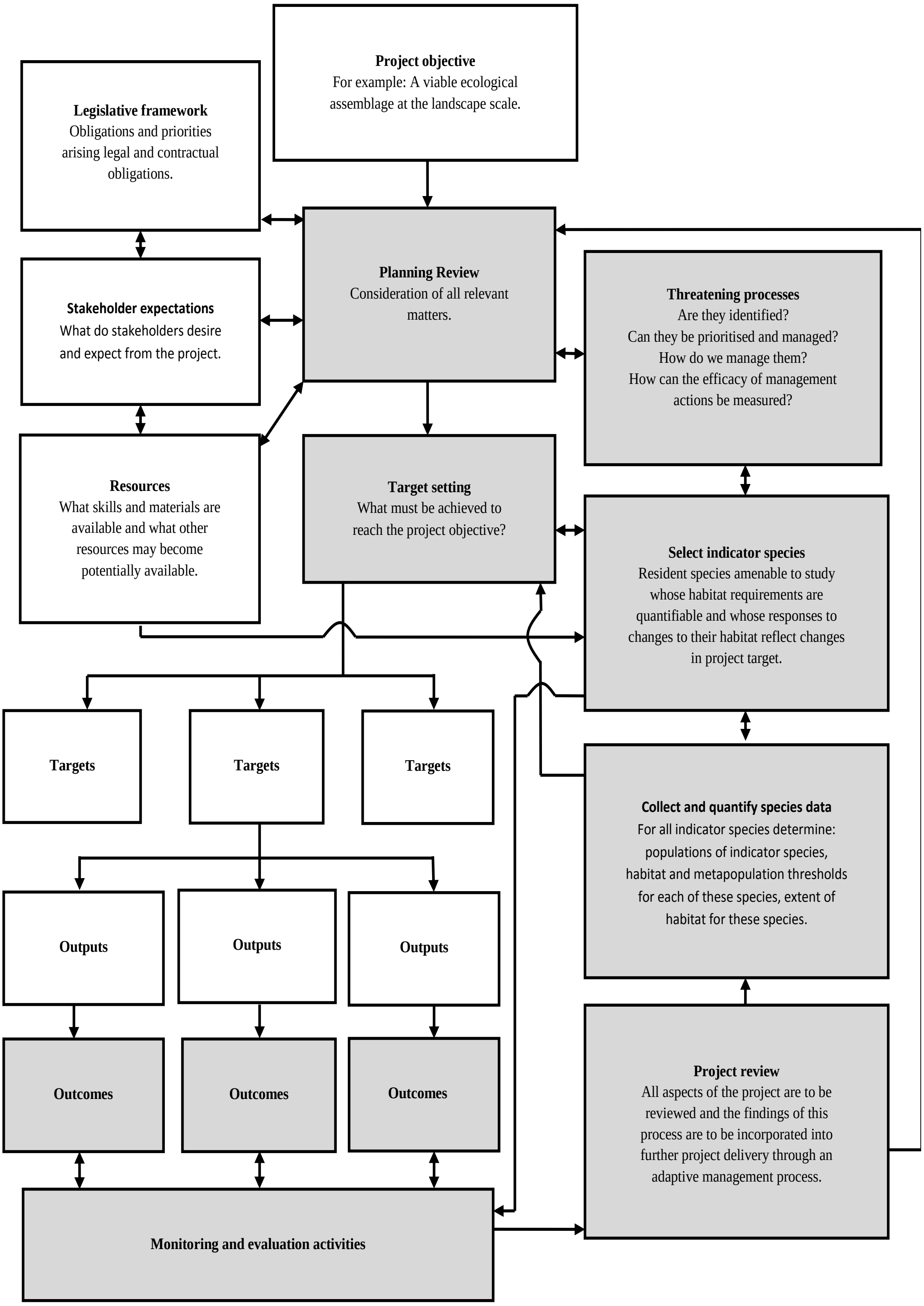

Figure 6: A conceptual framework for incorporating species requirements into biodiversity conservation project planning

2.6 Conclusions

The development of spatial modelling applications capable of demonstrating both the needs of regional biota and the response of that biota to perceived impacts and management actions is fundamental to meeting this bioregion's ongoing conservation planning needs. This requires a reduction in the level of assumption currently applied by conservation managers and replacing that assumption with data which is both relevant and quantifiable. This can be done by quantifying the metapopulation requirements of an appropriate suite of species (selected for their ability to demonstrate the effects of ecological impacts on ecological assemblages or for other conservation values) and using this data to demonstrate how species and communities will respond to changes in habitat values or management actions as probabilities for presence/absence. For example, where a site may be currently assumed to be either habitat or not habitat for species *Z* it is possible to use statistical analyses to demonstrate that, given the current set of management actions and habitat parameters, the probability of species *Z* being present at that site will be PxZ_1 and that if these management actions and/or habitat parameters were to change that probability would become PxZ_2. It will also be possible to calculate the accuracy of these models using standard statistical tests. In this way it is possible to effectively quantify and demonstrate how subject species and communities will respond to perceived changes in circumstance thereby enabling conservation managers to construct and apply spatial modelling applications based on quantifiable data applied through logic matrices such a Bayesian Belief Networks rather than on the simple application of assumption. In this way, quantifiable spatial models can be designed and applied to more effectively demonstrate the current and future needs of regional biota than management based largely on assumption. In so doing, this will enable the development of spatial modelling applications more capable of meeting the current and future challenges faced by species and communities wherever fragmentation threatens persistence and where a rapidly changing climate exacerbates that threat.

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3 Quantifying habitat value using existing survey data.

3.1 Introduction

3.1.1 Overview

In this chapter I will demonstrate a methodology by which habitat value can be indicated and quantified using readily available data applied through logistic regressions. This will enable conservation managers to identify and quantify habitat by determining how the probability of presence or absence of target species changes in response to landscape parameters and management regimes. This will enable conservation managers to quantify, model, and therefore demonstrate how target species will respond to foreseeable impacts and management actions.

As discussed in ch.2, one of the major problems facing conservation managers is determining how to quantify the most likely outcome when assessing the consequences of detrimental processes, such as clearing or climate change, or implementing management actions, such as revegetation or incorporation of land into the conservation estate (Herzog *et al.* 2001; Lindenmayer & Fischer 2006; Greg & Andrew 2009; Holland & Bennett 2009).

Given the capacity to model in this way, managers can identify and prioritise threats, test the efficacy of potential management actions and, in light of this information, devise effective solutions to threatening processes (Moore & Swihart 2005; Tattoni *et al.* 2010; Yates *et al.* 2010b; McLane *et al.* 2011; Reiss *et al.* 2011).

It is therefore hypothesised, that in my study region of south-western Australia, where much of the landscape has been, and continues to be, cleared of natural vegetation (Environmental Protection Authority 2007; Molloy *et al.* 2007; Burbidge 2010) and where major revegetation and conservation planning projects are being undertaken (Watson *et al.* 2008; Gondwana Link 2009; DEC 2012), conservation planning and management actions would benefit through managers being able to quantify the consequences of changes to both management actions and vegetation extent.

Statistical regression modelling enabling the correlation between independent, predictive, landscape variables and dependant, response, species variables to be identified and quantified is common practice in environmental modelling (Peeters *et al.* 1998; Brouwers & Newton 2009b; Gougeon 2009; Duchesne *et al.* 2010). In this type of modelling, a set of relevant predictive variables, quantifying change, is developed for a target landscape and these predictive variables are linked to a dependant or response variable, such as the presence or absence of an indicator species (Lambeck 1997; Caro 2010). It then becomes possible to develop a statistical model which can quantify the degree to which potential changes in predictive variables will bring about ecological consequences and thereby demonstrate the probable reactions of the subject, indicator species (Ball *et al.* 2005; Ferrier & Guisan 2006; Urban *et al.* 2009; Navarro-Cerrillo *et al.* 2011; Reiss *et al.* 2011; Broennimann *et al.* 2012; Guerin & Lowe 2012).

3.1.2 Indicator species (response variables)

In ch.2 I argued that biodiversity management has long been hampered by significant knowledge gaps, and quantifying habitat values usually involves undertaking comprehensive research, and that level of research is often beyond the capacity and resources of many project managers (Lambeck 1999; Smith *et al.* 2006; Environmental Protection Authority 2007; Pressey & Bottrill 2008). In such a scenario, assumption can become the primary, and often only, means of informing conservation management initiatives. For this reason, conservation managers often find it useful to employ the concepts of target, umbrella, focal, and/or surrogate species which all attempt to reduce inherent complexities and uncertainties by focussing on species which are deemed more important or influential in terms of their contribution to biodiversity patterns and/or processes (Lambeck 1997; Lindenmayer *et al.* 2002; Freudenberger & Brooker 2004; Collinge 2009). In so doing, managers are able to monitor and manage the response of ecological assemblages by identifying and quantifying the habitat requirements of a small number of relevant target species, rather than by trying to monitor and manage a large numbers of species within an assemblage (Caro 2010).

Historically, bird species have been commonly used as indicators of habitat value in south-western Australia because: 1) they can be readily observed; 2) observation is considered to have little direct impact on the target species; 3) bird presences at the landscape scale are comparatively well recorded; 4) bird species within an ecological assemblage will fill a variety of niches; and 5) because the presence of many species is directly related to variations in patch matrices and management regime, readily responding to changes in these variables (Lambeck 1997; Watson 2003; Huggett 2007; Davis *et al.* 2013).

3.1.3 Predictive (independent) variables

When modelling species distributions and movements in highly fragmented landscapes, conservation managers often conflate all patches of remnant vegetation as habitat (Hobbs & Saunders 1991; Lambeck 1999; Green Skills 2007; Gondwana Link 2009; Molloy *et al.* 2009). In doing this, managers make the broad assumption that all habitat is the same which, although potentially valid for some management applications, fails to identify or quantify habitat from a species-specific viewpoint. In other words, the nomination of a landscape attribute as habitat requires the recognition of what species it is habitat for and which quantifiable landscape variables can be used to define that habitat value (Tischendorf & Fahrig 2000a; Favreau *et al.* 2006; Huggett 2007; Fitzpatrick *et al.* 2008; Lindenmayer *et al.* 2008; Collinge 2009). This highlights the need for a conservation planning tool that reflects the way in which changes in management regime and landscape matrices impact on habitat value by quantifying the response of an indicator species to a proposed change in a nominated variable linked, either directly or indirectly, to habitat type and quality.

Individual bird species have proven to be ideal indicator species for this type of modelling in the past, however, the use of individual species is inherently biased by the narrow focus of a single species’ habitat requirements (Lindenmayer *et al.* 2002; Huggett 2007; Beier *et al.* 2008; Caro 2010). Consequently I have sought to minimise this bias by modelling habitat value from the perspective of a set of indicator species, using both individual and combined species models. This method, an application of commonly-used statistical sampling principles (Liu & Suesse 2008; Erdbrügge *et al.* 2011), averages the response of an impact, or change in a predictive variable, over an appropriate set of indicator species, or response variables. In doing this, the consequences of modelled variations in predictive variables becomes standardised, e.g. a variation in one variable might have a very high or low impact on one or two indicators but a much less dramatic impact on the set as a whole.

3.1.4 Model development

Outputs of models that can effectively define habitat or barriers to movement should be probabilistic by nature as the effects of a landscape matrix or management regime on habitat distribution can rarely be binary, i.e. landscape composed of habitat or non-habitat (Cabeza 2003; Fahrig 2007). For a given patch or landscape, a specific probability for presence or absence of a species can be quantified and the accuracy of that prediction determined (Phillips & Dudík 2008; Brouwers & Newton 2009b; Gougeon 2009; Santika & Hutchinson 2009; Saura & Rubio 2010; Fahrig & Triantis 2013). This can be done by gathering robust survey data for a subject or indicator species and matching populations or presences of such species with landscape variables to develop predictive models (Possingham *et al.* 1998; Tischendorf & Fahrig 2000a; Watson *et al.* 2005). These models can then be tested for accuracy, both statistically and via further field trials (Herzog *et al.* 2001; Dang *et al.* 2010; Broennimann *et al.* 2012).

Multivariate regressions enable the development of a formula that describes how changes in a group of independent predictive variables will impact on a response variable (McGarigal *et al.* 2000). This enables a probability for indicator species occurrence to be calculated based on the combined parameters of a set of predictive variables (Peeters *et al.* 1998; Brouwers & Newton 2009a; Gougeon 2009; Duchesne *et al.* 2010). Models derived through univariate regressions, although commonly used as a basis for quantifying presence or absence (Lambeck 1999; Lindenmayer *et al.* 2002; Davis 2004; Freudenberger & Brooker 2004; Huggett 2007), cannot account for the way that multiple variables tend to combine and interact to define habitat (McGarigal *et al.* 2000; Kobayashi *et al.* 2009; Mateo *et al.* 2010; Navarro-Cerrillo *et al.* 2011; Broennimann *et al.* 2012). For example, the habitat capacity of a remnant for a species is probably not simply defined by just the size of the remnant, but may well also vary in response to variables such as vegetation type and condition, and other landscape metrics (McGarigal *et al.* 2000; Brouwers & Newton 2009b; Saura & Rubio 2010; Broennimann *et al.* 2012).

3.1.5 Objectives

In this chapter I demonstrate a means by which pre-existing data can be used to quantifiably model the potential consequences of detrimental impacts or mitigating actions on habitat value at both patch and landscape levels. To do this I will:

1. Assess the effectiveness of using a combined set of indicator species to demonstrate the impacts on biota of changes in vegetation extent or management regime.

2. Develop landscape-specific spatial modelling tools capable of assigning a probabilistic habitat value to a patch based on the habitat requirements of a set of indicator species.

3. Compare these models with independent survey data for two test landscapes to test their accuracy.

4. Discuss the strengths and limitations of this methodology.

3.2 Methodology

Data used for this exercise covers a 40 km radius from the township of Margaret River, Western Australia (Figure 7). This area selected is part of the South West Floristic Region (Hopper & Gioia 2004) where the original vegetation is largely fragmented forests/woodlands with ongoing loss of vegetation. Levels of clearing vary significantly between sub-regions of the SW Floristic Region. For example, although remnant vegetation cover in the Avon Wheatbelt Region is <20%, with some Shires having <5%, cover in the Jarrah Forest region is closer to 50% (McKenzie & May 2003). Furthermore, anthropogenic climate change is expected to have a severe impact on biota of the region (Opdam *et al.* 2009; Yates *et al.* 2010a; Fordham *et al.* 2012; Prober *et al.* 2012).

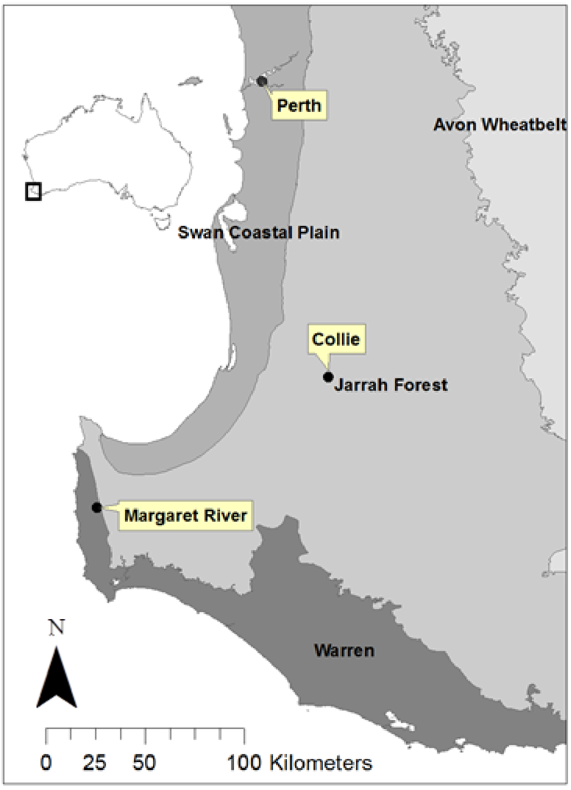

Figure 7: The project area depicting Margaret River, Collie and IBRA regions.

The study area covers elements of the Jarrah Forest and Warren Interim Biogeographical Regionalisation of Australia (IBRA) sub-regions (Department of Sustainability 2011) and is situated in south-western corner of the South West Floristic Region. Geologically, this is where Yilgarn Craton meets and intrudes into the Albany Orogen. Dominant vegetation is comprised of karri (*Eucalyptus diversicolor*) forest on deep loams and jarrah (*E. marginata*)/marri (*Corymbia. Calophylla*) woodland/forest on laterite with leached sandy soils in depressions and plains supporting low Jarrah woodlands and paperbark/sedge swamps (Dell *et al.* 1989; Havel & Mattiske 2000). Holocene dunes with Peppermint and Banksia woodlands predominate in coastal areas to the north and south of the study area (McKenzie & May 2003). The climate for this area is described as mild Mediterranean with warm dry summers and cool wet winters and annual rainfall of 1000 mm and a mean annual maximum temperature of 21^{o}C (BoM 2012) and similar patch matrices.

Major threats to biodiversity conservation in this region include climate change (Gibson *et al.* 2010; Yates *et al.* 2010b), weeds (Richardson 2007), feral animals (Robinson *et al.* 1993; Cowled 2009), clearing (Burbidge 2010), dieback (*Phytophthora cinnamomi*)

(Anderson *et al.* 2010), fragmentation impacts (Hobbs 1993b) and inappropriate fire regimes (Burrows *et al.* 2003).

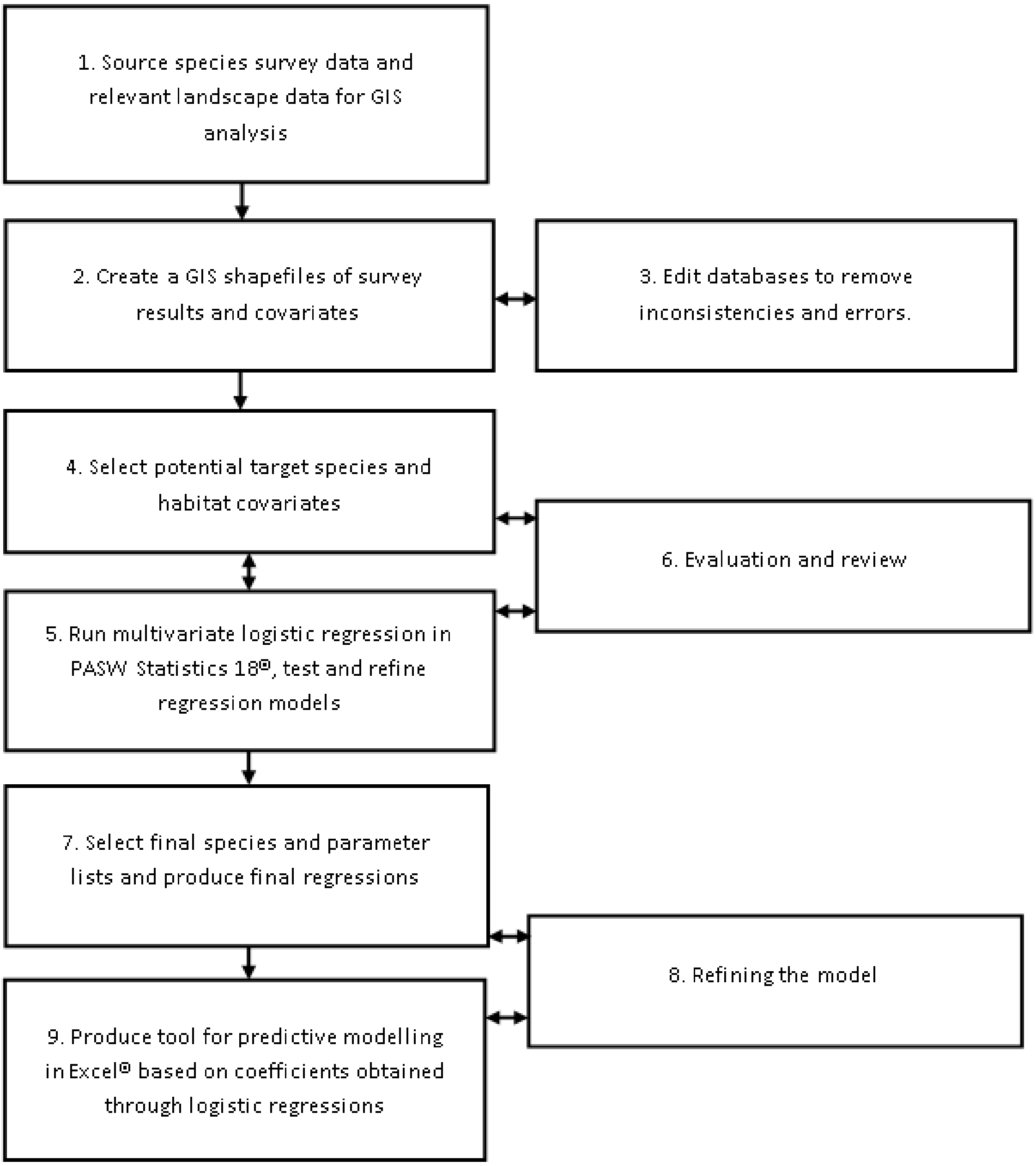

Figure 8: Overview of methodology used for model construction and testing.

Multiple logistic regression was chosen for the development of the predictive tool as it enables the use of both categorical and scale predictive variables, and quantifies the degree to which those variables determine a response, e.g. if the area of a patch is changed from *z* to *x* then the probability of presence for that indicator species changes from *Pz* to *Px* (Januchowski *et al.* 2008; Brouwers & Newton 2009b; Gougeon 2009;

Duchesne *et al.* 2010; Stankowski & Parker 2010). A process to develop and test these models was developed from a standardised adaptive management process (Dallmeier & Comiskey 1998) (Figure 8). This process is described below:

3.2.1 Source species survey data

Bird survey datum is utilised because it was the only species survey data available for the subject landscape with sufficient sample size. This datum was sourced from the BirdLife Australia Atlas Database (Barrett *et al.* 2003). This database provided geo-referenced, date-coded information on bird species presence. Only species for which there were greater than 30 records were considered (Table 3). This figure was required as >30 records, a minimum representative sample, are needed to have sufficient data to do modelling (McCullagh & Nelder 1983). The Atlas provided survey data for all surveys conducted within a 40 km radius of the Margaret River town site. The data set contained 8,829 recorded bird sightings taken from 897 surveys conducted between 1998 and 2010.

3.2.2 Shapefile creation

The x, y coordinates of these 8,829 sightings were used to develop a GIS shapefile using Arc Map® version 9.3. In doing so, it was found that many of the survey sites could still not be attributed to a patch of remnant vegetation (as sourced from the Department of Food and Agriculture Western Australia 2012 Remnant Vegetation GIS data set at 5 m resolution). Outlying sites that were near to remnants (<50 m) were repositioned centrally within those remnants as were sightings whose comments, record numbers, or place names allowed them to be repositioned with reasonable confidence to a particular remnant. Those site positions that were obviously wrong, or whose position could not be attributed to a patch of remnant vegetation with reasonable certainty, were deleted from the shapefile along with all coastal (shore and marine bird) survey records. In this way a GIS shapefile was produced containing the findings of 247, 2 ha (2 ha refers to a nominated search type in the data base) surveys conducted in terrestrial patches of remnant vegetation within a 40 km radius of the Margaret River town site. Given the defined nature of the search type and the and the experience and training given to survey participants through BirdLife Australia, the probability of detection for the presence and absence of modelled bird species has, for the purposes of this exercise, been assumed to be comparable for all surveys. Survey results are therefore assumed to be directly comparable.

3.2.3 Data correction and editing

To construct a database that will enable bird survey data to be compared with landscape parameters, individual bird survey records had to be fixed to site in a Geographic Information System (GIS) environment. Inconsistencies within the bird survey data meant that significant editing was required before this could be done. To prevent conflicts and minimise assumptions, only data which used the most common and current datum (GDA 1994) were used for this exercise, and records from all other datums were disregarded. Multiple survey types were also recorded in the data. To achieve consistency, only records of the most numerous survey type (2 ha search) were used. Faults were also found within the remnant vegetation GIS shapefile provided by the Western Australian Department of Agriculture in that multiple and separate polygons within this shapefile were identified in this shapefile as single polygons. This was rectified by clipping a smaller shapefile relevant to the test area in which these linked polygons were separated. The shapefile with smaller remnant vegetation patches was used in this analysis.

Table 3: Species used in the model testing process, i.e. those with greater than 30 Atlas records, and their preferred broad-scale habitats as given by Higgins *et al.* (2006). Woodland specialists are shaded.

Species id. No.	**Species**	**Habitat**
1	Australian Magpie Cracticus tibicen	Open forest, woodland, agricultural and urban land.
2	Australian Raven Corvus coronoides	Most types except closed forest.
3	Australian Ringneck Barnardius zonarius	Tall wet forest to mallee and mulga.
4	Common Bronzewing Phaps chalcoptera	Dry forest, woodlands, mallee, heath and coastal scrub.
5	Golden Whistler Pachycephala pectoralis	Rainforests, open forests, woodlands, mallee and coastal vegetation.
6	Grey Fantail Rhipidura albiscapa	Forests and woodlands.
7	Inland Thornbill Acanthiza apicalis	Dry scrub to coastal heaths.
8	New Holland honey-eater Phylidonyris novaehollandiae	Coastal heaths to woodlands.
9	Red Wattlebird Anthochaera carunculata	Generalist, forests, woodlands and suburbs.
10	Red-winged Fairy-wren Malurus elegans	Near water and swamps in Darling and Stirling Ranges of south-western Australia.

11	Silvereye Zosterops lateralis	Most natural vegetation types within their range, orchards and gardens.
12	Splendid Fairy-wren Malurus splendens	Forest margins to dryer inland areas, often feeds higher in trees and shrubs than other wrens.
13	Striated Pardalote Pardalotus striatus	Eucalypt forests and woodlands.
14	Tree Martin Petrochelidon nigricans	Open woodland.
15	Welcome Swallow Hirundo neoxena	All types, especially near water.
16	Western Gerygone Gerygone fusca	Open woodlands, mallee.
17	Western Rosella Platycercus icterotis	Open forests, woodlands and farmlands.
18	Western Spinebill Acanthorhynchus superciliosus	Heaths and woodlands.
19	White-breasted Robin Eopsaltria georgiana	Southern birds: open forests usually near streams. Northern birds: coastal scrubs or thickets.
20	White-browed Scrubwren Sericornis frontalis	Dense undergrowth all attitudes, including urban areas, salt marshes and heaths.
21	Willie Wagtail Rhipidura leucophrys	Generalist except very wet forests

3.2.4 Target species and habitat covariant selection

Of the available 21 species with a sample sufficient for modelling, only nine were considered to be woodland specialists (Higgins *et al.* 2006) and therefore considered potentially suitable for use as indicator species (Table 4).

Comparable modelling exercises of these nine species were undertaken using six predictor variables: patch size, vegetation condition, area of the nearest neighbouring patch, isolation, vegetation type and management regime as these variables and derivatives thereof figure prominently in the literature on modelling habitat values in fragmented landscapes. (McGarigal *et al.* 2000; Lindenmayer *et al.* 2002; Brooker & Brooker 2003; Fahrig 2003; Freudenberger & Brooker 2004; Moore & Swihart 2005; Watson *et al.* 2005; Huggett 2007; Urban *et al.* 2009). I trialled these variables, individually and in combination, to evaluate and quantify their influence on the presence of indicator species, i.e. to determine their suitability for use as predictive variables in a multivariate logistic regression model. Where suitable data to develop these variables was not available, surrogate data sets, as discussed below, were devised and trialled. As variables contribute differently to defining habitat for different species and a set of variables was required which could be applied to all nine indicator species, final selection of variables was based on the contribution each variable made to the set as indicated by

Wald chi-square statistics attained through logistic regressions (SPSS readouts, Appendices ch.3,1-9).

To test for covariance in all species models, ANCOVA analyses were conducted (McCullagh & Nelder 1983) using SPSS 20®. ® and *P* values >0.6 resulted for all models indicating that none of the regression slope and intercept were significant.

The BirdLife Australia dataset gives no indication of vegetation type or condition at survey sites. To compensate for this short-fall, GIS data bases were obtained from the Western Australian Department of Environment and Conservation showing different vestings of land (broad land tenure/ownership categories). These were used based on the assumption that different vestings experience particular management actions (e.g. prescribed fire, resource extraction such as timber harvesting, grazing by livestock) and, consequently, they would broadly provide some indication of vegetation condition. Seven vesting groups were identified for the subject landscape, these being: conservation, national park, none given (predominantly private land), protected, railway, recreation and state forest (which is subject to timber harvesting). Classification of vegetation type would also have been a variable worth testing, however the most suitable vegetation classification used in this region (Havel & Mattiske 2000) proved inappropriate for this landscape since most vegetation descriptions had small samples (<5).

Five spatial variables were included in the modelling process: distance to nearest neighbour patch, area of remnant vegetation within 5 km and 1 km radii, patch size and nearest neighbour patch size. These variables were created for each survey record site using the FRAGSTATS application (Kupfer 2012) in ArcMap® version 10.1 environment. These variables were then compared with species data using ACCESS® 2007. This allowed species richness at each survey site to be modelled against individual landscape variables using SPSS 20®.

The reasoning behind developing these ‘radii’ data sets was that patch size, distance to nearest neighbour patch, and nearest neighbour size, and the degree of fragmentation in a landscape were all inherent in the radii concept. Consequently, a nominated area, such as the area within a radius from a chosen point, containing a high percentage of remnant vegetation is statistically more likely to have more and larger patches, with smaller gaps between those patches, than a similar area with a smaller percentage of remnant vegetation (Bridle *et al.* 2009; McGarigal *et al.* 2009; Kupfer 2012). Furthermore, radii are not influenced by the cadastral errors such as “ghost objects” and “hidden linkages” that were encountered in the vegetation shapefile. The 1 and 5 km radii distances were selected through an exploratory process which found variables based on these distances to be the most effective predictive variables for most of the candidate indicator species (Figure 10).

3.2.5 Logistic regressions

The occurrence data for each of woodland bird species were used to construct multivariate logistic regression models of bird responses to the spatial variables using PASW Statistics 18® and the results given in the SPSS readouts (Appendices ch.3,1-9). It should be noted that the vesting for State Forest in all models is 0 as this was the reference condition for all other vestings (i.e., the comparison group).

3.2.6 Evaluation and review

Individual species models were initially evaluated by statistical testing, i.e. percentage of correct predictions, Hosmer and Lemeshow, and Nagelkerke R^2 test values. These tests were conducted in SPSS 20® as part of logistic regression process. Summaries of these tests are provided in Table 4.

3.2.7 Final species selection

Five species models were selected for incorporation into the final modelling tool as a confidence set (Shimodaira 1998). The reasons for this decision were: modelling with less than five species could give highly variable results through influence by outlier models; modelling with more than five species provided no discernible improvement in model accuracy for the additional effort or resources required; from a set of nine species model, removing the four least effective models meant removing those models whose performance was below the mean; and limiting the model to five species allowed the omission of less accurate species models. In so doing, it is acknowledged that although changing the mix of species used in the final model could result in a statistical change in model outputs; this risk is significantly reduced by presenting a group response to a change in predictive variables through the five species, confidence set approach. However, this potential for bias remains a concern to be monitored throughout the model refining process.

3.2.8 Refining the model

When building a species distribution model based on a statistical correlative approach the implicit nature of this form of model must be acknowledged (Dormann *et al.* 2012) as the philosophical nature of these models, and their statistical tests, means that they are impossible to verify (Oreskes *et al.* 1994). This is because these tests rely on running models against the data from which they are created and can therefore give a false impression of accuracy. For this reason, the testing of models against independent data has become preferred practice in verifying model accuracy (Lawler & Edwards 2002; Araujo *et al.* 2005; Randin *et al.* 2006; Burns & Grear 2008; Schmolke *et al.* 2010).

To develop independent test data, two test data sets were created. One was created from previously discarded survey records whose projections were not GDA84 datum (n=129). The second was extracted from a similarly developed data set taken from the Collie region, another Shire in the southern Jarrah Forest with comparable climate, vegetation, landscape fragmentation matrices and a similar set of avian fauna (n=224). Models were run against these test landscapes and predicted presences for each species compared with actual presences taken from the test data sets. Comparisons were made for individual species and Student's t-Tests (paired 2 sample for means) used to compare means of actual presences with predicted presences.

Models that could accurately predict presence or absence in more than 70% of cases were considered acceptable for further testing as this shows a statistically significant improvement over the 50% success rate expected from a null model (Hijmans 2012). This measure of accuracy depends on an arbitrary presence/absence model, i.e. not present is determined where P <0.5 and present determined where P ≥0.5). Although it is possible to develop more accurate models by altering this cut off figure from 0.5 and changing which variables are applied for individual species, the purpose of this exercise is to develop generalised tools which can be applied uniformly to a group of indicator species and be used by most landscape managers. Therefore such refinement was considered unnecessary.

The use of a simple binary output, i.e. present or absent, is usually less accurate than the sum of probabilities ($\sum P$) measurement. For example, if within a hundred sites there is a 10% P that species Y will be present at each site we can expect a total population of 10 ($\sum P$) where a simple present-absent model will give a total population of 0. Inversely, if the model predicted that there was a 70% P of presence at each of 10 sites, a total population of 10 would be given by the binary model. However, as in this case, where a data set is being tested against itself the $\sum P$ will always equal the number of presences for each species. For this reason regression models developed for this data set are tested against Margaret River and Collie test data sets.

3.2.9 Tool production

Selection of the five-most effective species regression models, from the nine constructed, was achieved by trialling the accuracy of the five most accurate models, as determined by statistical tests, i.e. Hosmer and Lemeshow statistics and Nagelkerke R^2, and by comparing predicted presences against actual recorded presences in two independent test landscapes. Further statistical tests (Cox and Snell R^2, Omnibus Squared and general descriptive statistics) and plots of model efficacy (ROC/AUC and Observed groups against predicted probabilities) are given in the SPSS readouts (Appendices ch.3,1-9).

To convert regression outputs into a predictive tool that will enable conservation managers to calculate the probability for the presence or absence of a species at a nominated site (as long as it is comparable to the sites used in the regression), spreadsheet tools; i.e., a utility spreadsheet designed to automatically provide users with a probability for presence conditional upon having been provided with appropriate values for the five predictive spatial variables, for each species were developed (Appendices ch.3,1-9). These tools use the β coefficients for all of the covariates used in the regression and enable users calculate P value of any given site or scenario by changing any of the covariate input values. These tools have been created in an Excel® 2007 spreadsheet by converting the following algorithms into spreadsheet functions:

P = elogit/1 + elogit

where

elogit= Exp. (β Constant + (β remarea x remarea) + (β NNDist x NNDist) + (β NNArea x NNArea) + (β Area5kBuffer x Area5KBuffer) + (β Area1kBuffer x Area1KBuffer) + (β VestedPurpose x1)).

This algorithm can also be used to develop tools which will calculate the P value for multiple species in response to any combination of values in the nominated covariates. It is also possible to substitute β coefficients with Wald statistics from the regression outputs where the covariates are based on scale inputs (McCullagh & Nelder 1983; Brouwers & Newton 2009b; Field 2009). As Wald statistics do not reflect changes in nominal or categorical inputs (i.e., different types of vesting), β coefficients were used for this exercise.

3.3 Results

The impacts of different variables and vestings varied significantly in importance between bird species (SPSS readouts, Appendices ch.3,1-9). e.g., based on Wald chi-square statistics, vesting is important for the Striated Pardalote and not the Western Gerygone, and the amount of remnant vegetation in the 5 km buffer has a much greater influence on the Common Bronzewing than it has on the Striated Pardalote. Furthermore, the ROC/AUC plots in these readouts demonstrate how scalar variables differ in their predictive influence on different species.

The number of species present in a patch varies with different vestings with the highest number found in state forest and the lowest found in railway reserve (Figure 9). This variation indicates that vesting may be an effective and important predictive variable for bird species richness. Similarly, when the number of bird species present are plotted against each landscape variable (Figure 10), a positive relationship was evident between species richness and the amount of vegetation within both a 1 km and 5 km buffer. Slight positive relationships were observed in patch and nearest neighbour patch sizes and no relationship was seen with the distance to nearest neighbour variable. These relationships are also mirrored in the ROC/AUC tests (SPSS readouts, Appendices ch.3,1-9) which consistently show the 1 km and 5 km buffers to be the best performing variables and the nearest neighbour distance variable to be the worst performing. Consequently, this nearest neighbour distance variable was not used in further regression modelling.

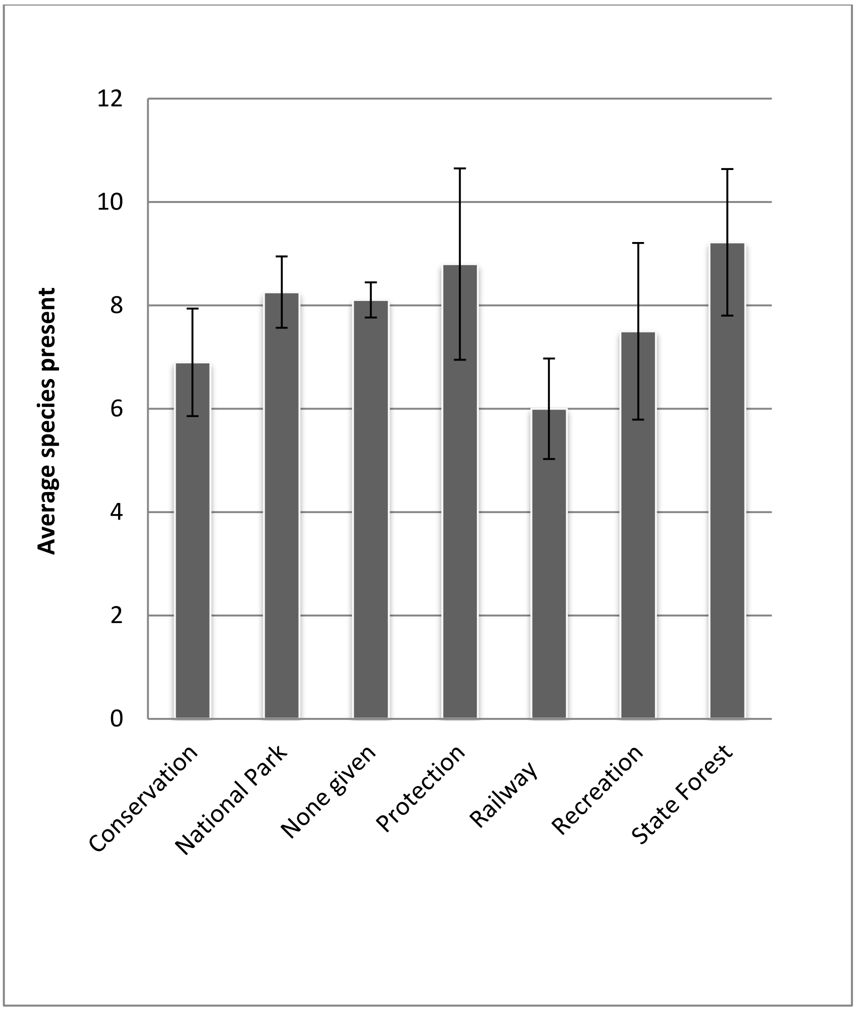

Figure 9: Average number of species recorded per 2 ha observation event by vesting with standard error. Vestings are considered and important variable as they reflect general differences in management regime and, therefore, condition. Those sites without a vesting relevant to conservation (mostly private property) were assigned to the "None given" category.

Statistical tests undertaken as part of the regressions such as total correct predicted, Hosmer and Lemeshow, and Nagelkerke R2 along with a separately calculated ∑P value (the sum of all probabilities for presence), show that of the nine woodland species selected, eight species responded to the chosen covariates with a degree of accuracy capable of providing a good indication of that habitat value of a given site with prediction success ranging from 66 to 85% (Table 4). The full readouts for all statistical tests are supplied in the individual species regression tools (Appendices ch.3,1-9).

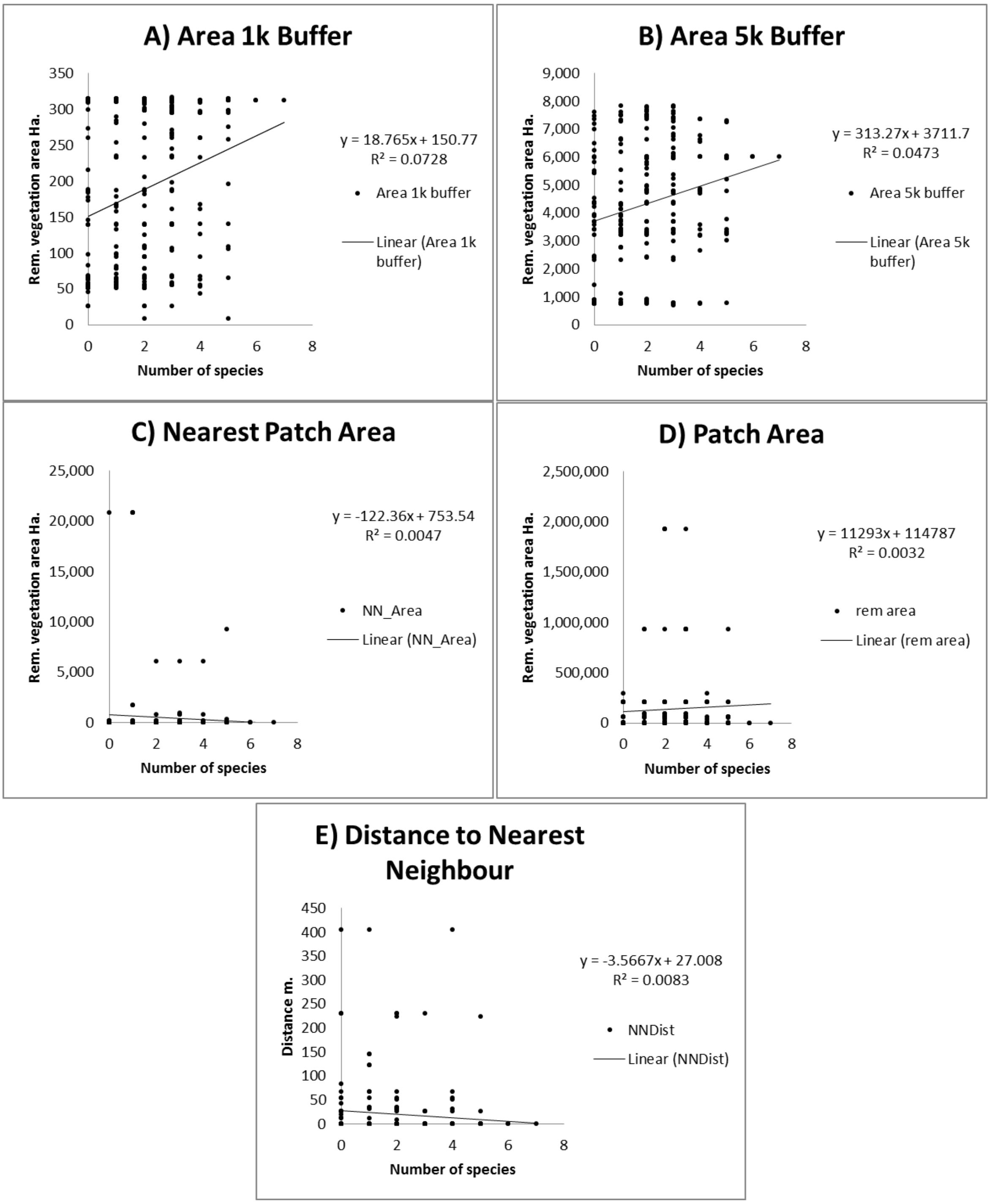

Figure 10: Number of species per survey site used in the GIS site shapefile relative to a) the area of remnant vegetation within a 1 km radius of that site, b) the area of remnant vegetation within a 5 km radius of the site, c) the area of the patch containing a site, d) the area of the nearest neighbouring patch to a patch containing a site, and e) the distance between site patches and nearest neighbour patches.

Table 4: Summary of regression outputs for woodland specialist spp.: number of species present in sample, the total of all probabilities for that species in sample, % of sites correctly predicted present, % of sites correctly predicted absent, % sites predicted correct overall, Hosmer & Lemeshow test results (test if model fits the data (significance > 0.05 = good model fit)), Nagelkerke effect size test (R^{2} = scale 0-1).

Species	# Present	Sum of *P* (∑*P*)	% Correctly predicted present	% Correctly predicted absent	% Total correctly predicted	Hos. & Lemeshow			Nagelk-erke R²
						X^2	*df*	*Sig*	
Common Bronzewing	38	38	0	100	84.6	17.04	8	0.03	0.148
Golden Whistler	68	68	17.6	91.6	71.3	19.165	8	0.014	0.225
Red-winged Fairy-wren	45	45	44.4	95	85.8	24.04	8	0.002	0.369
Striated Pardalote	52	52	15.4	97.9	80.6	10.304	7	0.172	0.259
Western Rosella	55	55	5.5	100	78.9	9.883	8	0.273	0.176
Western Gerygone	60	60	15	95.2	75.7	9.38	8	0.311	0.216
Western Spinebill	43	43	2.3	99.5	82.6	14.135	8	0.078	0.28
White-breasted Robin	56	56	46.4	91.1	81	23.769	8	0.003	0.303
White-browed Scrubwren	75	75	5.3	91.9	65.6	36.123	8	<0.001	0.159
Mean	70.09	70.09	27.91	84.24	70.71	16.701	7.9	0.207	0.189

Although the ∑*P* test shows a perfect correlation with recorded presences, as this test is examining the input presence data from which these result are derived, this result is to be expected as ∑*P* will equal input presences when regression outputs are correct. However, where the regression model is run against a different input data set, such as the two test landscapes, ∑*P* represents the total predicted occurrence for that species for the test landscape.

Where regression models for all 9 woodland species are run against independent data from both the Collie and Margaret River test landscapes (Table 5) a strong correlation is evident between the predicted and the actual presences. This is supported by a two-tailed t-Test P(T<=t) value of 0.18, which at a significance value of 0.05 supports the null hypothesis (H_0), means of presences and ∑*P* values for all species are the same across both test landscapes. On examination of this data it becomes evident that difference between these two values is particularly high for some “outlier” models and the removal of these species models would enable the development of a more effective modelling tool. The question then becomes one of recognising the most effective test with by which the five most effective species can be selected.

Table 5: Number of presences for each species in the test landscape data sets, the $\sum P$ predicted by the models for each species as derived from the original Margaret River bird survey data set, the difference in number of presences between these two figures, the number of presences (binary) predicted by these models, the number of correct predictions, the % predictions correct and means for each category.

Collie (N=169 sites)

Species	**Total Present**	$\sum P$	**Difference**	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	27	10	17	0	142	84
Golden Whistler	66	68	-2	57	98	58
Red-winged Fairy-wren	52	32	20	4	115	68
Striated Pardalote	76	92	-16	101	82	49
Western Gergone	97	57	40	15	77	46
Western Rosella	61	67	-6	53	101	60
Western Spinebill	39	24	15	0	130	77
White-breasted Robin	59	73	-14	91	105	62
White-browed Scrubwren	61	64	-3	26	104	62
Mean	**60**	**54**		**39**	**106**	**63**

Margaret River 2 (N=129 Sites)

Species	**Total Present**	$\sum P$	**Difference**	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	18	13	5	0	111	86
Golden Whistler	41	79	-38	95	67	52
Red-winged Fairy-wren	31	94	-63	100	60	47
Striated Pardalote	38	29	9	8	93	72
Western Gergone	45	53	-8	64	82	64
Western Rosella	33	61	-28	78	68	53
Western Spinebill	32	104	-72	111	50	39
White-breasted Robin	33	61	-28	64	88	68
White-browed Scrubwren	41	38	3	9	79	61
Mean	**35**	**59**		**59**	**78**	**60**

t-Test: Paired Two Sample for Means

	Present	$\sum P$
Mean	47.22222222	56.59119422
Variance	388.0653595	757.9267579
Observations	18	18
Pearson Correlation	0.31269253	
Hypothesized Mean Difference	0	
df	17	
t Stat	-1.399389085	
P(T<=t) one-tail	0.089839342	
t Critical one-tail	1.739606726	
P(T<=t) two-tail	0.179678684	
t Critical two-tail	2.109815578	

Where the four worst performing models, i.e. those with the greatest difference between presences and ∑*P* are removed for each test landscape, are removed (Table 6) the models become stronger and the P(T<=t) two-tail increases significantly to 0.47 reflecting an increased probability of H_0. However, this method effectively diminishes the test sample and compromises in accuracy may result.

Table 6: Comparison of model outputs with presences for the 5 species with the best performing models for each test landscape, i.e. with outliers removed.

Collie (N=169 sites)

Species	**Total Present**	∑***P***	**Number predicted**	**Correct predictions**	**% correct**
Golden Whistler	66	68	57	98	58
Western Rosella	61	67	53	101	60
Western Spinebill	39	24	0	130	77
White-breasted Robin	59	73	91	105	62
White-browed Scrubwren	61	64	26	104	62
Mean	**57**	**59**	**45**	**108**	**64**

Margaret River 2 (N=129 Sites)

Species	**Total Present**	∑***P***	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	18	13	0	111	86
Striated Pardalote	38	29	8	93	72
Western Gergone	45	53	64	82	64
White-breasted Robin	33	61	64	88	68
White-browed Scrubwren	41	38	9	79	61
Mean	**35**	**39**	**29**	**91**	**70**

t-Test: Paired Two Sample for Means

	Total Present	∑*P*
Mean	46.1	49.02482
Variance	234.5444444	458.6837
Observations	10	10
Pearson Correlation	0.825798147	
Hypothesized Mean Diffe	0	
df	9	
t Stat	-0.75141171	
P(T<=t) one-tail	0.235797896	
t Critical one-tail	1.833112933	
P(T<=t) two-tail	0.471595792	
t Critical two-tail	2.262157163	

By selecting the five species with the highest Hosmer & Lemeshow significance value a very effective modelling tool can also be produced with a very high P(T<=t) two-tail value of 0.67 (Table 7). Species selected in this manner can be confidently applied to all test landscapes. This method inherent rigour associated with a well-recognised statistical test applied to both test landscapes.

Table 7: Comparison of model outputs with presences for the 5 species with the best performing species by as defined by the Hosmer & Lemeshow significance value.

Collie (N=169 sites)

Species	**Total Present**	**∑*P***	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	27	10	0	142	84
Striated Pardalote	76	92	101	82	49
Western Gergone	97	57	15	77	46
Western Rosella	61	67	53	101	60
Western Spinebill	39	24	0	130	77
Mean	**60**	**50**	**34**	**106**	**63**

Margaret River 2 (N=129 Sites)

Species	**Total Present**	**∑*P***	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	18	13	0	111	86
Striated Pardalote	38	29	8	93	72
Western Gergone	45	53	64	82	64
Western Rosella	33	61	78	68	53
Western Spinebill	32	104	111	50	39
Mean	**33**	**52**	**52**	**81**	**63**

t-Test: Paired Two Sample for Means

	Actual	*∑P*
Mean	46.6	50.8705
Variance	594.0444444	1026.3
Observations	10	10
Pearson Correlation	0.447921177	
Hypothesized Mean Dif	0	
df	9	
t Stat	-0.44502081	
P(T<=t) one-tail	0.333407563	
t Critical one-tail	1.833112933	
P(T<=t) two-tail	0.666815127	
t Critical two-tail	2.262157163	

By using removing individual species models with low Nagelkerke R^2 values (Table 8), an effective model can also be produced which also uses a full test landscape and a well-supported statistical methodology. However with a P(T<=t) two-tail value of 0.32 and a greater variation between presences and $\sum P$ this method is less effective than using the Hosmer & Lemeshow test.

Table 8: Comparison of model outputs with presences for the 5 species with the best performing species by as defined by the Nagelkerke R^2 test.

Collie (N=169 sites)

Species	**Total Present**	$\sum P$	**Number predicted**	**Correct prediction**	**% correct**
Red-winged Fairy-wren	52	32	4	115	68
Striated Pardalote	76	92	101	82	49
Western Gergone	97	57	15	77	46
Western Spinebill	39	24	0	130	77
White-breasted Robin	59	73	91	105	62
Mean	**65**	**56**	**42**	**102**	**60**

Margaret River 2 (N=129 Sites)

Species	**Total Present**	$\sum P$	**Number predicted**	**Correct prediction**	**% correct**
Red-winged Fairy-wren	31	94	100	60	47
Striated Pardalote	38	29	8	93	72
Western Gergone	45	53	64	82	64
Western Spinebill	32	104	111	50	39
White-breasted Robin	33	61	64	88	68
Mean	**36**	**68**	**69**	**75**	**58**

t-Test: Paired Two Sample for Means

	Total Present	$\sum P$
Mean	50.2	61.85577
Variance	470.4	819.8172
Observations	10	10
Pearson Correlation	0.021203944	
Hypothesized Mean Dif	0	
df	9	
t Stat	-1.036783036	
P(T<=t) one-tail	0.163444667	
t Critical one-tail	1.833112933	
P(T<=t) two-tail	0.326889334	
t Critical two-tail	2.262157163	

As all species models are either "good" or very close to good statistically (Hosmer and Lemeshow significance is >0.05), it is also valid to select species models by simple efficacy (Table 9). By using the five species models with the highest percentage of correct prediction and applying them to the test landscapes compliance between total presences and $\sum P$ remains very strong and the P(T<=t) two-tail value of 0.94 is excellent. Consequently this set of species was selected for use in the final modelling tool.

Table 9: Comparison of model outputs with presences for the 5 species with the highest % correct for the Margaret River 2 sample.

Collie (N=169 sites)

Species	**Total Present**	**$\sum P$**	**Difference**	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	27	10	17	0	142	84
Striated Pardalote	76	92	-16	101	82	49
Western Gergone	97	57	40	15	77	46
White-breasted Robin	59	73	-14	91	105	62
White-browed Scrubwren	61	64	-3	26	104	62
Mean	**64**	**59**		**47**	**102**	**60**

Margaret River 2 (N=129 Sites)

Species	**Total Present**	**$\sum P$**	**Difference**	**Number predicted**	**Correct predictions**	**% correct**
Common Bronzewing	18	13	5	0	111	86
Striated Pardalote	38	29	9	8	93	72
Western Gergone	45	53	-8	64	82	64
White-breasted Robin	33	61	-28	64	88	68
White-browed Scrubwren	41	38	3	9	79	61
Mean	**35**	**39**		**29**	**91**	**70**

t-Test: Paired Two Sample for Means

	Total Present	*$\sum P$*
Mean	49.5	49.0095
Variance	575.1666667	692.154
Observations	10	10
Pearson Correlation	0.714541407	
Hypothesized Mean Differe	0	
df	9	
t Stat	0.081110209	
P(T<=t) one-tail	0.468564702	
t Critical one-tail	1.833112933	
P(T<=t) two-tail	0.937129403	
t Critical two-tail	2.262157163	

3.4 Discussion

3.4.1 The effectiveness of a combined set of indicator species

The use of multiple indicator species to define a habitat value and to monitor change in that value has long been common practice in conservation management (Karr 1991; Cairns *et al.* 1993; Tjørve 2002; Herman *et al.* 2005), and the use of multiple bird species as indicators of habitat value been shown to be effective for this purpose (Lambeck 1997; Tjørve 2002; Gregory *et al.* 2005; Watson *et al.* 2005; Huggett 2007). In this exercise the use of multiple indicator species has been taken one step further, in that, although probabilities of presence for individual species are given to show a species response to changes in a generic set of habitat parameters, a combined model is also given to indicate a median response as an implicit habitat value.

When model outputs were tested against survey results for two comparable test landscapes, the results showed the model to be capable of a high level of accuracy for indicator species, individually and collectively (Table 7). Although it can be argued that the collective model is a more effective indicator of habitat value than the individual models, because of the statistical propensity for larger and more diverse samples to reduce the influence of outlier (non-conforming) models and because it implicitly considers a greater diversity of habitat requirements and perspectives, the needs of individual species, particularly conservation priority species, may not be reflected in the collective model (Bonn & Schröder 2001; Herman *et al.* 2005; Franklin 2010). Therefore, a modelling tool with the capacity to reflect responses from both explicit species specific and implicit generalised perspectives in a complimentary manner will provide a more robust insight into the consequences of changes in predictive variables than a single species or combined model alone (Bascompte & Solé 1996; Hui *et al.* 2006; Dormann *et al.* 2012). These values have been incorporated into the development of the spreadsheet tool which can instantly demonstrate individual and collective responses to modelled change (Appendix 3.1.10).

3.4.2 Tool development

Models used by conservation managers are often based on univariate regressions that combine dependant variable data based on species survey data with single quantifiable landscape variables (Brooker & Brooker, 2002; Huggett, 2007; Watson et al., 2005).

However, rarely is a single variable responsible for defining habitat for any species or community. As previously discussed, the habitat value of a patch is defined by a combination of variables, many of which are quantifiable. Therefore the use of multivariate logistic regression models is an inherently more effective tool for defining habitat as it allows the use of the multiple covariates which better portray how habitat is quantified (Baker & Harris, 2007; Brouwers & Newton, 2009b; Duchesne et al., 2010; Peeters et al., 1998). Furthermore, inexpensive and readily available software packages now make the development and application of models based on logistic regressions a viable option for conservation managers who, because of skill and resource limitations, were previously unable to define habitat values and to demonstrate how species or communities would react to impacts or management actions.

3.4.3 Comparing models with independent test landscapes

Wald and chi-square statistics (SPSS readouts, Appendices ch.3,1-9) indicate that, while models developed for individual indicator species can be very accurate predictors of response, this is not always the case. Therefore, the question became how to select the best species models for use in the combined model? The inherent limitations of applying statistical tests (Dormann et al., 2012) meant that the value of these tests the best performing models for incorporation into a multi- species model.

To select the five best performing species models and to improve the integrity of the final combined model, it was found that the selecting species with the highest predictive success rate provided an effective means of selecting the most appropriate species models. However, in comparing populations of individual species there will always be stochastic anomalies. To minimise the impacts of these anomalies, the use of a mean ∑P for all species becomes a suitable, repeatable, quantifiable and reliable measure of habitat value for this set of species. Therefore, a mean ∑P model was selected for adoption as a suitable model for indicating a generalised habitat value in the Margaret River area and for demonstrating how changes to modelling covariates will impact upon that habitat value.

3.4.4 Strengths and limitations

This exercise has used a reactively selected set of species with the intention of delivering a quantifiable and generalised perspective of habitat using generic and readily available data. Its methodology can therefore be considered reactive in that it is driven by circumstances rather than being proactive in identifying surrogate species or communities for a specific purpose and gathering variable data which accurately reflects their requirements. Unfortunately this degree of specificity is all too often beyond the skills and resources of many conservation managers (Caro, 2010; Collinge, 2009). This methodology has been developed in response to the needs of conservation managers in this situation. Consequently, it is acknowledged that methodology has produces some statistically weak species models and therefore should be used as an alternative for more specific or proactive applications; instead, it is intended as a substitute for such models where resource limitations make more specific modelling impractical. Furthermore, through its application this methodology does demonstrate the need for more specific modelling and inspires the development of more relevant and detailed variant data sets such as block size, vegetation type, vegetation conditions, and management regimes.

The major limitations of this methodology as applied in this exercise are:

- Large sample sizes are required to make categorical covariates effective.
- Models inputs are limited to the range parameters of the landscape data used in the logistic regression: e.g., if the range of the 1 km buffer values was from 86-360,000 m^2, then values outside of this range would negatively affect model accuracy. Model parameters are given in the combined species modelling tool (Appendix 3.1.10).
- The probability of presence for all indicators will vary with differing vegetation types. This model has been designed to work at the landscape scale within the Margaret River region and generically applied the proportional mix of vegetation types found within that landscape. Therefore, the disproportionate application of this model to individual vegetation types will skew results.
- The set of covariates selected are generic in nature, having been selected to model the needs of a broad set of species. It is probable that more effective covariate data sets could be developed to address the needs of individual species.
- Species models used have been selected as broad woodland specialists from which survey data can be used to produce statistically valid models with the covariate

data supplied. The selection of surrogate species which, by their presence or absences from sites can determine a specific response to an impact or habitat characteristic would enable the development of models which would provide a more effective basis for modelling habitat value.

- Obtaining and applying covariate data sets which pertain more directly to those factors which define habitat for individual species could also be used to make models more effective and informative.
- It should always be recognised that the purpose of this, like any form of Spatial Distribution Model SDM, it to inform the planning process, not to replace it.
- This form of model is largely implicit by nature and relies therefore relies heavily on assumption. The use of independent test landscapes goes a long way minimising the level of assumption, but there remains an inherent weakness that should be acknowledged. Therefore model outputs should always held to an appropriate level of scrutiny.
- Probability maps were attempted but the results were very disappointing due to the large and varied area of the test landscape and the nature of the predictive tools: i.e. such maps were dominated by large patches, which by their nature were generally uniform in modelled values Meanwhile, the smaller patches, in more fragmented parts of the landscape, which gave greater variation in probability value did not show up. Therefore when producing probability maps at a landscape scale (as required for this purpose) it appeared that there was negligible variation in habitat value at even the highest practical resolutions hence they were not considered suitable for inclusion in this thesis.

Despite these limitations, this methodology can provide a repeatable and quantifiable insight into the habitat value of a nominated site and demonstrate how habitat value may change in response to changes in one or more of the input variables. This will enable conservation managers to: develop databases which will enable them to accurately model probabilities for presence and absence for a broad set of species; choose species models that will enable them predict the consequences of management actions or ecological impacts and thereby enable conservation managers to identify, develop and incorporate variable databases that will make modelling more activities more effective.

To date, conservation management and planning in south-western Australia, as in much of the world, has largely relied on an assumed habitat value for revegetation, clearing and reserve design (ch.2). The tool developed in this exercise is capable of quantifying the consequences of all of these impacts and modelling a range of management action scenarios by using no more than the software, skills and resources which are normally available to conservation managers. It should be noted that this is a demonstration exercise on the value and application of logistic regression outputs and that this methodology can, with appropriate regard given to its limitations, be readily altered to allow other predictor variables and indicators to be used in order to model the potential impacts of different threats in different landscapes. Therefore, tools based on logistic regression represent an opportunity to add quantifiability and rigor to the planning process.

3.5 Conclusions

This chapter provides a demonstration of how available survey data can be used in conjunction with spatial and management-related variables to build statistical models capable of quantifying and demonstrating changes in habitat value as a consequence of losing and/or degrading native vegetation. It also allows conservation managers to model the potential consequences of their management actions. For example, multiple revegetation scenarios could be modelled where potential revegetation projects, differing in site and extent, are run and the results of this exercise used to determine the best approach to improve landscape habitat value or to mitigate a potential threat. Similarly, multiple changes in vesting might be modelled to inform the selection of conservation estate.

These models, developed through multivariate logistic regressions can be applied to quantify impact responses for many species and communities where adequate survey data is obtainable and a response in that data to a variation in one or more nominated habitat parameters can be observed and quantified. Habitat variables as diverse as vegetation type and condition, fire or management regime, climate, geology, topography or hydrology can all be applied to species survey data through multivariate regressions to produce simple models with the capacity to quantify habitat from a species or community specific perspective and to quantifiably demonstrate how changes to that habitat will effect populations of target species.

3.6 Caveat

The author readily acknowledges that modelling based on a set of bird species alone may bias the findings of this exercise to a degree and that the use of a broader and more diverse set of species would have the potential to provide more robust findings. However, such data, as is often the case in conservation management, was not available. It is also not the intention of the author to demonstrate the quantification of habitat for individual target species; although this methodology could certainly be adapted to that purpose.

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4 Informing species management in a fragmented landscape; a case study of the koomal (*Trichosurus vulpecula hypoleucus* (Phlangeridae)).

4.1 Introduction

In this chapter I demonstrate a means by field studies can provide data on a target species which can used to facilitate and enhance species specific spatial models. The amount and type of datum gathered in this exercise was therefore limited to that deemed suitable for that purpose.

Climate change presents a major threat to global biodiversity with significant impacts predicted in south-western Australia (Sgrò *et al.* 2011; Adams-Hosking *et al.* 2012; Crossman *et al.* 2012; Prober *et al.* 2012). As global warming progresses, it is envisaged that these impacts will continue to increase in both magnitude and frequency throughout the current century (CSIRO & BOM 2007; IPCC 2007; Hughes 2011; Richardson *et al.* 2011).

Climate change has long been considered a driver of evolution in that species are forced to either adapt to their new and altered environment or become extinct (Hopper 2009; McInerny *et al.* 2009; Castro *et al.* 2010; Gross 2011; Gilman *et al.* 2012; Shoo *et al.* 2013). Therefore, to persist in a rapidly changing climate, species must; adapt to their altered environment (if species plasticity allows), migrate to a suitable climate or find a refuge affording the opportunity of adaptation(Watson *et al.* 2005; Beaumont *et al.* 2007; Carnaval & Moritz 2008; Dunlop & Brown 2008; Fitzpatrick *et al.* 2008; Fordham *et al.* 2012).

In a highly fragmented landscape, both movement and habitat values can be significantly impaired (Fahrig 2003; Hobbs & Yates 2003; Lindenmayer & Fischer 2006; Fischer & Lindenmayer 2007; Holland & Bennett 2009). Patches in fragmented landscapes have a tendency to be both fragile (i.e. susceptible to environmental impacts) and, as a consequence, degraded. This is because they lack the resources to support viable populations of a full suite of species and because movement between them is, to varying degrees, impaired (Hobbs & Yates 2003; Pryor 2003; Moore & Swihart 2005; Lindenmayer *et al.* 2008; Collinge 2009; Robertson & Radford 2009; Davis *et al.* 2013).

Consequently, the habitat value of apparently similar patches (and their ability to meet a species' requirements) may vary significantly, and by extension, conservation management in a fragmented landscape relies on the manager's ability to quantify habitat for a target species (Pryor 2003; Moore & Swihart 2005; Lindenmayer *et al.* 2008).

Inherent in the fragmentation process is the establishment of gaps between patches of habitat and the creation of infrastructure, all of which can impede the movements of wildlife (Hobbs & Yates 2003; Collinge 2009; Robertson & Radford 2009). The degree to which these obstacles restrict the movement of a species is defined by the individual characteristics and requirements of that species (Tischendorf & Fahrig 2000a; Amarasekare & Possingham 2001; Hanski & Ovaskainen 2003; Holland & Bennett 2009; Robertson & Radford 2009). For example, a gap between patches which may be a near impenetrable barrier to a small passerine bird, might not present any difficulty to a larger raptor. Therefore, the management of a species in a fragmented landscape largely requires the capacity to identify and quantify a barrier to movement for a target species (Belisle & Desrochers 2002; Fischer *et al.* 2004; Klausmeyer & Shaw 2009; Robertson & Radford 2009).

Although habitat fragmentation is inherently focussed on patches and has received much attention in the literature, it is now generally accepted that species in fragmented habitats often respond to management at a landscape scale. McIntyre and Hobbs (1999) propose a move away from considerations of individual fragments and urge consideration of the intactness of landscapes, or landscape fragmentation. As most species respond at the landscape scale, as defined by Tischendorf & Fahrig (2000), it may be the overall amount of vegetation in the landscape that is important, rather than the nature of the fragments themselves. This is particularly so for species which are dispersive or form metapopulations. This approach has been adopted by others and shown to produce realistic outcomes for managing species in both urban and rural landscapes (Davis *et al.* 2013). For the purposes of the rest of this chapter, landscape fragmentation refers to the intactness of a defined focal landscape, rather than a focus on individual remnants *per se*.

Although landscape fragmentation has a detrimental impact on most species, the combined impacts of climate change and landscape fragmentation have the potential to be catastrophic for many species throughout the world (Pearson 2004; Pearson & Dawson

2005; Vos *et al.* 2008; Yates *et al.* 2010b; Ramachandra & Uttam 2011; Sgrò *et al.* 2011; Cormont *et al.* 2012; Lawson *et al.* 2012; Shoo *et al.* 2013). To manage and ameliorate these impacts, biodiversity managers must be able to quantify the metapopulation requirements of species and the degree to which fragmentation impacts on these requirements (Lambeck 1999; Tischendorf & Fahrig 2000a; Fischer *et al.* 2004; Watson *et al.* 2005; Beier *et al.* 2008; Holland & Bennett 2009).

Endemic to south-western Australia, the koomal (*Trichosurus vulpecula hypoleucus* Phlangeridae), is a geographically isolated and distinct sub-species of the common brushtail possum, an arboreal marsupial (Kerle *et al.* 1991). It is a morphologically distinct sub-species of *T. vulpecula*, being considerably smaller in size, having a more omnivorous diet and denser fur than other sub-species (Kerle *et al.* 1991; How & Hillcox 2000; Wayne *et al.* 2005b). Since European settlement, the koomal has undergone a significant decline in both distribution and population size, now occupying less than 50% of its original distribution (How & Hillcox 2000; Jones 2004) (Figure 11). The reason for this reduction has largely been attributed to habitat loss and landscape fragmentation, habitat alteration/degradation and predation from the European red fox (*Vulpes vulpes*) and feral cats (*Felis catus*) (How & Hillcox 2000; Jones 2004). Historically, disease and commercial hunting have also taken their toll (Shortridge 1909). Consequently, the koomal has a conservation listing of "Lower Risk" (near threatened) (Maxwell *et al.* 1996). Although the koomal has been studied in relatively contiguous landscapes (Sampson 1971; Jones & Hillcox 1995; How & Hillcox 2000; Wayne *et al.* 2005b; Grimm & De Tores 2009), much of its habitat lies within highly fragmented landscapes (Sampson 1971; How & Hillcox 2000; Jones 2004). Furthermore, much of the koomal's current distribution occurs in fragmented landscapes which are already subject to the initial impacts of climate change (Burbidge 2010; CSIRO & BOM 2012).

Studies on populations of other sub-species of the common brushtail possum and other species of brushtail possum, which have been impacted by fragmentation, show changes in: demography (Stow *et al.* 2006); resource availability and utilisation (Harper 2005; Harper *et al.* 2008); and restriction of movement, thereby restricting metapopulation movements, access to resources and exposing individuals to an increased risk of predation (May & Norton 1996; Lindenmayer & Fischer 2006).

Although no similar studies have been undertaken on koomal populations resident in fragmented landscapes, studies have been undertaken in relatively contiguous habitats (Sampson 1971; How & Hillcox 2000; Wayne *et al.* 2005b; Grimm & De Tores 2009). This provides an excellent opportunity to compare findings and draw conclusions on the impacts of fragmentation on this taxon.

Facing the dual threat of fragmentation and climate change, persistence for the koomal relies on its capacity to find and exploit suitable refuges. To do this, koomal must have landscapes which provide it with suitable habitat and the capacity to access that habitat.

The effects of landscape fragmentation on the koomal are poorly understood. This research tests the hypothesis; that fewer koomal will be found in more fragmented landscapes with less movement between more isolated patches. This is done by investigating: a) how landscape fragmentation impacts on population demographics; b) which variables define a patch as suitable koomal habitat in a fragmented landscape; and c) the capacity of the koomal to move through a fragmented landscape. Effective management of this taxon, like many others facing the same threats throughout the world, is reliant on the ability to determine these three factors (Tischendorf & Fahrig 2000b; Paull 2003; Robertson & Radford 2009; Ramachandra & Uttam 2011; Schooley & Branch 2011; Sgrò *et al.* 2011).

To achieve our objective, a year-long study of a population of koomal in a pre-defined fragmented landscape was undertaken in the Margaret River region of south-western Australia. Activities undertaken in this focal landscape were: trapping (catch mark and release), radio tracking of individuals and observations on vegetation type, condition, extent and structure. Although I did not have a control in a contiguous landscape due to logistical constraints, demographic data were compared with koomal studies in a number of contiguous landscapes to assess the degree to which landscape fragmentation impacts on koomal demographics. Trapping and radio tracking data were compared with landscape observations to determine predictive habitat variables. Trapping and radio tracking data were also used to plot landscape movements and gap crossing behaviour.

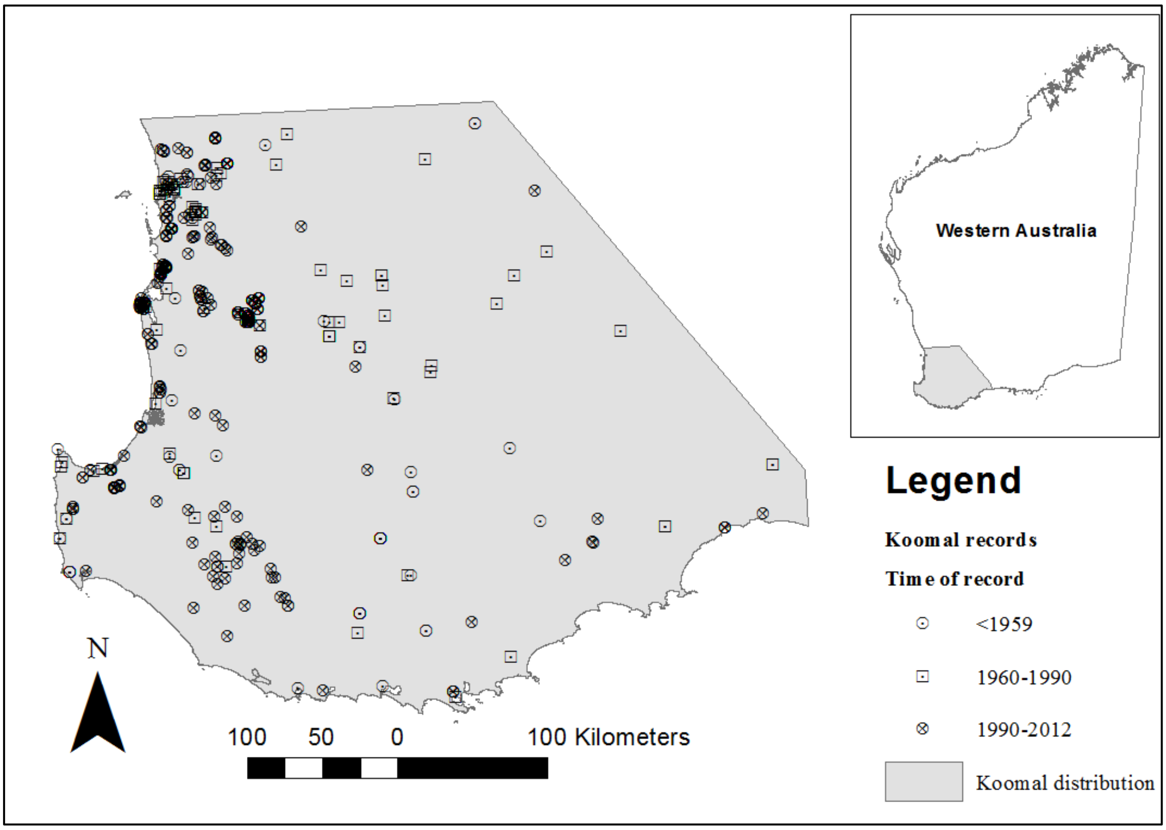


Figure 11: Koomal distribution at multiple timeframes.

4.2 Methodology

4.2.1 Study area

The study area, or focal landscape, was selected as being representative of the fragmented landscapes which comprise much of the koomal's habitat. It is comprised of a number of patches of remnant vegetation situated on four adjoining private properties in the Bramley Catchment, approximately 7 km NW of the township of Margaret River, Western Australia (Figure 12). The property owners state that all of these properties have been partially cleared for agricultural purposes since the early 1930s (although only one is currently in agricultural production). All native vegetation in this area has been subject to commercial timber harvesting (up until the late 1970s). Foxes and feral cats, major predators of koomal (Jones *et al.* 1994; de Tores *et al.* 2004; Possingham *et al.* 2004; Wayne *et al.* 2006), were regularly encountered during the course of this fieldwork and are assumed to be abundant. The only control for these predators undertaken within the study area was irregular shooting undertaken by one of the property owners.

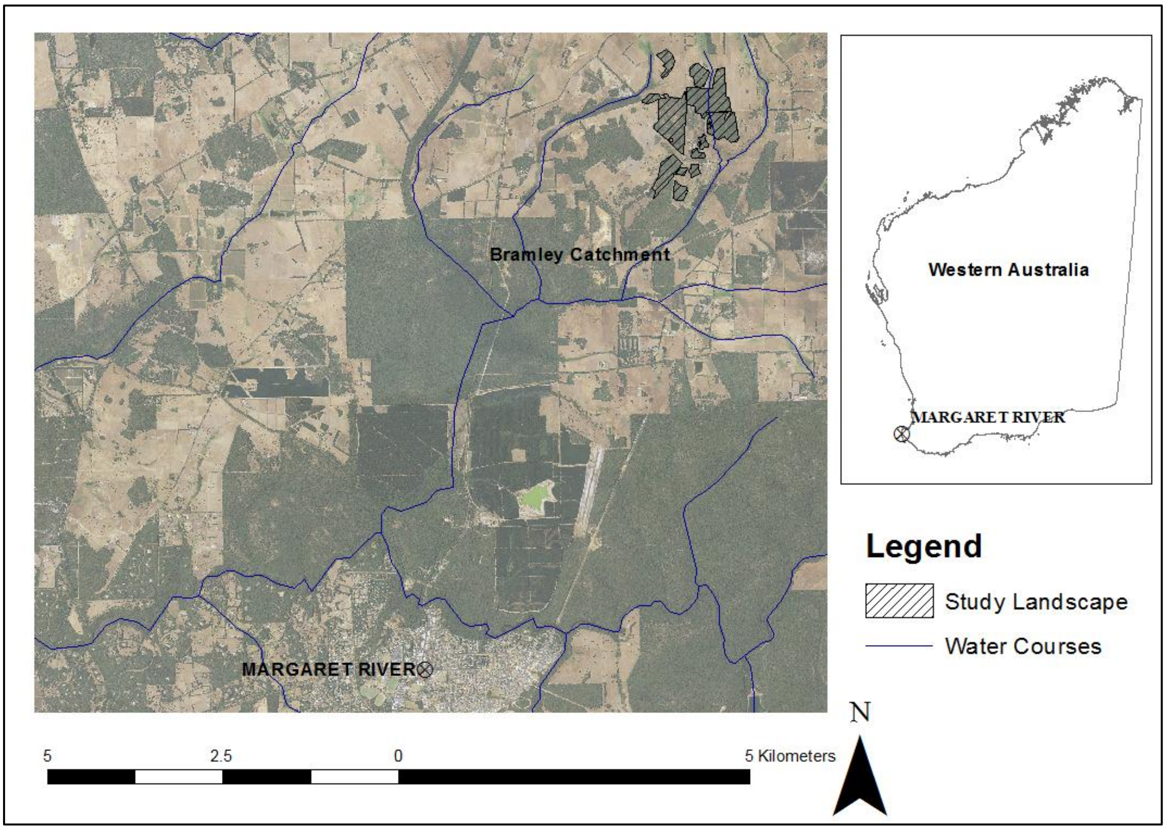
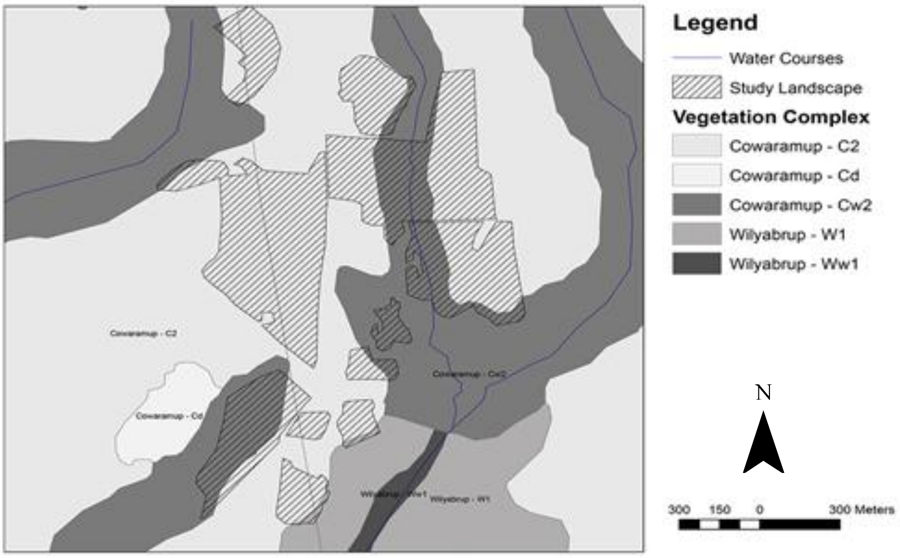


Figure 12: Study landscape

The study area is within the southern Jarrah Forest biogeographic subregion of south-western Australia (Thackway & Cresswell 1995). It has a Mediterranean climate of mild, wet winters and hot, dry summers. Annual average rainfall for this area is approximately 1100 mm, nearly all of which falls between May and November (Hearn *et al.* 2003; BOM 2012). Vegetation is largely dry, sclerophyll forests and woodlands dominated by jarrah (*Eucalyptus marginata*) and marri (*Corymbia calophylla*) over landforms that are gently undulating to incised over a granite basement with numerous weathered granite outcrops and lateritic cap-rock formations common on higher ground. Soils range from highly lateritic in higher ground through to sandy duplexes in lower ground with heavy, clay podzols in low lying areas (Figure 13) (Dell *et al.* 1989; Havel & Mattiske 2000; Hearn *et al.* 2003).



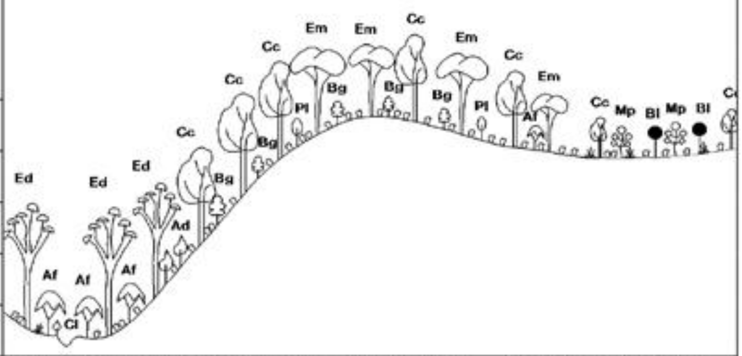
Geographic Region	Hyperhumid southwest		Margaret River
Geomorphologic catena – VC (EVS)	W1 – Wilyabrup	C1 – Cowaramup	Cw1 – Cowaramup
Landform and Vegetation profile			
100m			
80m			
60m			
40m			
20m			
Land form description	Deeply incised valley within a lateritized plateau over granitic basement	Gently undulating surface of a lateritized plateau over granitic basement rock	Mildly sloping depression within a lateritized plateau over granitic basement rock
Soil structure, texture and fertility	Red brown sandy loam over sandy clay, or gravelly yellow brown sand over yellow brown clay loam	Gravelly yellow brown sand or sandy loam over yellow brown sandy clay	Pale brown sand or sandy loam topsoil over mottled light grey sandy clay
Soil hydrology	Slopes water shedding but with good infiltration and storage capacity; floors water gaining but not waterlogged	Mildly water shedding with good infiltration and storage capacity except in minor depressions where seasonally waterlogged	Water gaining, seasonally waterlogged, with poor lateral and internal drainage
Over storey (canopy or emergents)	Tall Open Forest of *Eucalyptus diversicolor* (Ed) and *Corymbia calophylla* (Cc)	Open to Tall Open Forest of *Eucalyptus marginata* subsp. *marginata* (Em) and *Corymbia calophylla* (Cc)	Woodland of *Eucalyptus marginata* subsp. *marginata* (Em) and *Corymbia calophylla* (Cc) on slopes, Woodland of *Melaleuca preissiana* (Mp) and *Banksia littoralis* (Bl) in depression
Second storey	*Callistachys lanceolata* (Cl) on river banks, *Agonis flexuosa* (Af) ,*Allocasuarina decussata* (Ad) on lower slopes, *Banksia grandis* (Bg) on upper slopes	*Banksia grandis* (Bg) *Persoonia longifolia* (Pl)	Some *Agonis flexuosa* (Af) under *Eucalyptus marginata* subsp. *marginata* (Em) and *Corymbia calophylla* (Cc)
Shrub and herb storey	*Lepidosperma tetraquetrum* *Lepidosperma effusum* on valley floor, *Chorilaena quercifolia, Trymalium floribundum,Bossiaea linophylla,Acacia urophylla* *Tremandra stelligera* on slopes	*Leucopogon verticillatus* *Lepidosperma capitellatus* *Pteridium esculentum, Bossiaea linophylla, Bossiaea ornata,Hovea elliptica* *Lasiopetalum floribundum*	*Pericalymma ellipticum* *Astartea fascicularis* *Agonis linearifolia* *Mesomelaena tetragona* *Lepidosperma effusum*

Figure 13: A map of the vegetation complexes for the study landscape (above) and a topographic representation of those vegetation complexes from Havel and Mattiske (2000) (below).

4.2.2 Vegetation Mapping

Successful conservation of the koomal relies on the ability to quantify habitat values. To that end, vegetation type, condition and canopy characteristics were mapped in the project area, and the results compared with koomal dispersal and occupancy data from trapping and tracking studies. Vegetation is described by canopy plant species, structure, condition and fire history using the methods and definitions described in Molloy *et al.* (2007). The results of this exercise are shown in Figure 14 and described in Table 14.

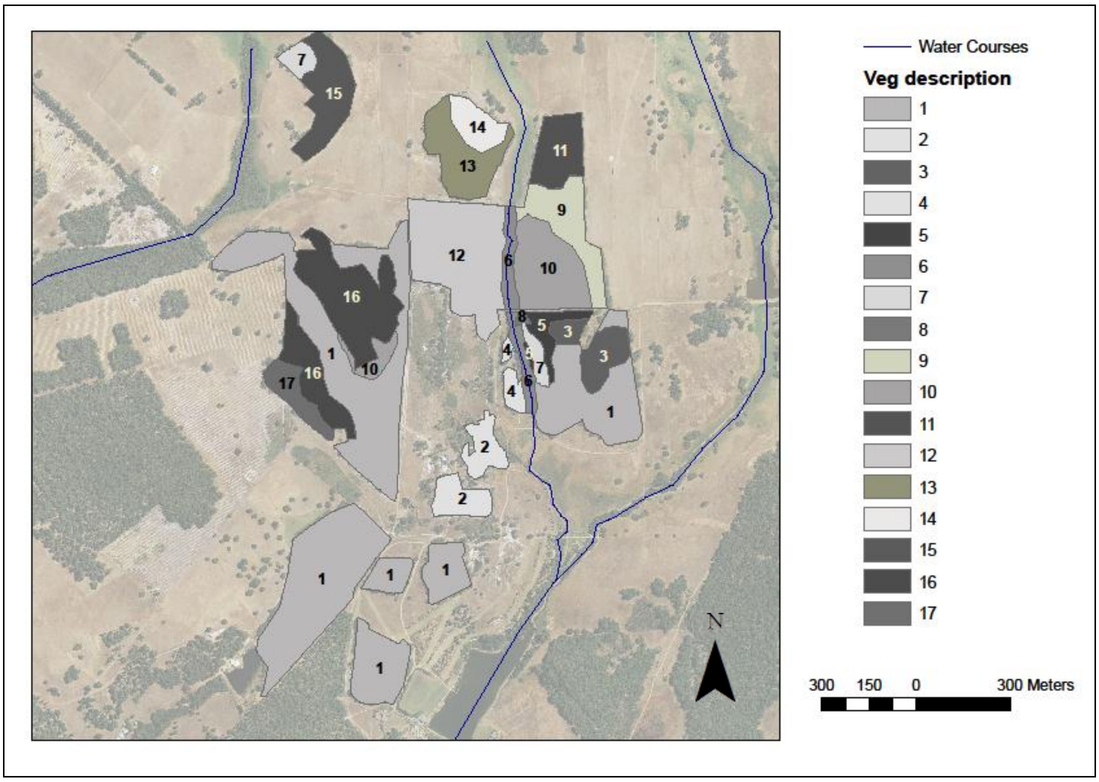


Figure 14: Vegetation mapping. Vegetation descriptions in Table 14.

Koomal are predominantly a folivore (Kerle *et al.* 1991; Grimm & De Tores 2009). Persistence was therefore assumed to be linked to habitat characteristics such as canopy cover, foliage cover, and consequently, leaf area index (LAI). LAI, an often used environmental parameter in habitat assessment, is defined as one-sided leaf area cover over ground and is given as an area of cover over a unit of ground area, or as a ratio (Coops *et al.* 2004; Macfarlane *et al.* 2007). To test if there is a link between LAI and koomal abundance, an average LAI was calculated for each mapped vegetation type by adapting the methodology described by Macfarlane *et al.* (2007). To do this, five photographs were taken of the canopy for each vegetation type at 10 m intervals at 1.2 m in height along a transect using a tripod mounted digital SLR camera. Photographs were taken using time delay to avoid shudder and were taken in morning light against a cloudless or uniformly grey sky to prevent excessive glare and to enable good canopy definition. Photographs were not taken directly beneath mid-level shrubs. Canopy cover (Fc), foliage cover (Ff) and LAI are then calculated for each photograph. Calculations are given as LAI=FcInv(1-Ff/Fc)/k, (k is assumed to be 0.5), Fc =1-Gl/Pixt, Ff =1-Gt/Pixt. Pixt refers to the total number of pixels in a photograph. GI refers to the total number of pixels in large gaps in canopy (greater than 1%) and Gt figures to the number of pixels in all gaps in canopy cover. Pixel counts are obtained using Photoshop CS6 ® software. Outputs are included in vegetation descriptions (Table 14).

4.2.3 Trapping and Tracking

Mark capture and release trapping occurred over a twelve month period. To investigate dispersal, radio tracking was undertaken concurrently using a representative group of trapped individuals (Lindenmayer *et al.* 1997; Lindenmayer *et al.* 2004; Harper 2005).

A series of 36 trap sites were established across the study area (Figure 15). Patches for the study were selected in a typical landscape for this area in regard to landscape metrics (Herzog *et al.* 2001; Cunningham & Johnson 2011; Kupfer 2012), land use, structural heterogeneity and management practices. Trap sites were then chosen by overlaying a 100 m square grid over patches with one trap placed in each grid square at a site selected as representative of that square’s vegetation and at a minimum distance of 100 meters apart. Traps were not set in shrublands as these are not recognised koomal habitat (Kerle *et al.* 1991; How & Hillcox 2000; Jones 2004). Trapping was conducted on a seasonal basis with an average of three trapping periods per season with trapping being conducted over three to five consecutive nights for each period for a total of 52 nights. This gave a total of 1,872 trap nights. Trapping periods were originally intended to be conducted over a single 4 night period per month; however this had to be varied because of severe weather events and logistical problems. Traps were of the medium Sheffield wire cage type, i.e. of a small wire cage traps, and these were baited with a 60/40 mixture of peanut butter and rolled oats.

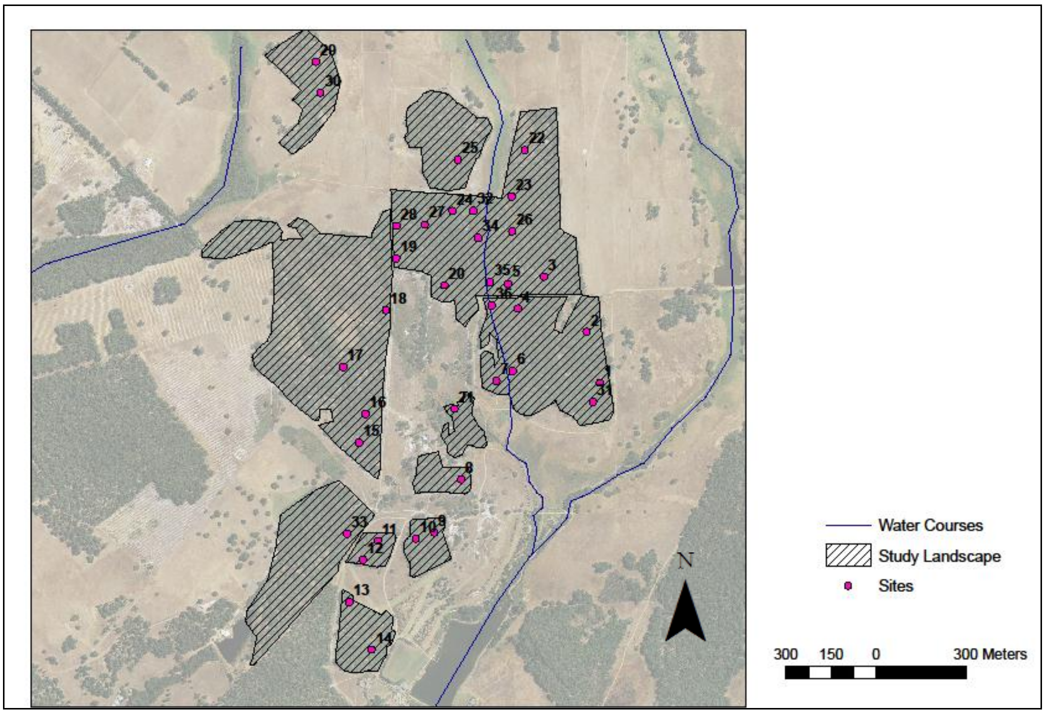


Figure 15: Trap sites.

A total of 11 animals had radio tracking devices fitted at various stages throughout the project ranging in periods from several weeks to the full length of the project (Table 18). Collared animals were tracked one day per week by triangulation to a daylight nesting site, over the full term of the project. Positions were taken with a hand held GPS to the northern side of the trunk of tree within which the subject was located. GPS analysis of error was normally <5m however this was sometimes exceeded. Readings with an analysis of error >10 m were not used. Tracking equipment was supplied by Sirtrack International. Animals fitted with “C” type collars (Table 9) were fitted with VSC 162D VHF transmitter collars. Animals fitted with “T” type collars were fitted with cable tie collars incorporating ZV1G 118 glue on VHF transmitters. The receiver used was a R1000 unit fitted to a yagi folding antenna.

4.2.4 Animal Handling and Data Collection

All traps were cleared as soon as daylight permitted. All koomal were micro-chipped using Global-ident FDX-B transponders and weighed on initial capture. Sex was also determined and pouches were examined in all females to determine if pouched young were present or if pouch condition indicated detached young. Comments were also made on the general condition of the animal and any observations deemed relevant. All animals were processed at the capture site and immediately released after processing. To minimise stress, animals were only processed in this manner once per season. Any animals recaptured within the same season were immediately released once they were identified and their capture recorded. All non-target species captured, other than quenda (*Isoodon obesulus fusciventer*), were immediately released without processing. Quenda datum was gathered concurrently for another study. All data was recorded onto *pro forma* sheets in the field and entered into an electronic database immediately on completion of daily fieldwork.

4.2.5 Nesting Trees

For koomal to persist they require trees within which they can nest or den (Bennett et al. 1994). Nesting hollows were not counted as individuals were observed using hollows less than 10 cm in diameter and it was felt that an accurate count of hollows could not be obtained. Furthermore, previous studies had shown that the documentation tree characteristics can be used as metrics in modelling brushtail possum habitat (Ji et al. 2003; le Mar & McArthur 2005). To better understand what characteristics a tree must have for a koomal to nest in them, the nesting trees of radio tracked individuals were photographed; tree species were recorded, as was trunk girth at a height of 1.5m above ground. This data was then compared with a baseline tree sample. To obtain this baseline sample, five 50m random transects (chosen as being representative of the described vegetation type) were walked, along each of which the species and girth of ten trees were recorded. Roosting, or denning, behaviour was only observed for radio-tracked individuals.

4.2.6 Home Range Estimates

Home ranges were estimated for all individuals that were radio tracked or captured five or more times. Koomal captured less than five times were not included in this exercise because the high number of transient individuals in this group were seen as a potential source of bias. Home ranges were estimated using a kernel density analysis using the Hawth’s Tools (Beyer 2004) application in a GIS environment, with home range nominated as being within the 95% probability isopleth. Both likelihood and least squares cross-validation methods were trialled in setting smoothing factors (Horne & Garton

2006) but these resulted in over-smoothing. A smoothing factor of 0.75, as used by Grimm and De Tores (2009), was found to provide more appropriate results and therefore was adopted for this exercise. Home range isohyets, with movements overlaid were then compiled as maps for individual animals to demonstrate the relationship between movements and modelled home ranges (Appendices ch.4,1-26). Home range isohyets were then clipped to the remnant vegetation shapefile (Figure 14) to remove cleared areas from the kernel analyses, on the assumption that these areas (although traversed by koomal) do not contribute to habitat.

4.2.7 Data Analysis

To determine the habitat value of individual vegetation types (Table 14), average numbers of captures and the number of individual koomal were calculated for traps in each vegetation type (Table 15) (vegetation types without traps were not included in this exercise). These averages were then tested against probable habitat parameters by plotting relationships and obtaining regression (R^2) values. These values were obtained through standard linear regressions between trap results and potential habitat parameters. The purpose of these values is to provide an indication on the influence of each parameter on koomal presence. To test for variability in home range size relative to vegetation type a Kolmogorov-Smirnov test was undertaken (Melles *et al.* 2009). Attempts at defining vegetation preference within home range using a permutation test (Potvin *et al.* 2001) failed as the test landscape is too metrically uniform in terms of spatial features: i.e. the fragstat analyses did not provide a diverse enough sample.

It is noted that although density alone may not be a good indicator of habitat value (Van Horne 1983) the weights, high fecundity rate and generally good condition of this population, indicate that density is a valid indicator of habitat value for koomal in the context of the subject landscape.

All GIS data was analysed using ArcMap 9.3®. Kernel movements and ranges were analysed using Hawth’s Tools (Beyer 2004). Populations were analysed using the Popan Jolly-Seber model contained in the Programme Mark software package (White & Burnham 1999). Population densities were calculated simply as remnant vegetation area (ha.) across the whole target landscape divided by average population. Data was contained and manipulated in a Microsoft Access® database. Additional statistical analyses were undertaken with SPSS 20®.

4.3 Results

4.3.1 Koomal surveys

In the focal fragmented landscape, 61 koomal were captured and micro-chipped (pouched young were not micro-chipped or counted) with a total of 360 captures. Of the animals captured; 31 were males of which 19 were adult, 11 sub-adult and 1 juvenile, and 30 were females of which 27 were adult, 1 sub adult and 2 juvenile. Sub adults were classified as animals whose weight was less than 1,200g (Wayne *et al.* 2005b) at the time of their first capture, and juveniles classified as those who were still with their mother at the time of first capture. Mean number of captures per trap night was 6.3 for males and 5.1 for females (Table 10).

Table 10: Mean number of captures per night for females and males

	Females	**Males**
Mean	5.07	6.32
S.E. ±	1.04	1.03
Median	2	4
StDev. ±	5.67	5.73
Minimum	1	1
Maximum	18	23
Sum	152	196
Count	30	31

The first four trapping periods produced low numbers of individuals with comparatively low recapture rates (Table 11). Observations of koomal in the field indicated that populations were much higher than capture rates suggested. It was hypothesised that this may be because both Jarrah and Marri were flowering heavily, and as koomal are known to feed on nectar and flowers in the summer and early autumn months (Cruz *et al.* 2012), it was decided to suspend trapping until the flowering event had subsided. When trapping was resumed (period 5), capture and recapture rates were much higher and remained relatively consistent for the rest of the study.

Table 11: Capture by trapping period, showing number of captures (Capt.), number of individuals (Ind.) captured during that capture period and demographics for those individuals.

					Male			**Female**		
Period	**From**	**To**	**Capt.**	**Ind.**	**Adult**	**Sub.**	**Juv.**	**Adult**	**Sub.**	**Juv.**
1	1/12/2011	5/12/2011	9	9	2	1	0	5	0	1
2	16/12/2011	18/12/2011	9	7	4	1	0	2	0	0
3	3/01/2012	5/01/2012	7	6	2	2	0	2	0	0
4	23/01/2012	26/01/2012	10	7	2	2	1	2	0	0
5	11/04/2012	15/04/2012	34	23	7	5	0	10	1	0
6	26/04/2012	29/04/2012	26	16	7	2	0	6	1	0
7	17/05/2012	20/05/2012	28	17	6	3	0	8	0	0
8	21/06/2012	24/06/2012	44	35	7	7	9	11	1	0
9	10/07/2012	13/07/2012	45	24	7	7	0	7	3	0
10	28/08/2012	31/08/2012	43	25	6	6	0	11	2	0
11	18/09/2012	21/09/2012	37	19	4	6	0	7	2	0
12	8/10/2012	11/10/2012	32	20	6	4	0	9	1	0
13	6/11/2012	9/11/2012	36	23	7	4	0	9	2	1

Average weight for an adult male was 1,623 g and 1,663 g for an adult female (Table 12). These figures varied seasonally although this variation was not significant (Figure 16). Male weights peaked in autumn with a mean of 1,728 g, while female weights peaked in winter/spring with mean weights of 1,683 g and 1,657 g respectively.

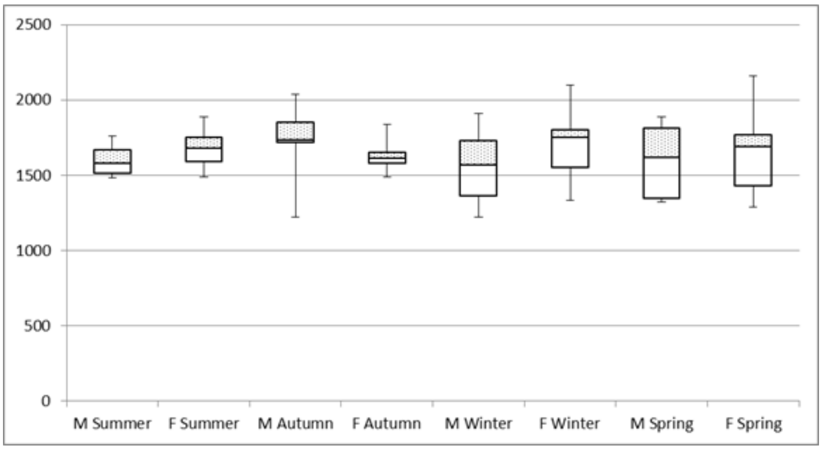


Figure 16: Adult weights by gender and season shown in quartiles.

Table 12: Weight (in grams) by gender and season

	Total M	**Total F**	**Summer M**	**Summer F**	**Autumn M**	**Autumn F**	**Winter M**	**Winter F**	**Spring M**	**Spring F**
Mean	1630	1664	1600	1677	1728	1638	1546	1683	1599	1657
Standard Error ±	33	26	63	41	60	29	59	49	65	69
Median	1690	1650	1580	1680	1735	1610	1570	1750	1620	1690
S.D.	223	191	126	122	224	106	228	204	226	267
Min.	1220	1290	1480	1490	1220	1490	1220	1330	1320	1290
Max.	2040	2160	1760	1890	2040	1840	1910	2100	1890	2160
Count	45	54	4	9	14	13	15	17	12	15

All but three adult females were known to have had young during the trapping period, in that they were at some stage found to have had young (pouched or carried) or to be lactating. Of the three with no indication of young, two were small dispersers which both weighed at less than 1,400 g during the spring period and the third was a large but thin adult female weighing 1,720 g which was caught only once in the final trapping period. Most joeys were born in winter although some were born in late autumn and early spring (Figure 17). All females known to have had young over this period were still carrying young or were lactating at the end of fieldwork in November. No multiple births were encountered during this study.

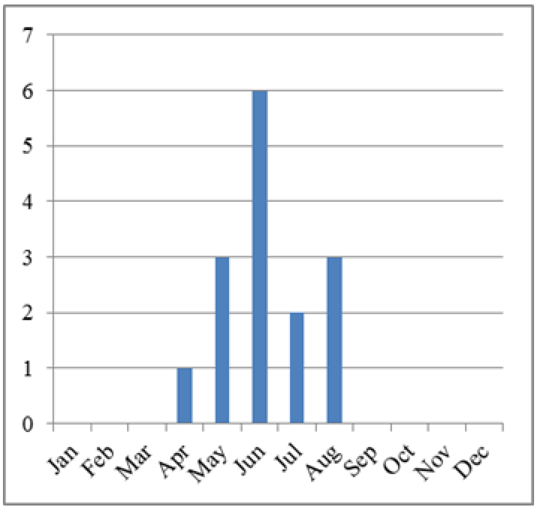


Figure 17: Known births by month.

A series of Jolly-Seber population models were run using the Popan population analysis tool in the Programme Mark software package (White 1999). The most successful model proving to be the P(*)Phi(*)Pent(t) model, i.e. the model where the probability of birth/entry (Pent) varied with each trapping event and the probability of capture (P) and the probability of survival (Phi) remained constant (Table 4). This model is statistically sound and estimates a total population of 69 individuals with a mean population of 27.75 (a population density of .28 per ha. for the study area). Variable population estimates for each trapping session from this model are shown in Figure 8. This model supports observations of low summer capture rates indicating a population averaging 13 individuals for that season while the more reliable data for autumn, winter and spring, shows a relatively static population of between 29 and 34 individuals. Parameter estimates for this model give constant survival rate of .996 (±.002 S.E.) for each capture event (estimating a total mortality of ≈ 21%) and a capture/recapture probability as of .255 (±.002 S.E.). It should be noted that all population estimates only refer to adult, sub adult and independent juveniles as pouched and carried joeys are not included in these analyses.

Table 13: Results of model test for Popan analyses.

Model	**AICc**	**Delta AICc**	**AICc Weight**	**Model Likeli-hood**	**Num. Par.**	**Deviance**	**Est. total individuals (N Hat)**	**S.E.**	**95% C.I Lower**	**95% C.I Upper**
P(*)Phi(*)Pent(t)	1562	0	1	1	23	1020	69	4	62	77
P(*)Phi(t)Pent(t)	1675	113	0	0	76	986	72	5	61	82
P(t)Phi(*)Pent(t)	1718	157	0	0	105	922	74	6	62	85
P(t)Phi(t)Pent(t)	1758	196	0	0	121	889	72	7	58	86

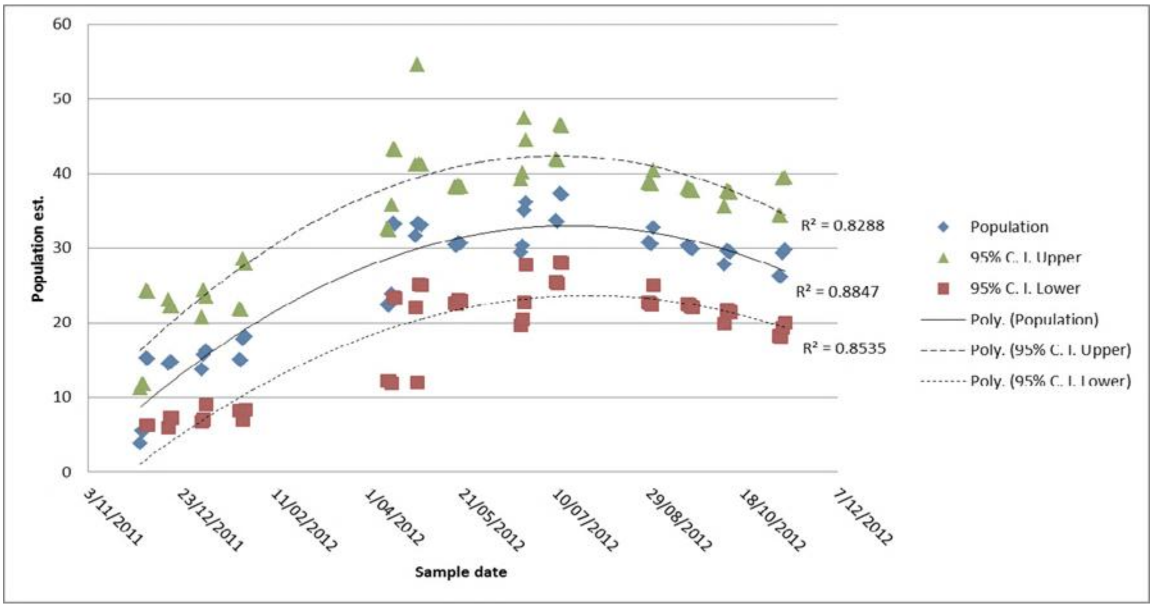


Figure 18: Popan analysis results for model P(*)Phi(*)Pent(t). Population estimates per trapping session.

4.3.2 Defining koomal habitat

On comparing individual vegetation types (Table 14), with trapping records for each vegetation type (Table 15) (vegetation types without traps were not included in this exercise), no significant indication of a link between canopy characteristics or fire history and koomal presence were found. However, the presence of dieback may be a significant parameter in defining koomal habitat. These findings should be treated with some caution as, other than in vegetation types 1 and 12, trap numbers were very small and therefore subject to skewing.

Table 14: Vegetation descriptions with (mean) canopy characteristics. Condition (Cond.) is given as a scale where 0 is parkland cleared, 1 poor and 5 excellent.

Veg #	Vegetation Description	Total m^2	% Total area	Cond.	$\bar{x}$ Fc	$\bar{x}$ Ff	$\bar{x}$ LAI
1	Jarrah, Sheoak, Excellent Condition, not burned 15 years plus, excellent canopy, sparse understory.	404,070	40.24	5	0.9	0.7	10.2
2	Jarrah, Marri, Peppermint, Good Condition, not burned 15 years plus, good canopy, medium understory.	36,703	3.65	3	0.8	0.6	6.7
3	Jarrah, Marri, Good Condition, not burned 15 years plus, open understory, some grassy weeds.	28,439	2.83	3	1.0	0.6	7.2
4	Jarrah, Marri, Good Condition, not burned 15 years plus, herbaceous understory, some grassy weeds	9,563	0.95	3	0.7	0.4	4.2

	(<20%).						
5	Jarrah, Marri, Fair Condition, not burned 15 years plus, open understory, some grassy weeds, Dieback.	14,611	1.45	2	0.6	0.5	6.7
6	Riparian, Jarrah, Marri, Peppermint, and Bullich. Excellent Condition, with a tall and dense shrub layer over reeds and other herbaceous growth, not burned for 5 years.	24,150	2.4	5	0.6	0.4	6.7
7	Shrubland, perched wetland, shallow soil over granite outcrops, light understory, degraded, and light dieback (*Phytophthora cinnamomi*) infestation.	16,543	1.65	2	N/A	N/A	N/A
8	Jarrah Marri, poor condition, traffic damage.	1,328	0.13	1	0.9	0.7	7.4
9	Jarrah, Marri, good condition, not burned 5 years, VG canopy, herbaceous understory, some grassy weeds.	41,259	4.11	3	0.7	0.6	9.0
10	Jarrah, Marri, good condition, not burned 5 years, open canopy, dense herbaceous understory, dieback present.	66,189	6.59	3	0.8	0.6	9.9
11	Jarrah, Marri, poor condition, 2 years since burn, very open canopy, weedy (>40%), heavily impacted by dieback.	31,929	3.18	1	0.5	0.2	3.7
12	Jarrah, Sheoak, very good condition 5 years since burned, more open canopy, herbaceous understory.	98,530	9.81	4	0.8	0.7	11.6
13	Jarrah, Sheoak, good condition 2 years since burned, more open canopy, open understory, grazed.	42,933	4.28	3	0.9	0.8	16.3
14	Jarrah, Sheoak, fair condition, 2 years since burned, relatively open canopy, open understory, grazed.	19,837	1.98	2	0.6	0.4	6.4
15	Jarrah, Marri, very good condition, not burned 2 years, herbaceous understory, relatively open canopy.	42,664	4.25	3	0.6	0.4	4.2
16	Perched wetland, Xanthorrhoea, Spearwood and grasses over shallow soils, fair condition, heavily grazed by rabbits and kangaroos, canopy decline, possibly symptomatic of early dieback infestation.	106,390	10.59	2	N/A	N/A	N/A
17	Jarrah, Sheoak, very good condition, not burned 15 years plus, excellent canopy, sparse understory, some grassy weeds.	19,099	1.9	4	0.6	0.5	7.5

By virtue of the relatively uniform size, shape and distribution of patches in the study area, the application of patch metrics (McGarigal *et al.* 2000), other than home range as defined through kernel analysis (Horne & Garton 2006), has proven to be impractical.

Table 15: Captures by vegetation type (as described in Table 14); number of traps within that veg. type (Veg. #), traps per hectare, captures and individuals, average number of captures and individuals per trap and vegetation characteristics. Fire is number of years since last known fire. P/c refers to level of dieback infestation, where 0 is no indication and 5 is total (or imminent) loss of all susceptible species. R^2 values were obtained through standard linear regressions between trap results and potential habitat parameters.

Veg. #	**Traps**	**Traps per ha.**	**Capts**	**Ind.**	**Capts. per trap**	**Indivs. per trap**	**$\bar{x}$ Fc**	**$\bar{x}$ Ff**	**$\bar{x}$ LAI**	**Cond.**	**Fire**	**P/c**	**Vegetation Type**
1	14	3.46	193	66	13.79	4.71	0.9	0.7	10.2	5	15	0	Jarrah, Sheoak, woodland
2	2	5.45	1	1	0.50	0.50	0.8	0.6	6.7	3	10	1	Jarrah, Marri, Peppermint, woodland
3	1	3.52	3	2	3.00	2.00	1	0.6	7.2	3	15	1	Jarrah, Marri, woodland
4	1	10.46	10	4	10.00	4.00	0.7	0.4	4.2	3	15	0	Jarrah, Marri, woodland
5	1	6.84	16	4	16.00	4.00	0.6	0.5	6.7	2	15	1	Jarrah, Marri, woodland
6	2	8.28	0	0	0.00	0.00	0.6	0.4	6.7	5	5	0	Riparian woodland
9	1	2.42	6	3	6.00	3.00	0.7	0.6	9	3	5	0	Jarrah, Marri, woodland
10	3	4.53	3	3	1.00	1.00	0.8	0.6	9.9	3	5	3	Jarrah, Marri, woodland
11	1	3.13	0	0	0.00	0.00	0.5	0.2	3.7	1	2	5	Jarrah, Marri, woodland
12	7	7.10	65	21	9.29	3.00	0.8	0.7	11.6	4	5	0	Jarrah, Sheoak, woodland
13	1	2.33	0	0	0.00	0.00	0.9	0.8	16.3	3	1	1	Jarrah, Sheoak, woodland (Grazed)
15	2	4.69	46	14	23.00	7.00	0.6	0.4	4.2	3	2	0	Jarrah, Marri, woodland
R2 Captures per trap							0.04	0.01	0.07	0.01	0.06	0.22	
R2 Individuals per trap							0.01	0.00	0.07	0.02	0.10	0.27	

Home range estimates, total and by area of veg. type, for all subject animals with 5 or more presences are given below (Table 16) with accumulative area plots for males and females provided (Figure 19). Areas refer to areas of remnant vegetation only. Pastoral areas have been clipped from this analysis on the assumption that these areas do not contribute to koomal habitat. Diam., refers to diameter of the 95% home range, as defined by kernel analysis. Gap, refers to the shortest distance between patches that the subject was known to have crossed, taken from the movements depicted in the Appendices (ch.4,1-26). To determine if some vegetation types were preferred over others, a use versus availability plot was prepared comparing the area of each vegetation type with the area used by all individuals for each kernel value (Figure 20). To support this, a comparison between total areas of each vegetation type and the average use of vegetation types by all individuals at both 95% and 50% kernel densities show that although preferences remain strongly linked to the extent of that vegetation type at the 95% density (both Kolmogorov-Smirnov and Shapiro Wilkinson tests give a significance of <0.01) differences become more pronounced at the finer scale 50% density (both Kolmogorov-Smirnov and Shapiro Wilkinson tests show a small but significant difference at 0.08 and 0.12 respectively). The results of these exercises indicate a preference for vegetation types 9, 12 and 1, and that vegetation types 2, 13 and 16 are significantly less utilised.

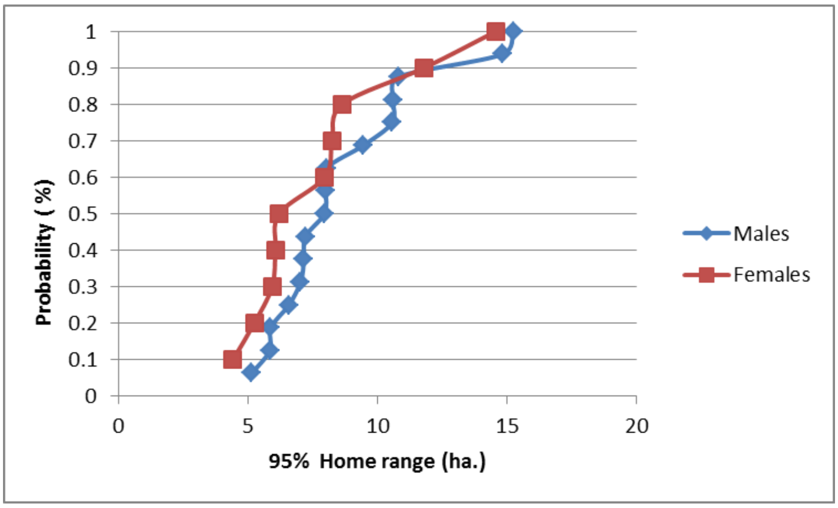


Figure 19: Accumulative home range area plots for remnant vegetation within the 95% kernel analyses for both male and female as given in Table 16.

Table 16: Estimated 95% home ranges of individuals. Trap = number of times captured. Track=number of times position recorded through radio location. Diam. = diameter of 95% home range. Gap= largest gap in home range crossed. In meters.

Males							
Collar	**Chip#**	**Trap**	**Track**	**Area m^2**	**Veg#/Area m^2**	**Diam. m**	**Gap m**
C1	11539	4	7	51362	1/46094 3/5268	372	0
C2	10000	15	14	58744	1/57785 2/959	524	73
C5	24328	8	15	106009	1/12361 7/8803 10/41631 15/40351 16/2863	921	380
T1	8648	2	4	148450	1/148450	620	127
T2	28836	18	16	79452	1/65681 10/5281 16/8091 17/399	446	10
T4	10340	10	20	105628	1/65785 3/10131 4/5578 5/10796 6/5466 7/5963 8/586 10/1323	612	10
	2287		9	94552	1/95552	697	201
	9591		12	107955	1/17980 6/2675 12/72296 13/7457 16/7547	490	20
	11691		6	58385	1/27548 2/4096 4/9131 5/3871 6/7636 7/6103	369	32

	14884		7	70268	1/70268	604	146
	24169		5	71563	6/5501 9/28340 10/17563 11/12196 12/7963 13/1137	338	0
	24878		5	152407	1/63885 10/9575 12/33054 16/45893	705	10
	25673		13	80031	1/7333 3/7927 4/2062 5/14231 6/10931 7/6635 8/1328 9/48 10/25072 12/4464	338	0
	28403		14	80457	1/20134 12/45544 16/14779	415	5
	47088		7	72114	1/67323 2/799 16/3269 17/723	725	180
	51171		11	65738	1/65738	410	10
			Mean **SE** **StDev**	**87695** **± 7494** **29024**		**537** **± 42**	
Females							
C3	27762	13	40	61967	1/52008 3/9959	423	0
C4	14162	9	30	52364	1/1506 7/8803 12/4750 15/37305	948	399
C6	29371	16	34	145719	1/19768 2/3730 12/69264 13/1424 15/39598 16/11935	959	399
C7	1004	18	10	59277	1/59277	447	73
T3	442	7	19	79605	1/33991 2/395 3/8249 4/9563 5/9737 6/9757 7/7667 8/246	404	10
	10624		8	60557	1/48811 3/11746	432	0
	10626		15	44116	1/35835 2/8281	419	72
	11669		17	118052	1/60484 10/9744 16/38854 17/8970	406	10
	14577		7	82462	1/9074 12/68697 13/4383 16/308	348	5
	6394		10	86368	6/7568 9/6072 10/11434 11/7 12/49069 13/12218	341	5
			Mean **SE** **StDev**	**79045** **± 9994** **29981**		**512** **± 74**	

Examination of the kernel analyses for all subjects (Appendices ch.4) showed that the number of captures or tracks did not greatly influence home range estimates once $n \geq 5$. Factors such as period of engagement (longer time between first and last record) and age of subject (the dispersal movements of some younger subjects) could provide indications of larger 90 and 95% kernels. However, 50% kernel areas showed much less variation and with links to vegetation type becoming more prominent.

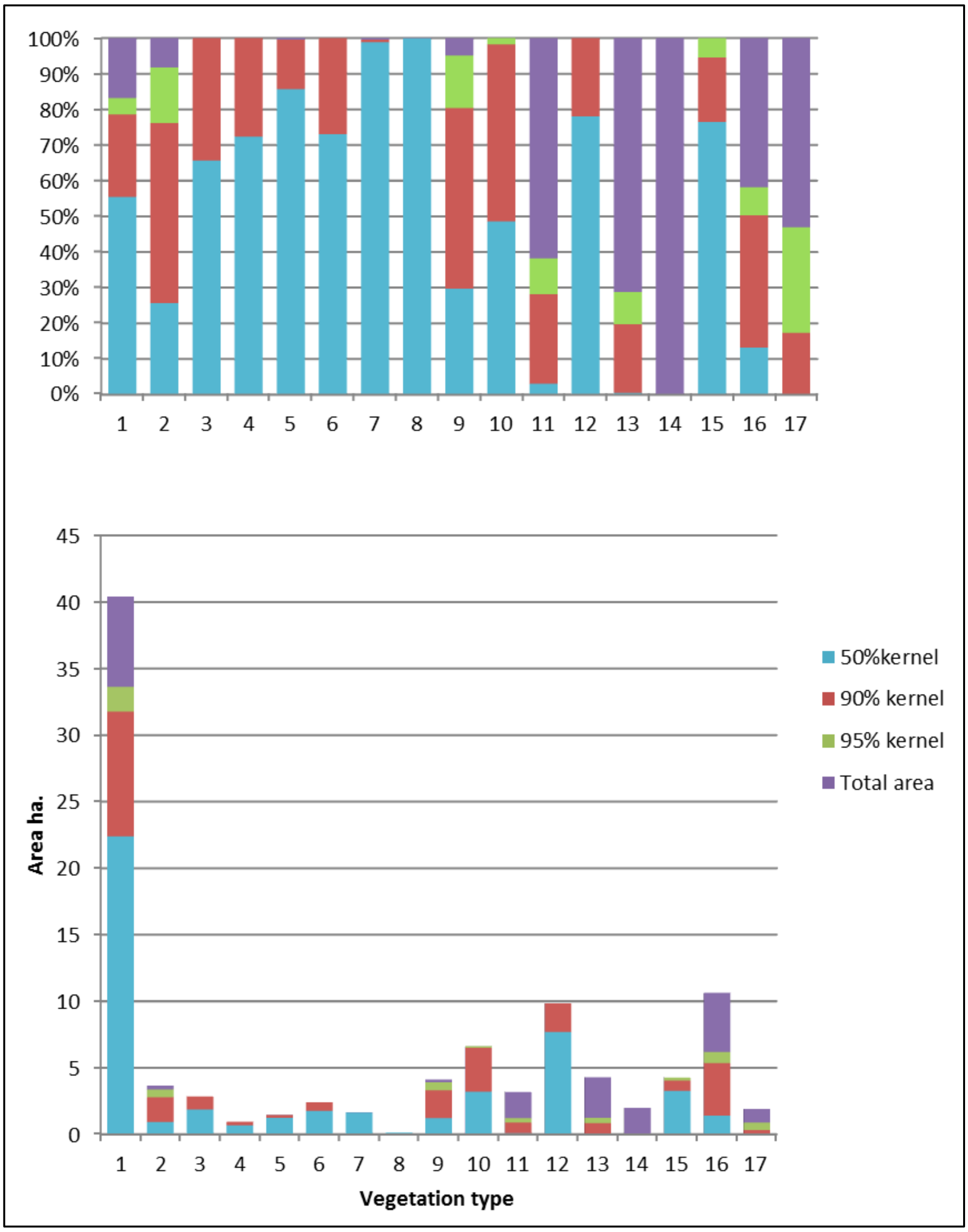


Figure 20: Vegetation type use versus availability analyses. Total available areas for each vegetation type along with total areas used in 95, 90 and 50% kernel analyses as depicted in Appendices ch.4 (below) and proportional use chart (above).

All recorded nesting was in living trees (Table 17). These trees were usually Jarrah or Marri, and less frequently, forest sheoak (*Allocasuarina fraseriana*). Individuals were observed to have 3 to 12 denning trees (Figure 21; Appendices ch.4,1-26). Where many trees were used, most activity would centre on three or four large trees with well above average girth (Table 17). In all tree species the mean girth of nesting trees was greater than that of background trees. Species proportion of background trees was marri 42%, jarrah 36% and sheoak 22% while koomal nesting trees were marri 61%, jarrah 30% and sheoak 9%. As shown in Table 17, individuals displayed a preference for marri over jarrah, however marri were generally of greater girth reflecting the fact that, until recently, jarrah, unlike marri was the subject of widespread commercial timber harvesting (Dell *et al.* 1989). Therefore, there is no indication of a preference between these two species other than physical characteristics of individual trees such as girth. By comparison, sheoak was infrequently used for nesting purposes and appears much less preferred species for nesting purposes.

Table 17: Girths (m) of nesting and background trees by species.

	Marri		**Jarrah**		**Sheoak**	
	Nesting	**Background**	**Nesting**	**Background**	**Nesting**	**Background**
Mean	3.29	2.29	2.69	1.77	2.23	1.92
Standard Error ±	0.24	0.30	0.26	0.23	0.12	0.09
Median	2.9	2.1	2.5	1.32	2.1	1.85
Range	4.7	4.95	3.55	3.03	0.8	0.88
Minimum	1.2	0.45	1	0.77	1.95	1.52
Maximum	5.9	5.4	4.55	3.8	2.75	2.4
Count	40	21	20	18	6	11

4.3.3 Dispersal capacity

The crossing of gaps (the minimum distance between neighbouring patches of vegetation regardless of paddock trees) by koomal between patches of remnant vegetation was frequently observed (Figure 21; Appendices ch.4,1-26). Of the 26 individuals with ≥5 records (Table 16), gap crossing behaviour was observed in 20, three individuals were seen to have crossed gaps of ≥ 380 m, two of which were seen to return over the same gap, a further four regularly crossed gaps >100 m and 13 repeatedly crossed gaps of <100 m. In Figure 21a it can be seen that gaps of between 80 and 200 m are regularly crossed. It should be noted that movements across ±200 m gaps by tracked subject T1 and trapped subjects with micro-chip numbers 2287, 14884 and 47088 are depicted as straight movements across gaps, in reality these movements may have been less direct and covered a matrix of smaller gaps. Nonetheless, the matrix remains highly permeable to koomal. This is best exemplified by individuals C2 and C7 who shared territories comprised of at least three patches within which they crossed gaps of <100 m with impunity. Figure 21b shows the movements of three radio tracked koomal, all of which crossed a gap >400 m. C4 having crossed and returned back across the same gap some weeks later. Unlike the examples in Figure 21a, there are few options for crossing this gap via a landscape matrix as there have been no indications of koomal activity in these areas particularly in the shrublands directly to the north east.

Maps portraying capture/track records, movements and home range estimates (kernel density analysis) for all subjects with greater than five records (Table 16) have been supplied as appendices for this chapter (Appendices ch.4,1-26).

4.3.4 Comparison

In comparison with other koomal studies (Table 18), the population density within this study area is considerably lower than all but the Tutanning study (Sampson 1971), and extremely low in comparison to the Perth Zoo study (Patt 1995). As the Tutanning population is situated in the Western Australian Wheatbelt (where koomal have suffered the greatest decline (Jones 2004) and where rainfall, vegetation structure and composition vary greatly from all other study sites), and the Perth Zoo population situated in a metropolitan area (where koomal numbers are highly inflated because of an abundance of food (Patt 1995)), these population densities are not readily comparable with those of the Bramley catchment. However, climate and vegetation similarities between Bramley, Abba River (How & Hillcox 2000), Tuart Forest (Grimm & De Tores 2009) and particularly Chariup (a study also conducted in the southern jarrah forest (Wayne *et al.* 2005b), enable a reasonable comparison of results with those of this study.

Note: In making this comparison it should be noted that there are only five peer reviewed studies made on koomal movement prior to this study, all of which have differing methodologies which may in turn influence their findings. However, given this small number of studies available for comparison, the fact that they have passed a peer review process and that the findings of all studies remain comparable, their use in this exercise is considered appropriate.

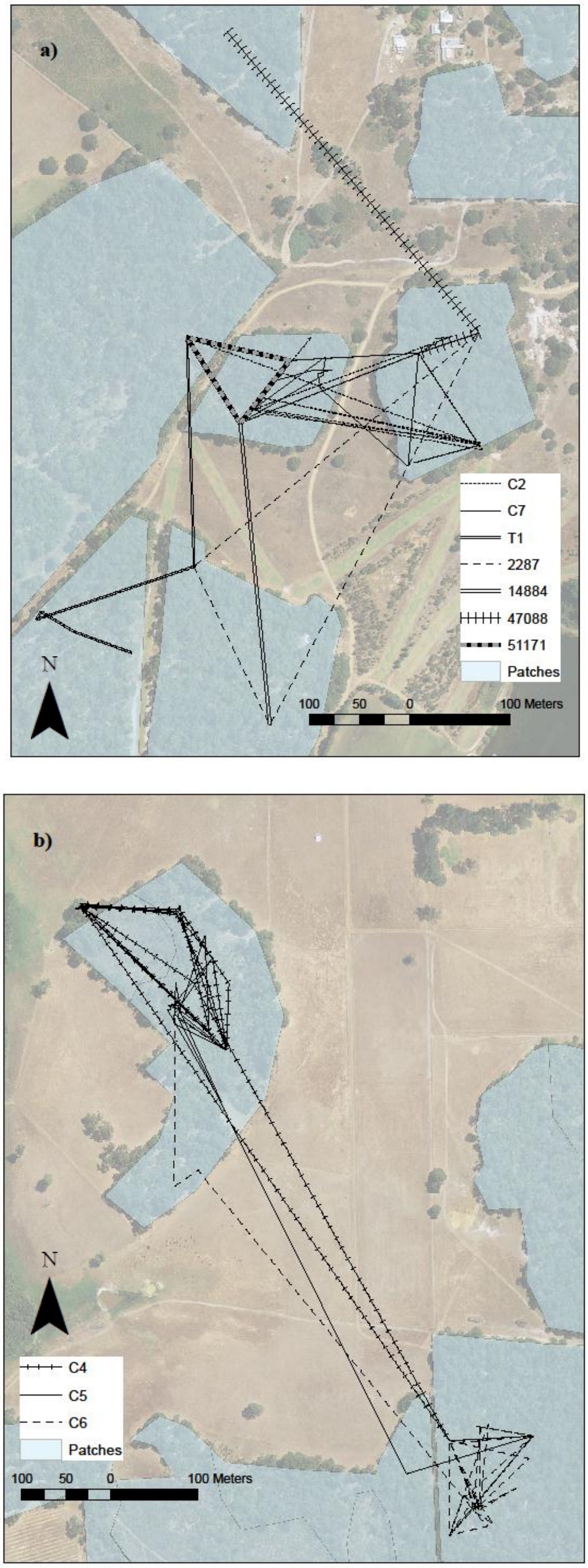


Figure 21: Movements of individual koomal demonstrating gap crossing activity. Note, movements are shown as direct lines between points. Actual movements may vary from these paths significantly.

The population density of the study area is considerably less than those of Abba and Chariup. This is also reflected in the larger mean home range area of individuals in the area. This mirrors the findings of le Mar and McArthur (2005), Ji *et al.* (2003) and Grimm and De Tores (2009) who all found that, for common brushtail possums, less suitable habitat resulted in expanded home ranges. Although, the removal of areas not found to be habitat in this study, i.e. the removal of 23.5 ha of riparian, shrubland and dieback infested areas from the 100.4 ha study area would increase the population density from 0.28 to 0.36 (n^{ha-1}), this population density would still be significantly lower than those of the Chariup and Abba River studies.

Table 18: Comparison of findings between this study and other koomal studies. Sexual dimorphism = mean male body mass/mean female body mass. It should also be noted that the mean home ranges calculated for Grimm and De Tores (2009) are based on a 90% gradient whereas this study uses a 95% gradient

Variable	**Tutanning (Sampson 1971)**	**Perth Zoo (Patt 1995)**	**Abba River (How & Hillcox 2000)**	**Chariup (Wayne *et al.* 2005b)**	**Tuart Forest (Grimm & De Tores 2009)**	**Bramley (present study)**
Population density (n^{ha-1})	0.07	3.83	1.77	1.7	n/a	0.28
Mean male home range area (ha)	n/a	n/a	2.21	n/a	6.17	8.77
Mean female home range area (ha)	n/a	n/a	1.26	n/a	4.39	7.72
% Breeding peak 2 months	59	59	79	69	n/a	64%
Breeding, peak 2 months	Apr/Oct	Mar/Apr	May/Jun	Apr/May	n/a	Apr(Aug)/Jun
Adult sex ration (M/F)	1.35	1.21	0.84	1.32	n/a	0.97
Sexual dimorphism	n/a	1.06	1.17	1.1	n/a	0.98
Mean male weight (g)± s.d.	n/a	1619 ± 346	1764 ± 215	1616 ± 166	n/a	1630 ± 223
Mean female weight (g)± s.d.	n/a	1523 ± 382	1509 ± 171	1470 ± 243	n/a	1664 ± 191

4.4 Discussion

4.4.1 Population demographics.

It was considered that this lower population density might be the result of predation by foxes and feral cats. All other study areas in this comparison are subject to regular feral predator controls. As previously stated, the only feral animal control undertaken in the study area is irregular shooting by one property owner. However, the Popan analysis predicted a 12 month mortality rate of 21% for the study population this gives an estimated average lifespan of 4.76 years. This is directly comparable with estimated average lifespan of 4.5 years given for the Chariup study (Wayne *et al.* 2005b). Therefore, there is no evidence of increased predation of koomal despite different feral predator control programmes and no evidence that increased home range is a consequence of feral predation.

Part of the difference in population densities and home ranges between studies may also be explained by the different methodologies used. Both this and the Tuart Forest studies have used similar radio tracking and kernel analysis methods to determine home ranges, whereas all other studies have used trap data alone. This may partially explain why home ranges in both of these studies remain comparable to each other and not to any other studies. It also points to the hazards of relying only on trapping data in models. An indication of this is the disparity of home ranges between the Tuart Forest and Abba River studies despite their largely shared study areas and similar management regimes.

Breeding months remain comparable between all studies although a peak breeding month of October for Tutanning is considerably later than for all other studies, this too may be explained by bioclimatic differences between the WA Wheatbelt's Tutanning site and the other study sites which are generally similar in climate and vegetation structure.

The male/female ratio remains comparable in all studies although sexual dimorphism (mean male weight/mean female weight) varies marginally between this study and all others. This is a direct result of higher average female weights in this study than any other. This is also the only study in which average female weights exceed those of males. Whether this is the result of weighing females with pouched joeys attached, an accurate reflection of greater weight in females, or a statistical anomaly, cannot be properly ascertained from the available data. It should be noted that mean male weights remain highly comparable between all studies.

4.4.2 Defining koomal habitat

All koomal, both trapped and tracked, were found in woodland/forest areas (no animals were found in shrublands, wetlands or riparian areas); no koomal were found, or observed, in areas heavily affected by dieback. This is consistent with observations from other studies. No koomal were trapped or observed in a particular patch (vegetation types

13/14) that appeared to be very suitable and was adjacent to a remnant with a relatively large koomal population. There was some suspicion that this patch was not used as it was unfenced and was the only patch to be grazed by cattle. However, one individual (C4) regularly nested in a very substantial paddock tree (whose canopy reached into that of an adjoining patch) under which cattle often rested, indicating that the presence of cattle may not influence koomal nesting behaviour. Another possible reason for koomal not entering this patch may relate to the nutritional and chemical content of leaves. It has been demonstrated that the foraging activities of common brushtail possums are linked to leaf chemistry, in particular, the influence of turpenes, nitrogen and moisture content in defining the nutrient value of myrtaceous leaves (Wallis *et al.* 2002; Moore *et al.* 2004; Scrivener *et al.* 2004; Foley & Moore 2005). There has, to date, been no similar study made investigating the link between koomal habitat and leaf presence. This represents a serious shortfall in the ability to define and quantify habitat for this taxon.

By viewing capture data and comparing home ranges as defined by Hawth's tools with movements overlaid (Appendices ch.4), it can be seen that territorial overlap between males and females was common, as was overlap between adults and sub-adults. Although overlap between adult females occurred regularly, territories for established adult males appeared to have marginal overlaps with regular intrusion by sub adults and transients. Overall, home ranges for adults appeared to be quite fluid. During the course of fieldwork it was often noted that, as individuals moved around their territories small individuals would quickly move into vacated areas only to leave when the larger animal returned. It appeared that sub adults and less dominant animals could, in this way, carve out an existence on the territorial margins of dominant and established individuals. This behaviour reflects denning and territory sharing behaviour exhibited by common brushtail possums in both Australia and New Zealand (Ball *et al.* 2005; Nersesian *et al.* 2012).

In forest and woodland areas, common brushtail possums require tree hollows to nest/den in (Harper *et al.* 2005). Tree hollows need to be large enough to meet the possum's requirements and there needs to be enough of them dispersed around a territory to enable an individuals to meet their autecological needs (Lindenmayer *et al.* 1997; Ji *et al.* 2003; Wormington *et al.* 2005; Nersesian *et al.* 2012). As tree girth is directly related to the number and size of hollows available for nesting (Bennett *et al.* 1994; Ji *et al.* 2003), this behaviour was expected. Hollows were not counted as the height and complexity of the canopy, along with the small hollows used by some individuals (individuals were seen using hollows <10 cm in diameter) meant that this could not be done with a reasonable accurately. As observed by Ji *et al.* (2003), larger individuals, tend to dominate larger trees and possessed territories with a greater proportion of large trees. The koomal in this study have demonstrated a nesting preference for trees of an above average girth greater than 1m at breast height (which are more likely to have suitable nesting hollows (Williams *et al.* 2008)) dispersed throughout their home ranges. This indicates that, like other sub-species of the common brushtail possum, a requisite number of suitable trees need to be retained in a landscape for koomal to persist. However, studies of common brushtail possums indicate that a lack of suitable nesting trees may be partially mitigated through the use of nesting boxes (Harper *et al.* 2005).

4.4.3 Dispersal capacity

Gap crossing by individuals was common place with overnight movements across gaps of 100- 400 m commonly observed (Table 16; Figure 20; Appendices ch.4,1-26). For example, of the 26 resident, or non-transient, individuals 3 (15%) crossed gaps covered distances ≥380 m, and 2 of these individuals recrossed these gaps. A further 4 individuals crossed gaps in excess of 100 m, 3 of which repeatedly recrossed these gaps. Of the other 13 individuals who were observed to cross gaps of <100 m, gap crossing was generally frequent with gaps of this size providing no discernible impediment to movement. These observed movements are, by and large, home range movements, with animals moving within a patch or group of patches which they utilise to meet their autecological requirements. Of the 26 subject koomal, only two individuals displayed a relocation of home range, i.e. dispersal behaviour. This indicates that once home ranges are well established, individuals are very reluctant to leave them.

By removing, from a total estimated population of 69.3 (100%), an average estimated population of 27.75 (40%) and an indicated mortality rate of 21%, there remains a minimum population of 27 (39%) transients, i.e. those who have effectively moved through the test landscape. This supports our earlier assumption that this is an open population. This indicates that this landscape (with 41% remnant vegetation cover within a 1 km radius) was highly permeable from a koomal perspective, i.e. the movement of individuals was not prevented by this degree of fragmentation and individuals could move freely between patches enabling them to utilise multiple patches as home range. The high number of transients in the study population strongly indicated that this population formed part of a much greater meta-population at the landscape level. Although there was no evidence of crossing of obstacles such as water courses and major roads in this study, such behaviour has been often observed by the author. The presence of foxes, feral cats and cattle did not deter gap crossing activity although the presence of introduced predators would certainly increase the risk of predation for koomal moving over open paddocks.

The gap crossing limit of the koomal, i.e. the maximum gap in vegetation cover that a koomal may cross was not determined in this study. All gaps within the study landscape proved permeable where there was suitable habitat at each end of the gap and that this destination was visible from the point of embarkation. This supports a landscape matrix approach to planning (Fischer *et al.* 2004; Watson *et al.* 2005; Lindenmayer & Fischer 2006; Fahrig 2007; Robertson & Radford 2009; Saura & Rubio 2010; Fahrig & Triantis 2013) for this taxon in that it is neither the patches or the gaps which define habitat, but the spatial arrangements of suitable patches of habitat within the landscape which appears to define habitat for this taxon in the context of a fragmented landscape.

4.5 Conclusions

Existing in a southern jarrah forest landscape with a heterogeneous 41% remnant vegetation cover and access to source-sink populations, as defined by Amarasekare & Possingham (2001), the koomal of the Bramley catchment appears to be currently stable (although further studies are required to confirm this). Source-sink populations are assumed because the population models predicted that individuals were constantly entering and leaving the test landscape and the surrounding patch matrix was capable of supporting this sort of movement. Although the population density is not as high as some other studies, it remains comparable. The weights, birth rates and estimated survival rate of this population are comparable with koomal populations found in relatively contiguous, conservation managed landscapes. This indicates that that the demographic characteristics of populations in a fragmented landscape, with adequate resources, may not be negatively impacted. It appears that the greatest constraint on these populations is the amount of suitable vegetation available to them, and access to hollow bearing trees. The greatest question therefore becomes, what is suitable vegetation? This study has shown that shrublands, dieback infested areas and riparian areas appear to not be habitat (although they do not impede movement) and many areas of the test landscape which appeared to be suitable habitat, were not utilised. This may be the result of variations in leaf chemistry and moisture content. The relationship between koomal browsing preferences and the chemical properties of the species upon which they feed remains largely assumed.

The long term viability of this population in the face of a rapidly changing climate is still not well understood. Although this landscape currently appears to be suitable habitat, repeat studies are required to obtain population trend data. This will enable the long term viability of this population and the impacts of climate change on it to be better understood. The patch matrix remains permeable to koomal, allowing ready migration. How the woodlands upon which the koomal depend will respond to climate change remains poorly understood. What is known is that leaf toxin levels increase when trees are stressed through heat and drought (Ramakrishna & Ravishankar 2011) and by changing the habitat value of patches within the matrix, landscape permeability will also be impacted (Luque, Saura & Fortin 2012). How koomal will respond to this potential threat remains a major knowledge gap in the management of this taxon and many others facing similar threats throughout the world.

Data obtained through this study can be used to inform conservation planning through spatial modelling applications. Models can focus on conservation of the koomal in its own right and also improve general conservation by enabling the koomal to be used as one of a suite of indicator species. This will be the focus of ch.6.

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5 Species distribution modelling using bioclimatic variables to determine the impacts of a changing climate on the western ringtail possum (*Pseudocheirus occidentals* (Pseudocheiridae)

5.1 Introduction

This exercise uses a combination of spatial models and climate change scenarios to determine the impacts of climate change on this species, thereby enabling the development of management actions for a species which is highly vulnerable to the impacts of global warming.

At the regional scale, most species and ecological communities exist within a definable bioclimatic niche, where habitat value is largely controlled by a set of variable climate parameters including precipitation and temperature (Hutchinson 1957). When there are changes in these variables, the habitat value for that area will also change (Beaumont *et al.* 2005).

Climate change presents a major threat to biodiversity around the world (IPCC 2007); these impacts are expected to increase in both magnitude and frequency throughout the 21st century (Richardson *et al.* 2011). The task of understanding how species and communities respond to changes in climate is made particularly difficult by the non-linear nature of impacts, which means that not all areas will be affected to the same degree. Climate impacts may vary dramatically between landscapes and in response to a species' or community's sensitivity to that change (Perkins *et al.* 2007; Opdam *et al.* 2009; Yates *et al.* 2010a; Richardson *et al.* 2011).

The Australian continent may be highly vulnerable to global warming (CSIRO & BOM 2007; CSIRO & BOM 2012) with predicted impacts of climate change on Australian biodiversity ranging from mild to severe, depending on the ecology of subject species and communities (Hughes 2003).

South-western Australia (Figure 22) is recognized as a global biodiversity hotspot (Myers *et al.* 2000). Threats such as land clearing, inappropriate fire regimes, exotic species, pathogens and demands for expanded infrastructure have contributed to a decline in the extent and condition of native vegetation throughout the region (Environmental

Protection Authority 2007). South-western Australia has been nominated as a region vulnerable to climate change (Hughes 2003; Klausmeyer & Shaw 2009) and has already been affected by global warming in that there has already been a generally significant fall in rainfall, changes in the intensity and frequency of severe weather events and a trend towards increasing mean temperatures across much of this region (Burbidge 2010; Indian Ocean Climate Initiative 2012; Prober *et al.* 2012). Global climate models (GCMs) predict that by the end of the 21st century, in comparison to averages prior to the 1980s, global warming will bring about: a 3–4 °C increase in mean temperature, a 30–40% decrease in rainfall, significant changes in seasonality, a rise in sea levels and more frequent severe weather events relative to pre 1980s records (CSIRO & BOM 2007; IPCC 2007; Burbidge 2010; Hughes 2011; CSIRO & BOM 2012; Indian Ocean Climate Initiative 2012; Prober *et al.* 2012). Climate variations of this magnitude are likely to have significant detrimental impacts on regional biodiversity (Gritti *et al.* 2006; Cowled 2009; Hughes 2011; Ziska *et al.* 2011; Crossman *et al.* 2012).

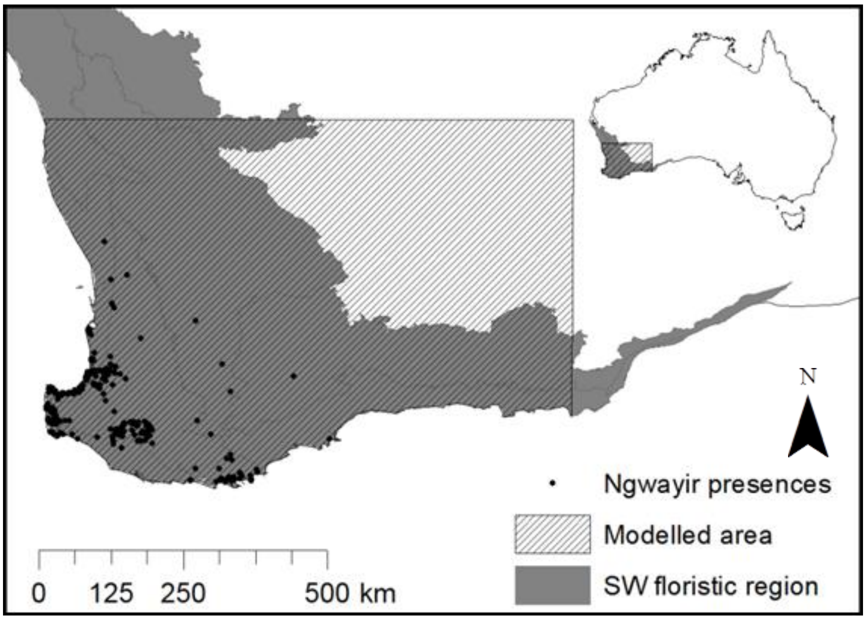

Figure 22: The South-west Australian Floristic Region and sub regions. Ngwayir (*Pseudocheirus occidentalis*) presence records and modelled area for this project are overlaid.

Australian protected areas have nevertheless largely been selected without consideration of the impacts of climate change on the reserves themselves or on the needs of species and communities outside of reserves (Dunlop & Brown 2008). Consequently, reserve systems urgently require review to better understand their capacity to withstand the impacts of climate change and to facilitate biodiversity conservation at the landscape scale.

The ngwayir (pronounced ‘n-wa-ear’) or western ringtail possum (*Pseudocheirus occidentalis*), a small (0.8–1.3 kg) arboreal marsupial, endemic to the forests of south-western Australia, provides an ideal candidate to model range shifts in response to the predicted impacts of climate change. This species is listed as vulnerable (Morris *et al.* 2008) and, because of this and its public popularity, is a regional conservation icon (Jones *et al.* 2007; de Tores 2008). The ngwayir is a strict folivore, feeding on a few myrtaceous tree species that meet nearly all of its food and water requirements, and is highly susceptible to extremes of temperature, especially when combined with low moisture levels in leaves (Jones 2004; Yin 2006).

The ngwayir had a pre-European distribution from north of Perth to east of Albany, extending into the Western Australian agricultural region, where populations were recorded in *Casuarina* spp. woodlands until the 1970s (Jones 2004). Local extinction has been extensive in the inland and northern parts of its pre-European range, and the current distribution both patchy and *c.* 10% of the original. The ngwayir now occurs most commonly in coastal or near-coastal forests and woodlands of the southern Swan Coastal Plain, where the peppermint tree (*Agonis flexuosa*) is a major component of local vegetation (Jones & Hillcox 1995).

Habitat loss, modification and fragmentation have caused significant negative impacts on ngwayir populations (Wayne *et al.* 2006; Wilson 2009). Much of the coastal area where ngwayir population densities are at their highest is subject to large-scale development pressure from the rapidly-growing human population (Environmental Protection Authority 2007; Jones *et al.* 2007; Molloy *et al.* 2007).

The ngwayir is vulnerable to high temperatures and dehydration (Yin 2006), changes in diet, changes in fire regimes (Wayne *et al.* 2006), landscape fragmentation (Jones 2004), feral predators (de Tores *et al.* 2004) and introduced pathogens (Wayne 2009). These vulnerabilities, combined with its rarity, specialized habitat preferences, and low capacity to migrate and disperse, indicate that the ngwayir is likely to be highly sensitive to the predicted impacts of climate change (de Tores 2009). For these reasons, the ngwayir is an ideal candidate to test how effective species distribution models are for determining impacts of anthropogenic global warming on vulnerable species.

Species distribution models (SDMs) are effective in determining current and potential distributions when using climate data alone (Hijmans & Graham 2006; Beaumont *et al.* 2007; Elith *et al.* 2011) allowing historical distributions to be modelled against climate records to form high quality baseline models, which can then be overlaid with GCMs to demonstrate how predicted changes in climate may affect species distributions (Green *et al.* 2008; Yates *et al.* 2010b; Adams-Hosking *et al.* 2011; Fordham *et al.* 2012; Guerin & Lowe 2012; Prober *et al.* 2012). SDMs have become popular in response to increased availability and quality of relevant data (Marcial & Hemminger 2010) and corresponding increases in the availability and complexity of SDMs (Beaumont *et al.* 2005; Guo & Liu 2010; Marcial & Hemminger 2010).

I investigated potential range shifts of this sedentary, specialist endemic, habitat-restricted vertebrate, in response to the potential impacts of global warming. My hypothesis is that the ngwayir will be at high risk from climate change. Specifically, I predict that, based on climate change models for south-western Australia, this species will lose much of its core range, and this will further threaten the viability of future populations. I also sought to evaluate the idea that a broader understanding of the impacts of global warming on target species can be obtained by seeking congruence between predictions from multiple spatial distribution models each using multiple climate change scenarios.

5.2 Methods

5.2.1 Model selection

Three SDMs were chosen to examine the impacts of three IPCC IV, scenario A2A, GCMs (Worldclim 2012) on the potential distribution of ngwayir. I used multiple models because our aim was to obtain a broader understanding of the potential impacts of climate change, and to identify and investigate misleading results arising from anomalies in the application of any one particular model. I selected SDMs that have been shown previously to be successful in predicting species distributions from presence-only data, each employing a different methodology to do so (Guo & Liu 2010; Elith *et al.* 2011). By comparing such diverse SDMs, and applying them to the three most accurate GCMs available, I sought to gain a more robust understanding of the potential impacts of global warming on this species. I sought congruence between predictions from the different models as evidence for the most likely response of the species to climate change.

I also performed MaxEnt (Phillips *et al.* 2006; Elith *et al.* 2011) analyses on the three tree species most commonly associated with ngwayir habitat: jarrah (*Eucalyptus marginata),* marri *(Corymbia calophylla)* and peppermint (*Agonis flexuosa).* These tree species provide the bulk of the ngwayir's dietary intake and they are keystone species in the ecological assemblages most commonly recognized as ngwayir habitat (Jones *et al.* 1994; Jones 2004; Wayne *et al.* 2005a; Yin 2006; de Tores 2008). I conducted the tree distribution models using the same method and bioclimatic variables as those undertaken for the ngwayir. Because areas identified as being bioclimatically suitable for the ngwayir may not be suitable for the trees upon which it depends, I sought insight into the potential impacts of global warming on ngwayir habitat as distinct from impacts on the animal itself. I present these analyses in the absence of more detailed modelling on the impacts of global warming on the three tree species (Yates *et al.* 2010b; Fordham *et al.* 2012).

I used MaxEnt (Phillips *et al.* 2006) as the principal SDM. Some drawbacks have been noted with MaxEnt, notably the tendency for it to underperform where there is a spatial bias within datasets (Bystriakova *et al.* 2012). However, it remains a well-supported and popular application with land managers, and has the capacity to link fine-scale bioclimatic data to species distributions and produce probability-based outputs (Hijmans & Graham 2006; Guo & Liu 2010; Elith *et al.* 2011; Vasconcelos *et al.* 2012). MaxEnt has been successfully used in similar species modelling applications (Green *et al.* 2008; Yates *et al.* 2010b; Adams-Hosking *et al.* 2011; Guerin & Lowe 2012; Prober *et al.* 2012). The two other SDMs I used were Domain (Carpenter *et al.* 1993; Hijmans & Graham 2006) and Two Class Support Vector Machine (SVM-TC) (Vapnik 1995; Cristianini & Scholkopf 2002), both of which generally lack the accuracy and probabilistic capacity of MaxEnt. However, I used these SDMs because the results of the MaxEnt analyses might be further supported and validated by congruence with other models.

MaxEnt (application of a machine learning technique called ‘maximum-entropy’) explores the relationships between presence data and relevant habitat variables, thereby enabling it to calculate the probability of presence of the target species within a GIS grid square using habitat values (Hijmans & Graham 2006; Phillips *et al.* 2006; Elith *et al.* 2011). MaxEnt v.3.3.3 for Windows was used in these analyses. Our model settings were 500 maximum iterations with a convergence threshold = 0.00001, prevalence = 0.5 (default) and a 10% training presence. I used a full presence data set for these analyses. Input data were prepared using Diva-GIS 7.5 (Hijmans *et al.* 2012) and output display and analysis for all SDMs were prepared and analysed with ESRI ArcMap 10.1.

SVM-TCs are supervised learning models that analyse data and recognize patterns, which are then used for classification and regression analyses. They take a training sample to build a model used to determine presence or absence in response to variable parameters (Vapnik 1995). SVM-TCs require both presence and absence (or assumed absence) species data. In this study, absence datum was not available and assumed absence datum was developed at a rate of five absences for every presence using ModEco (Guo & Liu 2010). This was the highest available ratio and was chosen because of the relatively small number of ngwayir presences in the modelled area. SVM-TC was part of the ModEco 3.02 software package (UCMERCED 2011). Our model settings for the SVM-TC analyses were 10% hold out for testing, degree = 3, Nu = 0.05 and cost = 1.

Domain assigns a classification value to an unknown site based on the distance to its closest similar site in environmental space (Carpenter *et al.* 1993) using presence-only data (Tognelli *et al.* 2009; Hawkes 2010; Monk *et al.* 2010; Jimenez-Valverde *et al.* 2011; Khatchikian *et al.* 2011; Navarro-Cerrillo *et al.* 2011). I used Domain in both ModEco and Diva-GIS software packages; the outputs I selected for use in this analysis being those developed using the ModEco software package. Domain outputs can be highly biased by outliers (i.e., where $P<0.01$) in the presence data, whereas both MaxEnt and SVM-TC have the capacity to recognize and limit the influence of outliers in species presences. Consequently, outliers had to be removed manually when using Domain (Hijmans 2012). I then produced a separate species database with outliers removed using Diva-GIS and used the resultant ‘extract’ database in the Domain analyses. Our model settings for the Domain analyses were 10% withheld for testing and 95% similarity threshold.

I only used bioclimatic variables in the predictive modelling because I assumed that global warming is the predominant threat to the ngwayir and that this threat will foreseeably increase in intensity during the first half of the twenty-first century and occur throughout its current and potential distribution. IPCC IV (IPCC 2007) GCMs were downloaded from the International Centre for Tropical Agriculture (CCAFS 2008), and were already downscaled to a 1 km grid spatial resolution using the delta method (Ramirez & Jarvis 2008). I selected the MIROC-m, CSIRO mk3 and ECHO-G models from the IPCC IV group of models, as these three were the most accurate for Australia (Perkins *et al.* 2007). Furthermore, each model represents a different methodology, reflecting the diverse interests, perspectives and objectives of the organizations that developed them (IPCC 2007). The model scenario chosen for all GCMs was the A2A scenario, which was the 'conservative scenario' for both CO_2 emissions and future energy requirements, on the assumption that extreme predictions might be avoided. Since CO_2 emissions will, most probably, be higher than predicted in this scenario (Allison *et al.* 2009), range contractions indicated in this paper are consequently likely to be conservative in nature. These data were also cut and processed into bioclimatic variables using Diva-GIS, and the same altitude (topographic) data set used to produce the baseline data. All GCMs were based on 2050 scenarios. As GCMs are constantly being reviewed and improved (IPCC 2007), I considered it appropriate that models for post-2050 scenarios be based on more current climate change models as they become available.

I modelled a rectangular section of the South-west Australian Floristic Region (Figure 22), large enough to encompass all recorded ngwayir occurrences, but not so large as to imbue models with an inflated appearance of accuracy (Elith *et al.* 2011). Natural migration of ngwayir beyond this area was considered to be highly improbable given the highly fragmented nature of the Western Australian Wheatbelt (Smith 2008; Lawes & Dodd 2009). Given the highly variable nature of the project area (Hopper & Gioia 2004), I decided that it was appropriate to model data at the highest available resolution (grid cells of 1 km^2) (Hijmans *et al.* 2005).

5.2.2 Data

I obtained presence data for ngwayir, jarrah, marri and peppermint from the Western Australian Department of Environment and Conservation's NatureMap database V 1.5.0.10 (Department of Environment and Conservation 2007-2013). There were 510 ngwayir presences recorded in this database, which, after disregarding duplicate records and those with erroneous coordinates, resulted in a database of 392 presences. Similarly, 506 presences were used to model jarrah, 344 marri and 374 peppermint; these represent the entire range for each species. These corrected presences were used in both the MaxEnt and SVM-TC analyses. Further correction was undertaken for the Domain analyses. As this data is sourced heavily from extensive surveys across many reserves and remnants, I assumed that sampling bias (such as favouring roadsides or particular regions) was minimal.

Baseline climate data were sourced from the WorldClim 1.4 (release 3) database (WorldClim 2012) of Hijmans *et al.* (2005), developed as interpolated climate surfaces for global land areas other than Antarctica at a 1 km grid cell spatial resolution using 1950–2000 climate data. The WorldClim data were provided in the form of average monthly precipitation, maximum temperature, minimum temperature, mean temperature and topography data that were then cut to the size of the project area and converted into 19 bioclimatic variables (Table 19) using Diva-GIS.

Table 19: Variable use in SDMs showing the contribution of each variable in the MaxEnt and the variables used in the Domain and SVM-TC SDMs

Variable	**Description**	**MaxEnt (%)**	**Domain**	**SVM-TC**
BIO1	Annual mean temperature	5.4		
BIO2	Mean diurnal range (max temp – min temp) (monthly average)	1.1		1
BIO3	Isothermality (BIO1/BIO7) * 100	0.6		1
BIO4	Temperature seasonality (coefficient of variation)	12	1	1
BIO5	Max temperature of warmest period	0.3	1	1
BIO6	Min temperature of coldest period	0.3		
BIO7	Temperature annual range (BIO5-BIO6)	0.3	1	1
BIO8	Mean temperature of wettest quarter	0		
BIO9	Mean temperature of driest quarter	0.3		
BIO10	Mean temperature of warmest quarter	0.6		
BIO11	Mean temperature of coldest quarter	0.9		
BIO12	Annual precipitation	67.1	1	1
BIO13	Precipitation of wettest period	1.1	1	1
BIO14	Precipitation of driest period	1		

BIO15	Precipitation seasonality (coefficient of variation)	3.9		1
BIO16	Precipitation of wettest quarter	1.6	1	1
BIO17	Precipitation of driest quarter	0.1		
BIO18	Precipitation of warmest quarter	0.1		
BIO19	Precipitation of coldest quarter	3.4	1	1

5.2.3 Variable selection

As each SDM uses different algorithms and species inputs, they also require the use of differing sets of variables in their respective analyses (Guo & Liu 2010; Fordham *et al.* 2012). To obtain optimum efficiency, minimize multicollinearity and prevent overfitting (Beaumont *et al.* 2005; Elith *et al.* 2011; Hijmans *et al.* 2012), I first tested the variables to establish the most appropriate set for inclusion in each SDM analysis. All 19 bioclimatic variables were used in the MaxEnt analyses, as this SDM calculated and implicitly incorporated the percentage contribution of each variable to the final solution (Table 19) (Elith *et al.* 2011). Because the contribution of many variables was negligible and tested sub-sets did not improve on and, in some cases, produced highly unlikely results, I decided that, for the sake of accuracy and consistency, all 19 variables be applied to all MaxEnt models (Phillips & Dudík 2008).

For the SVM-TC and Domain models, the proportionate contribution of variables was not an option. In these situations, variables were either included or rejected based on the results of a kappa analysis, which determined variable contribution. I undertook Kappa analyses using ModEco (Table 20). For both SDMs, the cut-off for inclusion (0.2) delivered the best results based on trial and error.

Table 20: Kappa analyses of variable suitability for both SVM-TC and Domain

	TC SVM -- Based on WRP (2_class)		**Domain—Based on WRP (extract)**	
Variable	**With only variable: Kappa**	**Without variable: Kappa**	**With only variable: Kappa**	**Without variable: Kappa**
Bio 1	0.143769	0.710622	0.084754	0.970691
Bio 2	0.276338	0.652922	0.044331	0.923615
Bio 3	0.257780	0.672743	0.000000	0.925690
Bio 4	0.276158	0.631778	0.512489	0.762014
Bio 5	0.337488	0.638824	0.298348	0.770207

Bio 6	0.018493	0.640919	0.000000	0.771858
Bio 7	0.314547	0.612912	0.255751	0.763644
Bio 8	0.006408	0.622398	0.008333	0.766917
Bio 9	0.070975	0.630227	0.016401	0.768560
Bio 10	0.279917	0.742019	0.193038	0.972905
Bio 11	0.004758	0.725412	0.003612	0.970691
Bio 12	0.399418	0.652334	0.733373	0.959721
Bio 13	0.502570	0.678986	0.583136	0.964089
Bio 14	0.002498	0.723176	0.001799	0.966283
Bio 15	0.364282	0.716788	0.206059	0.959721
Bio 16	0.520031	0.760190	0.621643	0.942505
Bio 17	-0.000834	0.690658	0.007013	0.942505
Bio 18	0.009255	0.721611	0.004653	0.942505
Bio 19	0.454846	0.692416	0.621643	0.915378

I applied landscape metrics, such as vegetation association, patch size and isolation, in early SDM trials; however these did not improve on the use of bioclimatic variables alone, and modelling results became erratic in a manner symptomatic of overfitting (Welsh *et al.* 2013). Consequently, their use was abandoned.

Core areas were used to display results (Figure 23). I determined core areas by applying the 10% training presence threshold (0.387); only those areas with bioclimatic parameters within which 90% of presences were recorded were designated as habitat. Those areas where I assigned a lesser value were considered marginal habitat, and thus disregarded. This enables conservation managers to focus on those areas that are likely to more important for the conservation of the target species or community (Phillips *et al.* 2006; Hijmans *et al.* 2012).

5.3 Results

The MaxEnt modelling of ngwayir distribution using baseline WorldClim 1950-2000 averages (Hijmans *et al.* 2005) and 2050 model scenarios for CSIRO Mk3, MIROC-m and Echo-G IPCC IV models (IPCC 2007) are shown in Figure 23. All three GCMs demonstrated a marked and similar contraction of ngwayir distribution towards the south-west, as compared to the total baseline bioclimatic envelope for this species. Figure 23a, b, c and d show modelled probability of presence for each scenario. Figure 23e, f, g and h display core habitat areas; i.e. a cut off training value which shows only those bioclimatic values within which 90% of presences are found is applied. Figure 23i, shows an overlay of core habitat areas. The core area count reflects the number of times each pixel appears as core habitat.

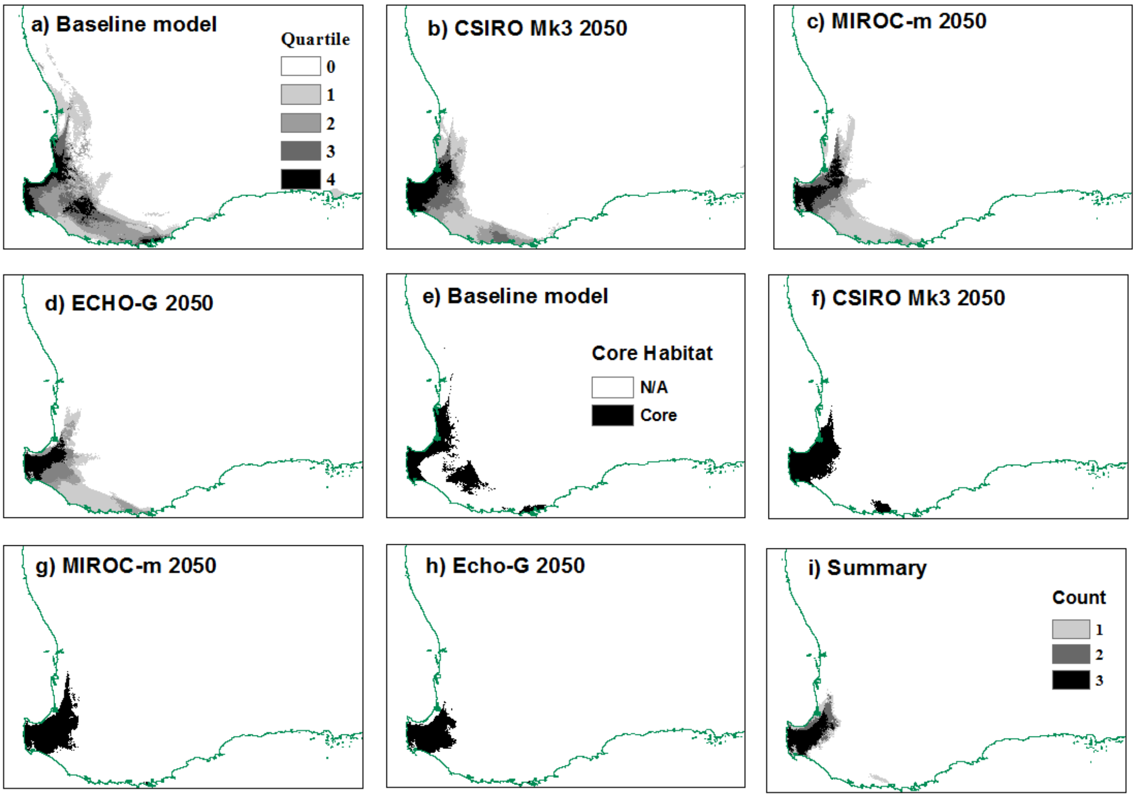

Figure 23: MaxEnt predictions of ngwayir distribution from baseline averages and 2050 GCM scenarios for CSIRO Mk3, MIROC-m and Echo-G IPCC IV models. The core area reflects the number of times each pixel appears as core habitat.

For habitat parameters within which 90% of presences occurred, the contraction in the potential core distribution became much more pronounced for all three GCMs. Potential distribution predictions were remarkably similar for all GCMs, indicating that the modelled GCM scenarios were robust. The MaxEnt area under curve (AUC) goodness of fit value for this model was 0.973, indicating a good model in terms of predictive ability (Phillips *et al.* 2006), further supported by a high 10% training presence value of 0.387.

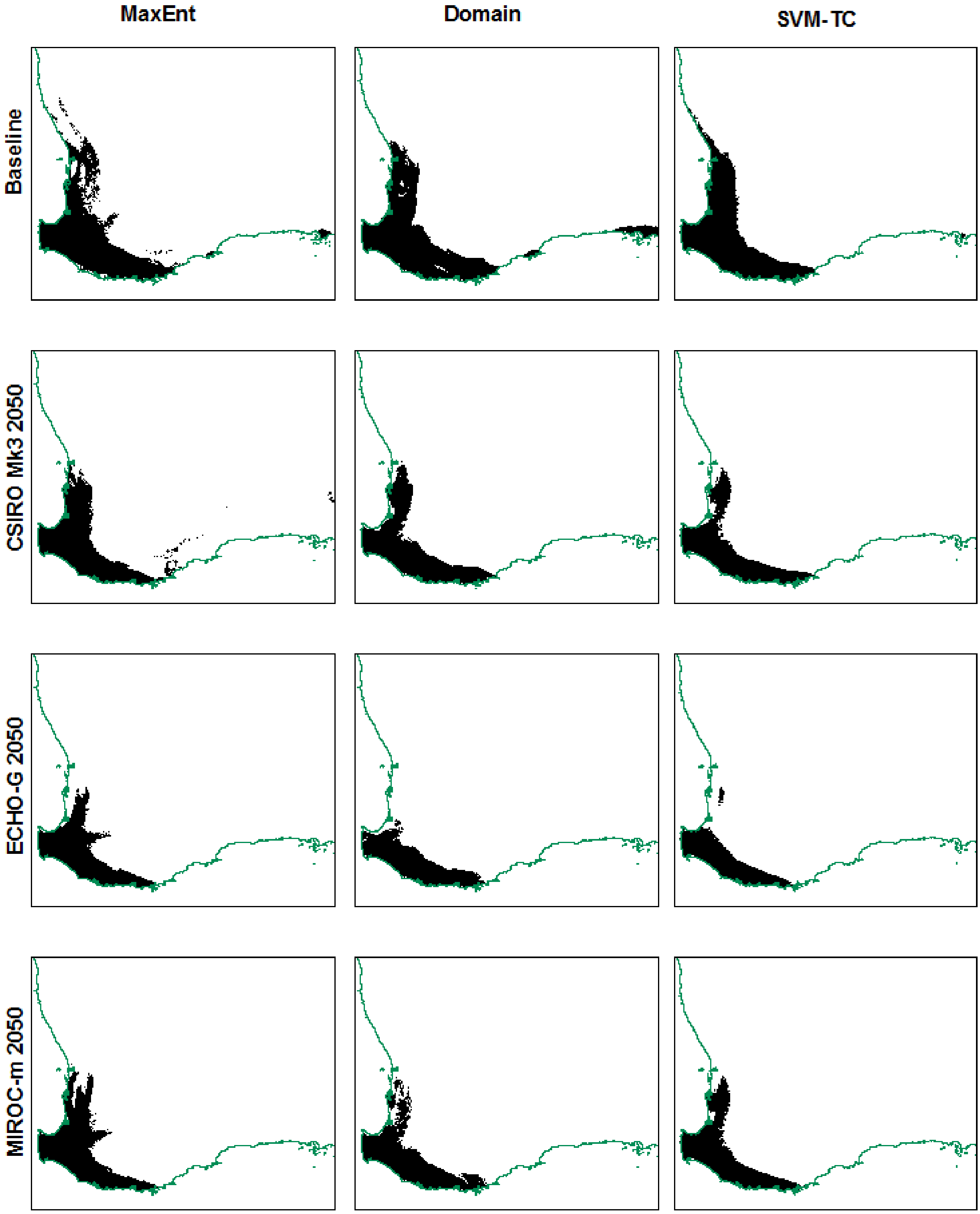

Figure 24: A comparison of ngwayir predictions using baseline climate data and three GCM 2050 scenarios as undertaken with the three SDMs. Data is given as presence-absence in that pixels with a probability value of less than 5% are not displayed.

Table 21: Areas (km^2) selected as habitat for projections shown in Figure 24. Total modelled area = 561 059 km^2.

Model	MaxEnt area	% Total area	Domain area	% Total area	SVM-TC area	% Total area	Mean area	% Total area
Worldclim (baseline)	59 341	10.58	61 133	10.90	55 106	9.82	58 527	10.43
CSIRO Mk III	44 278	7.89	39 797	7.09	39 007	6.95	41 027	7.31
ECHO-G	35 870	6.39	27 024	4.82	29 948	5.34	30 947	5.52
MIROC-m	44 375	7.91	33 934	6.05	38 780	6.91	39 029	6.96
Mean 2050	41 508	7.40	33 585	5.99	35 912	6.40	37 001	6.59
Mean area reduction	17 833	3.18	27 548	4.91	19 194	3.42	21 526	3.84

Each of the SDMs predicted broadly similar baseline patterns of ngwayir distribution and resulted in similar predicted distributions for all three climate change scenarios for 2050 (Figure 24). These predictions show only predicted presences, in that pixels with a probability value of < 5% are not displayed. All models gave a marked and similar contraction in ngwayir potential distribution towards the south-west. Overall, MaxEnt appeared to have a marginally greater sensitivity to topographic variation, selecting low-lying areas in the northern Darling Range and parts of the lower Blackwood River Basin that were not highlighted in the Domain and SVM-TC models. MaxEnt predicted larger areas of potential distribution (that is, MaxEnt predicted the smallest reduction in core distributions). Domain predicted the greatest reduction in area, although the difference between the mean areas was < 2% (Table 21). The AUC and kappa values for both the Domain and SVM-TC analyses indicate that these models are strong (Table 22).

Table 22: Kappa index and AUC values for Domain and SVM-TC models along with sample number used in each model.

	SVM-TC	Domain
AUC	.924	.977
Kappa	.7314	.7193
Number	392	261

The contraction in the potential distribution of ngwayir to the south-west became significantly more severe when the 10% training presence was applied to demonstrate core habitat (Figure 23e–h). When these projections were overlaid (Figure 23i), the similarities between them were clear and indicated potentially important landscapes for the conservation of the ngwayir.

Most 2050 projections in this exercise identified highly complementary potential distributions for the ngwayir, with the majority of grid cells identified as potential distribution being the same in all projections. There was a mean baseline area of potential distribution of 10.4% of the total modelled area of 561 059 km^2, with a maximum area of 10.9% and a minimum of 9.8% (Table 21). All projections showed a significant contraction in area by 2050, to an average 6.6% of total modelled area ranging from a high of 7.8% (MaxEnt/CSIRO) to a low of 4.8% (Domain/ECHO). For all SDMs, the ECHO GCM showed the greatest impact on the ngwayir, with an average 2050 distribution of 5.5%; the MIROC-m and CSIRO models were very similar, with averages of 7.0% and 7.3%, respectively. Of the SDMs, MaxEnt was the most optimistic, with a mean 2050 area of 7.4% compared to an area of 6.4% for SVM-TC and 6.0% for Domain. The similarities between all modelled scenarios, both baseline and predicted, for all three SDMs across all GCMs indicated strongly that the MaxEnt modelling exercise produced a highly plausible scenario.

MaxEnt modelling of the three tree species showed the potential distribution of all three species contracted strongly towards the south-west (Figure 25). For all species, but particularly for jarrah and marri, there was a tendency for distribution to be split into northern and southern populations, with the southern populations appearing to be more robust. The CSIRO/Marri projection, and, to a lesser extent, the ECHO/Marri projection, indicated large inland areas becoming suitable for marri; although the reasons for this are not currently understood, these areas were outside the ngwayir dispersal range and not relevant to this analysis.

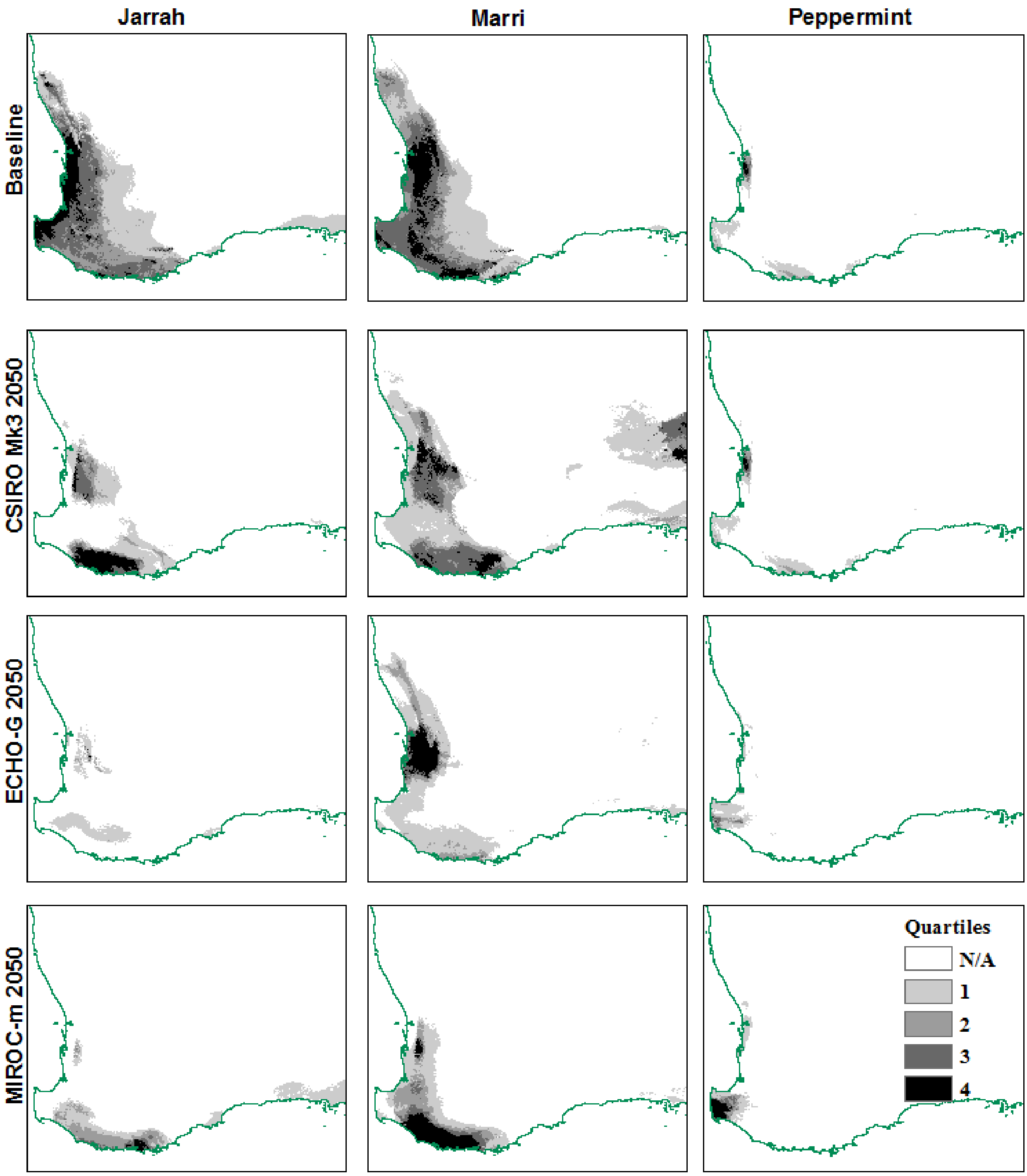

Figure 25: MaxEnt models comparing baseline distribution of jarrah, marri and peppermint with the three IPCC IV 2050 climate scenarios.

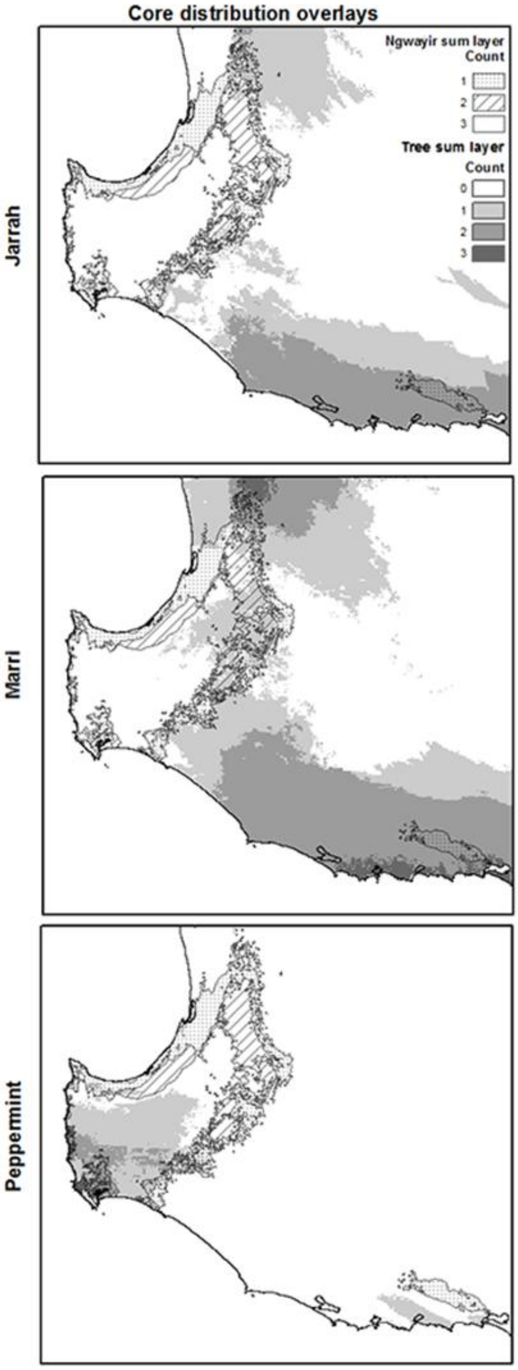

Figure 26: Core area count (the number of times each pixel appears as core habitat) for tree species with ngwayir core area count (Figure 23i) overlaid.

When I compared predicted ngwayir core habitat with that of the three tree species (Figure 26) and with conservation and forestry land tenure (Figure 27), extensive stands of either jarrah/marri and/or peppermint stands persisted alongside all projected potential model distributions of ngwayir, with much of these vegetation types continuing to occur on conservation/forestry land. It is expected that relictual populations of all of these species will persist beyond 2050, outside of these parameters (Table 23). Statistical tests show that all models in these analyses are good, although models for each species differed markedly in the variable contributions used (Table 24).

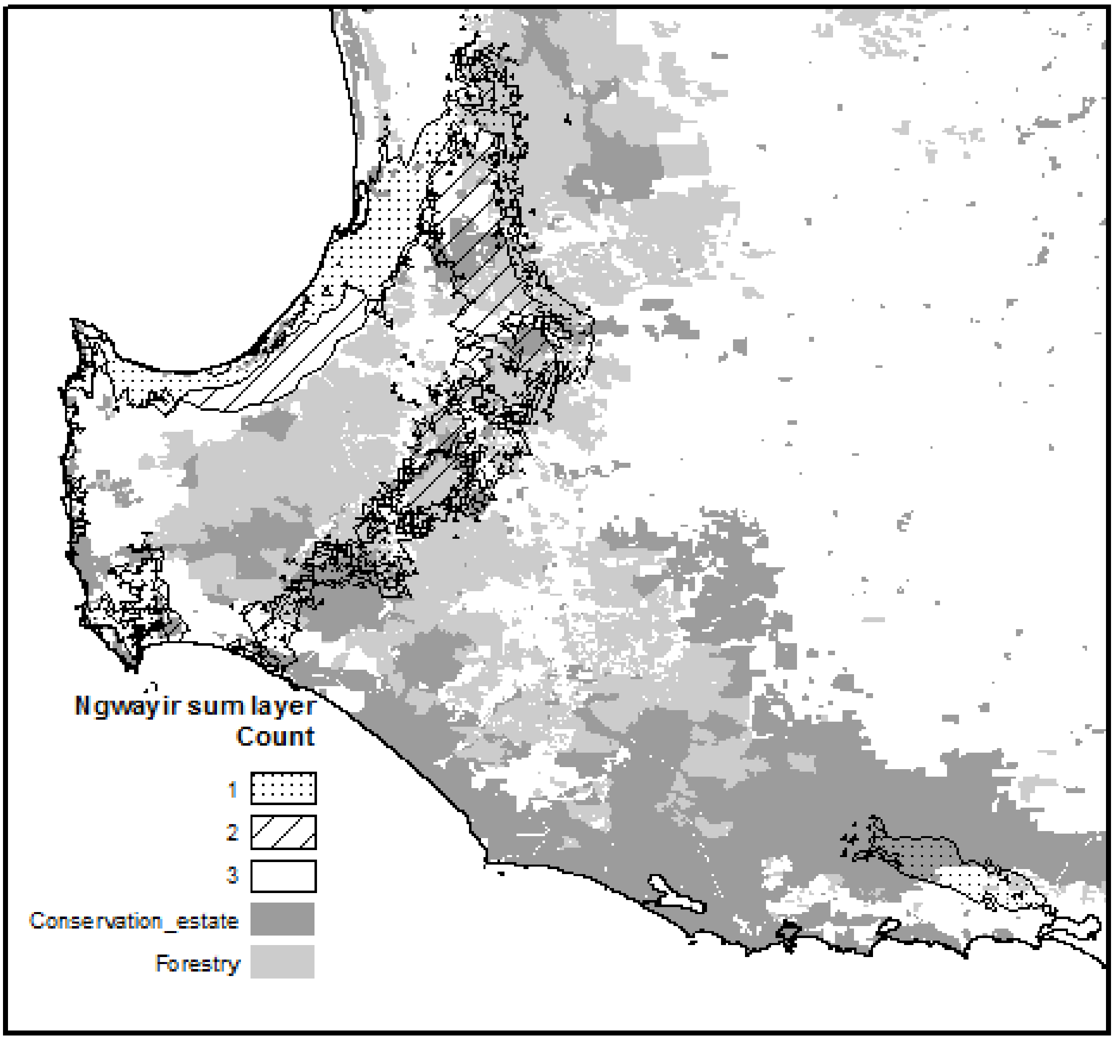

Figure 27: Conservation/Forestry vested estate with ngwayir core area count (Figure 23i) overlaid.

Table 23: Areas from ngwayir core area overlay (Figure 22i) with corresponding total core areas for each tree species (Figure 25) both individually and merged, and areas of conservation/forestry vested lands (Figure 26) in hectares.

Ngwayir count	**Total area**	**Cons.**	**Forestry**	**Peppe-rmint**	**Marri**	**Jarrah**	**Tree sp. merged**
1	283,385	89,556	133,602	44,088	106,773	68,941	219,803
3	217,748	28,537	60,203	28,420	91,542	17,971	137,933
3	475,669	38,349	150,268	295,179	82,248	100	377,526
Totals	976,802	156,442	344,073	367,687	280,563	87,012	735,262

Table 24: Variable contributions, 10% training presence and number of training presences for the model projections for habitat trees (Figure 25)

Variable	Description	Jarrah	Marri	Peppermint
BIO1	Annual mean temperature	3.5	1.9	0.3
BIO2	Mean diurnal range (max temp – min temp) (monthly average)	0.1	0	3.6
BIO3	Isothermality (BIO1/BIO7) * 100	0.9	0.9	2.0
BIO4	Temperature Seasonality (Coefficient of Variation)	0.9	1.6	14.7
BIO5	Max Temperature of Warmest Period	1.5	0.3	1.9
BIO6	Min Temperature of Coldest Period	0.1	0.5	6.9
BIO7	Temperature Annual Range (BIO5-BIO6)	0.1	0.1	0.1
BIO8	Mean Temperature of Wettest Quarter	0.4	1.0	0.1
BIO9	Mean Temperature of Driest Quarter	1.3	1.8	0
BIO10	Mean Temperature of Warmest Quarter	3.9	2.6	0.2
BIO11	Mean Temperature of Coldest Quarter	0.2	1.3	4.1
BIO12	Annual Precipitation	47.3	32.8	55.1
BIO13	Precipitation of Wettest Period	14.3	8.1	2.0
BIO14	Precipitation of Driest Period	0.6	0.5	0.7
BIO15	Precipitation Seasonality (Coefficient of Variation)	4.8	4.0	1.2
BIO16	Precipitation of Wettest Quarter	2.5	15.1	3.2
BIO17	Precipitation of Driest Quarter	0.1	0.2	0.5
BIO18	Precipitation of Warmest Quarter	1.1	0.7	0.8
BIO19	Precipitation of Coldest Quarter	16.4	26.6	2.7
10%	10% Training presence	.288	.359	.291
N	Number of training presences	506	345	375

5.4 Discussion

In modelling the potential distribution of ngwayir, all three SDMs, although differing in type and sets of predictor variables, predicted similar binary distributions for the species, both for their current distributions and in the projections for 2050. Although there were some differences between the three climate change scenarios for 2050, all nine predictions demonstrated strong support for a significantly reduced ngwayir distribution, with a strong contraction towards the south-west. MaxEnt modelling showed that areas of core habitat within predicted potential distribution areas may suffer greater contractions than the binary outputs indicate. The contraction to the higher rainfall coastal areas of the south-west is consistent with other predictions of species-level climate change impacts within the region (Yates *et al.* 2010a; Yates *et al.* 2010b).

Although climatic envelope modelling predictions of species contractions due to climate change are now relatively common, it is widely recognized that modellers need to consider habitat preference or quality and potential interactions with other species to more accurately predict future climate change impacts (Williams *et al.* 2008). In this study, I used predicted contractions in the preferred tree species (for feeding and nesting) to further explore potential impacts of climate change on the ngwayir. MaxEnt modelling shows that, although the preferred tree species of ngwayir will also be strongly impacted by climate change, at least one of the core tree species will persist through much of the ngwayir's future predicted distribution. Such severe tree species range contractions are supported by many studies on the observed and predicted impacts of anthropogenic global warming on woodland and forest species throughout the world (Williams *et al.* 2008; Allen *et al.* 2010; Littell *et al.* 2010; Chaturvedi *et al.* 2011; Milad *et al.* 2011; Prober *et al.* 2012). Of the three tree species modelled, the contraction in core peppermint habitat appears to be the most significant and is of most concern, as ngwayir is most common in the dense vegetation dominated by this species (Jones *et al.* 1994; Jones 2004). For two climate change scenarios in particular, core peppermint habitat is predicted to contract to the extreme south-west corner of the landscape. This prediction has important conservation implications, as many reserves with peppermint that currently support healthy populations of ngwayir may not be within the predicted future range of peppermint, highlighting the problems associated with maintaining a static reserve system in the face of climate-induced shifts in species distributions (Williams *et al.* 2008). Although the bioclimatic modelling of the preferred tree species is preliminary, it helps improve understanding of the vulnerability of ngwayir to climate change. In similar fashion, Bateman *et al.* (2012) improved predictions and understandings of climate change impacts on northern bettong in the tropical rainforests of Queensland by combining this with bioclimatic modelling of its major food species.

Unless anthropogenic greenhouse gas emissions decline dramatically, the question becomes one of how to manage a vulnerable species in the face of an almost certain reduction in habitat quantity and quality. This will require further recognition of what landscape parameters actually define habitat for this species at more local scales (Pearson & Dawson 2003; Guisan & Thuiller 2005).

Other factors potentially contributing to the habitat of ngwayir at finer scales are the feed quality of foliage (which is influenced by the nutrient status of trees) and the quantity and type of volatile oils. As a cecum ruminant, it is probable that ngwayir's habitat choice is influenced by the secondary metabolite content of the plants upon which it feeds (Wallis *et al.* 2002; Moore *et al.* 2004; Scrivener *et al.* 2004; Foley *et al.* 2008). Secondary metabolite levels vary significantly in response to genotypic and phenotypic factors even within plants of the same species, and habitat for many cecum ruminants is often defined by the density of plants, with similarly low levels of secondary metabolites (DeGabriel *et al.* 2008). Areas of suitable foliage can be readily identified through remote sensing techniques, which can also quantify other relevant habitat parameters such as nutrient and moisture levels (Ebbers *et al.* 2002; Malenovský *et al.* 2009). Thus it is possible to remotely identify areas of prime habitat and, by applying bioclimatic modelling techniques, obtain a strong indication as to which of these habitats will persist into the foreseeable future. Such areas should be given a high priority for conservation acquisition and management.

It is important to recognize that neither ngwayir movement nor metapopulation requirements have been modelled in this study. This is because no literature defining ngwayir metapopulation requirements exists, and because those areas identified as future potential distribution for the ngwayir are generally contiguous, enabling good landscape permeability. Outside of these contiguous landscapes, there are areas recognized as potential future habitat that are not currently occupied by ngwayir, and to which they cannot naturally migrate. This presents a potential opportunity for ngwayir populations to be established through translocation. However, before doing so, a great many factors would need to be investigated, and any potential translocations should be evaluated on a case-by-case basis using an adaptive management approach (Williams *et al.* 2008).

5.5 Conclusion

My prediction of a significant reduction in the range of the ngwayir and its supporting vegetation as a result of anthropogenic global warming concurs with much research on the adverse impacts of changing climate on forest and woodland ecosystems around the world. The frequency and intensity of such negative effects will increase if greenhouse gas emissions are not reduced (IPCC 2007).

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6 Incorporating the outcomes of fieldwork into species distribution and climate change modelling on the koomal (*Trichosurus vulpecula hypoleucus* (Phlangeridae)).

6.1 Introduction

6.1.1 Background

The taxon-specific data referred to (ch.4), describes the findings of a year-long field study of a koomal population in the Margaret River region of south-western Australia. The purpose of this chapter was to investigate the ecology of this sub-species of the common brushtail possum, which is facing the combined threats of climate change and landscape fragmentation, thereby enabling the development of informed and effective conservation management strategies for this taxon.

This study (ch.4), conducted over a 100 ha landscape with 41% remnant vegetation cover, found a mean population of 27.75 individuals present at any given trapping event with a total estimated population of 69 individuals having resided in this landscape during the study period. It was found that koomal distribution was patchy with no animals caught in some habitat remnants. Gaps between remnants of up to 100 m presented no discernible barrier to movement and gaps of approximately 400 m were crossed regularly. Weights, sexual dimorphism and breeding data, remained comparable with populations in contiguous, conservation-managed landscapes. Kernel density estimates (at 95% probability) gave mean home ranges for males of 8.77ha of remnant vegetation and 7.9 ha for females which varied from 300 m to 1.1 km in length (as demonstrated in Appendices ch.4). Although subjects probably passed through areas infected with dieback (*Phytophthora cinnamomi*), none were observed or captured in infected areas indicating that infected areas were not habitat for this taxon.

The modelling example referred to (ch.5), demonstrated that MaxEnt (Phillips & Dudík 2008), an SDM software package which, when used with a full acknowledgment of its limitations and appropriate input data (Elith *et al.* 2011; Navarro-Cerrillo *et al.* 2011), has the capacity to inform conservation planning by providing consistent and useful species distribution data and to demonstrate the consequences of predicted impacts on a species or community (Hijmans & Graham 2006; Carnaval & Moritz 2008; Gibson *et al.* 2010; Evangelista *et al.* 2011).

In ch.5, potential impacts arising from global warming on the PD of the ngwayir or western ringtail possum (*Pseudocheirus occidentalis*) were predicted using a range of global warming scenarios applied to a selection of SDMs. All modelled scenarios predicted a reduction of up to 60% in the PD of the ngwayir, as a result of global warming, towards the south-west of the project area. Models applied to key habitat trees, namely, jarrah (*Eucalyptus marginata*), marri (*Corymbia calophylla*) and peppermint (*Agonis flexuosa*) revealed that these are also predicted to experience similar contractions in range and distribution shifts, throughout most of the predicted ngwayir range. It was also found that populations of ngwayir persisting outside predicted core habitat areas still present major conservation opportunities.

6.1.2 Contextual consideration

The development of habitat variable data sets suitable for SDM applications entails addressing the following considerations:

- **For a variable to be suitable for inclusion into an SDM it must be relevant to the modelled taxon and be able to be represented in a Geographic Information System (GIS) format (Ferrier 2002; Skidmore 2002):** Data must be available for the full extent of the modelled area, it must be quantifiable in nature and its application must enhance the predictive capacity of the model: i.e., a change in the value of a predictive variable will reflect a corresponding and quantifiable change in the value of the target or response variable (Peeters *et al.* 1998; Gougeon 2009; Santika & Hutchinson 2009; Duchesne *et al.* 2010; Stankowski & Parker 2010). For example, a reduction in the area of habitat, a predictive variable, may bring about a fall in the population of species *x*, a response variable. However, such a relationship between response and predictor variables need not be linear or causal to be effective (Mac Nally 2000).

- **Many of the factors observed during the koomal field study cannot be represented in format suitable for incorporation into a SDM:** Data accurately directly depicting relevant variables such as: remnant vegetation type, the availability of suitable nesting trees, leaf chemistry and vegetation condition, do not exist. However, this study has shown that a fragmented landscape with 41% of remnant vegetation can support a large and apparently stable metapopulation which, through the constant movement of individuals to and from the study area, interacts with a greater overall population at a larger landscape scale (Amarasekare & Possingham 2001; Hanski & Ovaskainen 2003; Fischer & Lindenmayer 2007; Cassini 2011). The link between the presence of the common brushtail possum and patch matrices in fragmented landscapes has previously been recognised (Ji *et al.* 2003; Ball *et al.* 2005; Harper 2005; le Mar & McArthur 2005). The Western Australian Department of Agriculture and Food's remnant vegetation extent data set allows the investigation of relationships between koomal presence and patch matrices. Furthermore, field study indicated a strong negative relationship between koomal presence and dieback. Project Dieback's dieback extent mapping, both current and potential, enables the incorporation of this variable into an SDM.

- **How can predictive variables suitable for modelling purposes be derived from general observations on habitat requirements?** It was shown in the koomal habitat kernel densities (Appendices ch.4), that koomal home ranges could to be up to, and in some cases exceed, 1 km in breadth. It was also shown that these home ranges should encompass 5-9ha of remnant vegetation, not all of which needs to be suitable, and gaps between patches of vegetation of up to, and probably beyond, 500 m could be crossed by individuals of either gender. It was therefore hypothesised, as an application of landscape metric theory (Herzog *et al.* 2001; Kindlmann & Burel 2008; Ramachandra & Uttam 2011; Kupfer 2012), that koomal habitat can largely be defined as a percentage of remnant vegetation cover when examined at scale/perspective relevant to koomal habitat requirements. For example, the ch.4 study demonstrated that koomal can persist in a landscape with 41% of remnant vegetation cover as measured within a 1 km radius. However, it is not known if that 41% parameter could be applied using a 10 km radius, where patches and/or gaps between patches may considerably larger, or a 100 m radius where gaps and patches would naturally be much smaller. This highlights the question of which scale, or perspective, is the most appropriate for quantifying the koomal’s response to the proportion of remnant vegetation cover in a landscape, as the development of a predictive variable suitable for incorporation into a SDM requires that this question must be addressed.

6.1.3 Objectives

This chapter will demonstrate a means by which taxon specific observations, gathered through fieldwork, can be used to add resolution and robustness to species distribution models (SDMs) when defining potential distributions (PD). This will be done by developing appropriate model inputs, based on observed habitat preferences, and using those inputs to enhance models which, as demonstrated in the previous chapter (ch.5), are often solely reliant on generic species presence and bioclimatic data.

In this chapter, taxon-specific ecological variables will be used in conjunction with generic bioclimatic data to produce a PD model for the koomal (the south-western sub-species of the common brushtail possum (*Trichosurus vulpecula hypoleucus*) and to demonstrate means by which the modelling of climate change impacts on the koomal PD can be made more accurate. This will be done by combining MaxEnt (Phillips *et al.* 2006; Elith *et al.* 2011) and basic Geographic Information Systems (GIS) modelling techniques. To achieve this, MaxEnt will be used to combine koomal presence data with remnant vegetation and bioclimatic data to ascertain the current PD for the koomal and the predicted 2050 impacts of climate change on that distribution resulting from the application of selected Global Climate Models (GCMs). GIS overlays will then be used demonstrate how dieback might impact on those distributions.

6.2 Methodology

To produce a predictive variable suitable for use in a SDM and derived from general observations on habitat requirements three GIS raster data sets were constructed based on the same Department of Food and Agriculture Western Australia (DAFWA) remnant vegetation mapping used in previous chapters. These were used to calculate the percentage of remnant vegetation from three different scales/perspectives, i.e.:

1. The percentage of remnant vegetation cover within each pixel, with a pixel size of 1 km^2 (this scale directly reflects observations on home range movements).

2. 1 km^2 buffered, i.e. the percentage of remnant vegetation cover within each pixel and within a 1 km radius of that pixel, with a pixel size of 1 km^2 (this scale is potentially relevant to home range movements beyond the grid square).

3. The percentage of remnant vegetation cover within each pixel, with a pixel size of 5 km x 5 km or 25 km^2 (this scale is potentially relevant to metapopulation movements).

Initial trials using grid squares greater than 5 x 5 km provided unacceptable resolution in initial test models and consequently was not continued.

All data sets covered the full extent of the bioclimatic data sets used in the ch.5 modelling exercise. This landscape was considered appropriate for modelling koomal PD because all recorded presences fell within its boundaries and contains enough excess area to demonstrate a possible increase in distribution.

As a response variable for this exercise, 1,114 records of koomal presences were obtained from the Department of Environment and Conservation’s NatureMap database (Department of Environment and Conservation 2007-2013). For this exercise all pre-1980 records were removed as extensive land clearing throughout much of the koomal distribution during this period (Saunders 1990; Hobbs 1993a; Rijavec *et al.* 2002) means that many of the woodlands from which presences were recorded have now been cleared. Therefore, remnant vegetation cover for these recorded presences cannot be ascertained. This is also a risk for post-1980 records, but as land clearing has significantly slowed post 1980 (Hobbs 1993a; Rijavec *et al.* 2002) and as nearly all koomal records for this period can be attributed to existing native vegetation extent, the impact of clearing on these records is considered by the author to be, comparatively, marginal and offset by the rigour provided by a robust sample size of 918 presences.

On examination, koomal presence records were shown to be heavily biased by ongoing trapping programs. For example, of the 918 presences approximately 300 originated from the research undertaken in ch.4. To mitigate this bias in testing the effectiveness of the three test perspectives a low-bias sample was created (Phillips & Dudík 2008; Giovanelli *et al.* 2010; Hijmans 2012). To do this, presences were put into a 1 km^2 grid raster using the same scale as the bioclimatic variable data sets. In this way presence was represented as either present or absent in each 1 km^2 grid square, thereby providing a representation of koomal distribution based on 167 grid squares with greatly diminished trapping bias (Giovanelli *et al.* 2010). This raster data set was then overlaid on all three perspective data sets in a GIS environment and the results analysed using histograms, summary statistics and MaxEnt modelling to determine which data set best suited to incorporating into a MaxEnt model. The full presence only data set was retained for use in all MaxEnt models as the MaxEnt software automatically sorts presence data into presence by grid squares as part of the modelling process.

For the MaxEnt modelling, the bioclimatic data used was the same as that used in ch.5: i.e., the CSIRO MkIII, MIROC-m and ECHO-G GCMs. As in ch.5, these three GCMs were chosen as they have been shown to be the most reliable, to date, of the IPCC IV models in predicting the impacts of global warming in south-western Australia (Perkins *et al.* 2007; Hughes 2011). All GCMs, selected at the A2A medium emission scenario, were downloaded from the International Centre for Tropical Agriculture (CCAFS 2008).

As there is a strong possibility that the use of any of the remnant vegetation data sets along with the full suite of bioclimatic variables may lead to “over-fitting” (Fitzpatrick *et al.* 2008; Benito *et al.* 2009; Elith *et al.* 2011; Hijmans 2012) it was decided to use the minimum number of bioclimatic variables required to give an Area Under Curve (AUC) value (Hijmans 2012) greater than .955 before the inclusion of the remnant vegetation data. This figure was selected as any value above this indicates a very high level of model accuracy in comparison to the .50 null model result. Bioclimatic variables will be removed from the SDM by conducting multiple model runs and removing the worst performing variables, according to “jacknife” analysis and % contribution in each run. The model produced using final suite of selected variables, was compared with the original, 19 variable, model to ensure that model integrity had not been compromised. When running the model a 10 % training presence threshold will be set, all other MaxEnt settings will be left at default.

To model the potential impacts of dieback on koomal PD a dieback extent data set was required. Sub-regional dieback extent GIS shapefiles for the Northern, Southern, South-West and Swan NRM regions (Strelein *et al.* 2007) were sourced from Project Dieback and adapted for inclusion in a MaxEnt model by merging these data sets, simplifying outputs to “probably present, probably absent and unknown,” and converting the resulting shapefile to an ascII format. Although initial trials found that the broad scale (>1:250,000) and the fragmented and categorical nature of this data made it unsuitable for this form of modelling, overlaying this data set over MaxEnt outputs in a GIS format provided an insight into the potential impacts of this pathogen on koomal distribution.

6.3 Results

6.3.1 Modelling PD using bioclimatic data only

By running a MaxEnt model against the post-1980 koomal presence records using all 19 bioclimatic variables, removing variables with a contribution less than 1%, and repeating the process twice more, a final group of 5 bioclimatic variables was selected for use in this exercise (Table 25). Although this resulted in a very small reduction in the AUC value, from .97 to .965, the AUC value remains very high, the difference in the PD was negligible (Figure 27) and potential problems associated with over-fitting in further modelling scenarios greatly reduced.

Table 25: Contribution of variables to the koomal PD model.

Variable	**Description**	**% Contribution all variables**	**% Contribution selected variables**
BIO1	Annual mean temperature	1.4	
BIO2	Mean diurnal range	2.8	
BIO3	Isothermality (BIO1/BIO7) * 100	0.1	
BIO4	Temperature Seasonality (Coefficient of Variation)	3.5	6
BIO5	Max Temperature of Warmest Period	0.7	
BIO6	Min Temperature of Coldest Period	0.3	
BIO7	Temperature Annual Range (BIO5-BIO6)	1.3	
BIO8	Mean Temperature of Wettest Quarter	1.8	
BIO9	Mean Temperature of Driest Quarter	0.0	
BIO10	Mean Temperature of Warmest Quarter	3.2	4.7
BIO11	Mean Temperature of Coldest Quarter	0.2	
BIO12	Annual Precipitation	37.1	46.0
BIO13	Precipitation of Wettest Period	4.1	
BIO14	Precipitation of Driest Period	3.0	8.2
BIO15	Precipitation Seasonality (Coefficient of Variation)	4.1	
BIO16	Precipitation of Wettest Quarter	1.3	
BIO17	Precipitation of Driest Quarter	1.0	
BIO18	Precipitation of Warmest Quarter	0.1	
BIO19	Precipitation of Coldest Quarter	34.0	35.1

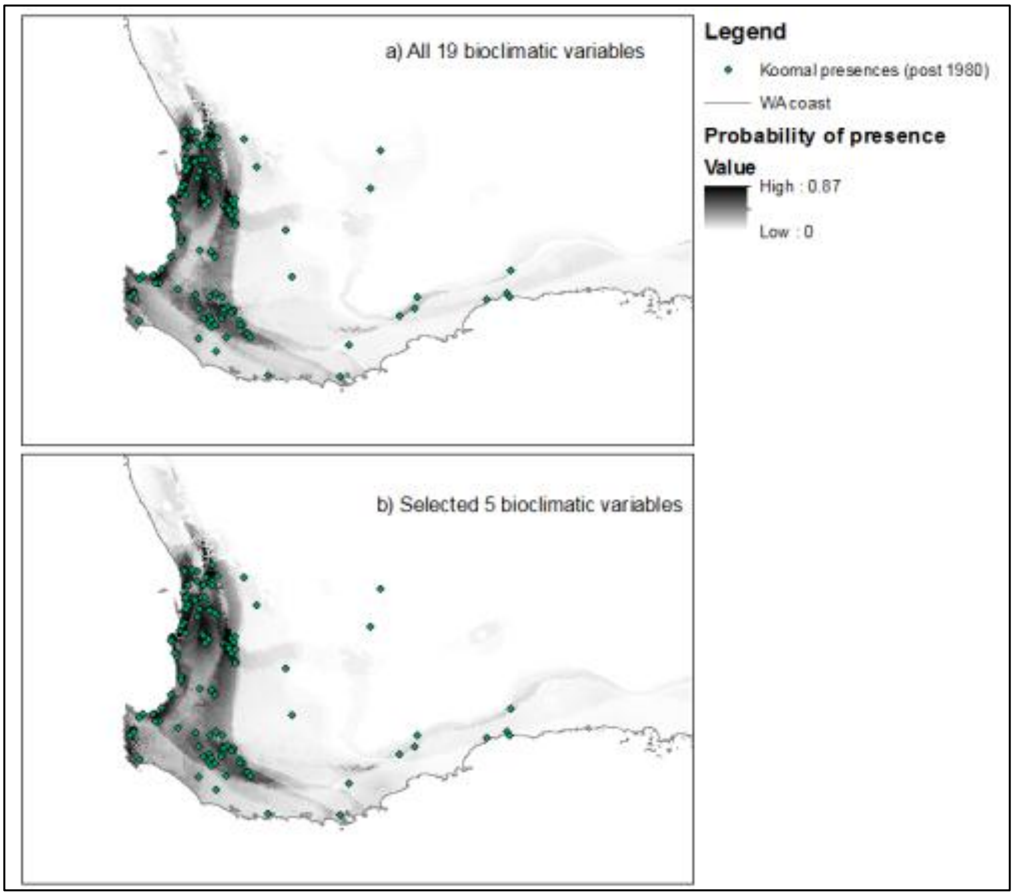

Figure 28: Comparison between MaxEnt koomal SDMs using full suite of 19 bioclimatic variables (a) and selected suite of 5 most significant variables (b).

6.3.2 Incorporating future climate scenarios

Having selected an appropriate suite of five bioclimatic variables, these variables were run against the three selected GCMs using the post-1980 koomal presences. Current core koomal PD (core PD is produced by using a 10% threshold cut off to display SDM variable parameters within which 90% of training presences occur) were overlaid with core PD for each of the 2050 GCM scenarios and all 2050 scenario core distributions overlaid to produce a sum value which shows the number of times each pixel has been identified as core PD (Figure 28). The difference in area between post 1980 PD and 2050 PD for all modelled GCMs was then quantified (Table 26).

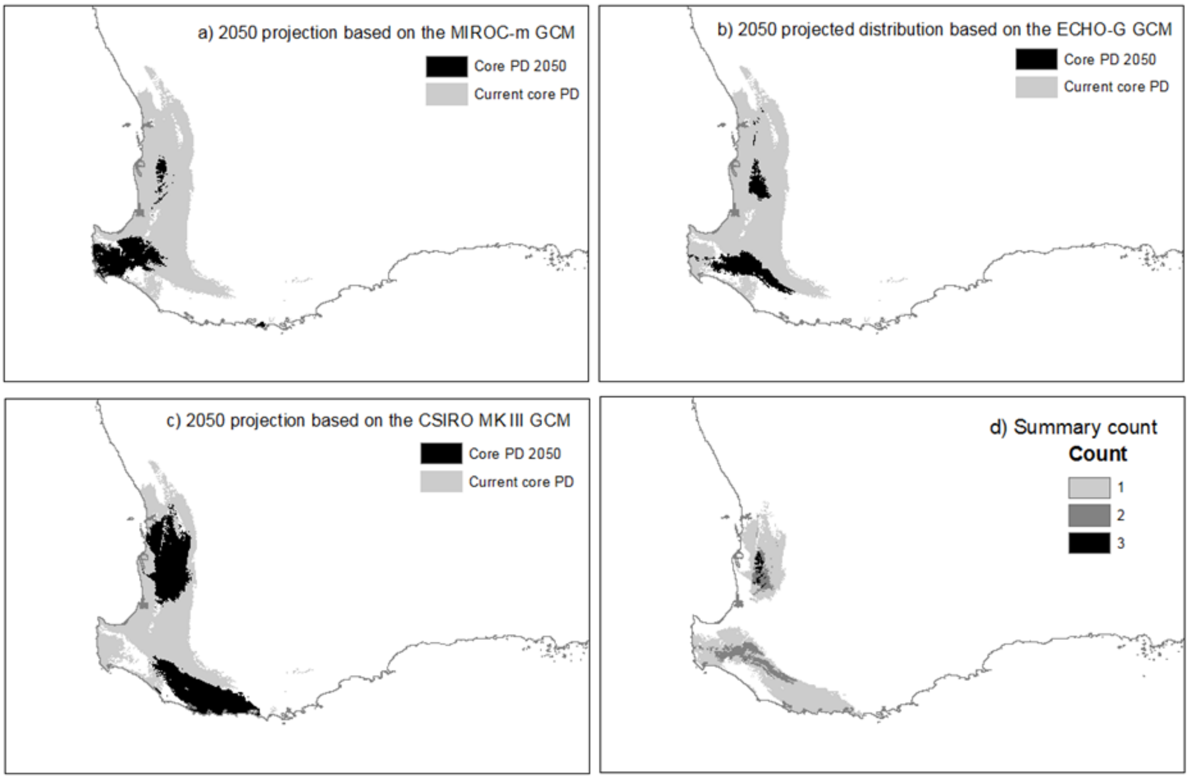

Figure 29: MaxEnt outputs using 5 bioclimatic variables. Post-1980 PD overlaid with 2050 GCM PDs overlaid (displayed as core areas) and GCM PDs overlaid to produce a summary count (The number of times each pixel appears as core habitat).

Table 26: Change in core PD for each GCM and areas for sum values from 2050 overlays, as displayed in Figure 28.

Model	**Post 1980**	**MIROC-m**	**ECHO-G**	**CSIRO MKIII**
Area (ha)	2,928,894	489,001	388,947	1,257,784
Change in PD at 2050 (%)	0	-83.3	-86.7	-57.1
Sum value	1	2	3	Total
Area (ha)	1,432,605	297,901	36,003	1,766,509
%	81.1	16.9	2.0	100.0

6.3.3 Selection of remnant vegetation perspective

Having overlaid the low bias sample of post-1980 koomal presences were overlaid over each the proportion of remnant vegetation from each perspective was be attributed to each presence in the sample. Resulting histograms showed a preference for: a) full vegetation cover in the 1 km^2 perspective, b) a relatively flat response with a small preference for approximately 40% of remnant vegetation cover for the 5 km perspective and c) a less pronounced preference for full vegetation cover with a 40% spike for the 1 km buffered perspective (Figure 30).

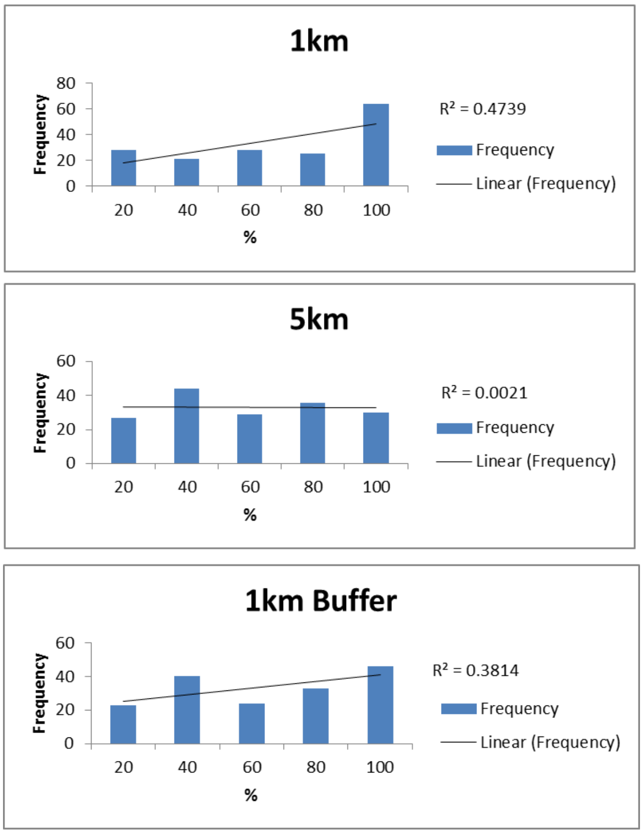

Figure 30: Histograms representing the response of koomal to the proportion of remnant vegetation cover as calculated from three perspectives.

Although summary statistics (Table 27) showed no significant difference between the three perspectives, in the categories of mean, standard deviation, and median 1 km scored highest, 5 km, lowest and 1 km buffered providing the median value. However, as demonstrated in Figure 30, the 1 km buffered perspective was shown to be much less skewed.

Table 27: Summary statistics for 3 perspectives.

	1 km	5 km	1 km Buffer
Mean	60.19	50.65	55.53
Standard Error	2.58	2.14	2.27
Median	65.69	45.98	56.95
Standard Deviation	33.08	27.48	29.3
Sample Variance	1094.14	754.91	858.29
Kurtosis	-1.26	-1.07	-1.3
Skewness	-0.34	0.288	-0.06
Range	100	94.38	99.9
Minimum	0	4.65	0.1
Maximum	100	99.02	100
Sum	9932.02	8356.99	9218.05
Count	165	165	166
Confidence Level (95.0%)	5.08	4.22	4.49

When incorporated into the MaxEnt SDMs there was little difference in statistical tests of model accuracy between the model with no added perspectives and those with the remnant vegetation perspective data sets added (Table 28). In this exercise it was shown that AUC values for the models run with the 5 km and the 1 km buffered data sets were marginally superior to the model run without any perspective and the rankings, contribution and 10 % threshold values of these two models being superior to model run with the 1 km perspective. In all values the 5 km and 1k m buffered perspectives remained very similar with the 5 km perspective scoring slightly higher in all indicators.

Table 28: Model accuracy indicators with remnant vegetation perspective data sets added

Perspective	AUC	Ranking (1- 6)	Contribution (%)	10 % Threshold
None	0.965			0.229
1 km	0.965	5	5.3	0.182
1 km buffered	0.967	3	8.5	0.221
5 km	0.967	3	10.3	0.226

The 1 km buffered and the 5 km perspectives were to be significantly superior to the 1 km perspective in all tests. Although the 5 km perspective has been shown to slightly superior to the 1 km buffered in some regards the latter’s significantly lower skewing value, while still reflecting both the 40 % spike demonstrated by the 5 km perspective and the full cover preference demonstrated by the 1 km perspective, and a greater inherent capacity for model definition, enabling more precise interpretation in highly fragmented landscapes, have led to the selection of this perspective for incorporation in further modelling.

6.3.4 Incorporation of remnant vegetation perspective.

When comparing the results of the MaxEnt model with five selected bioclimatic variables to those of the model which incorporated the 1 km buffered remnant vegetation perspective (Figure 31) it appears that PDs remain generally similar in both probability of presence and extent. The most observable difference is the greatly increased detail in 1 km buffered model which reflects the percentage of remnant vegetation within and surrounding each pixel, and by extension the level of landscape fragmentation, and the koomal’s predicted response to that variable.

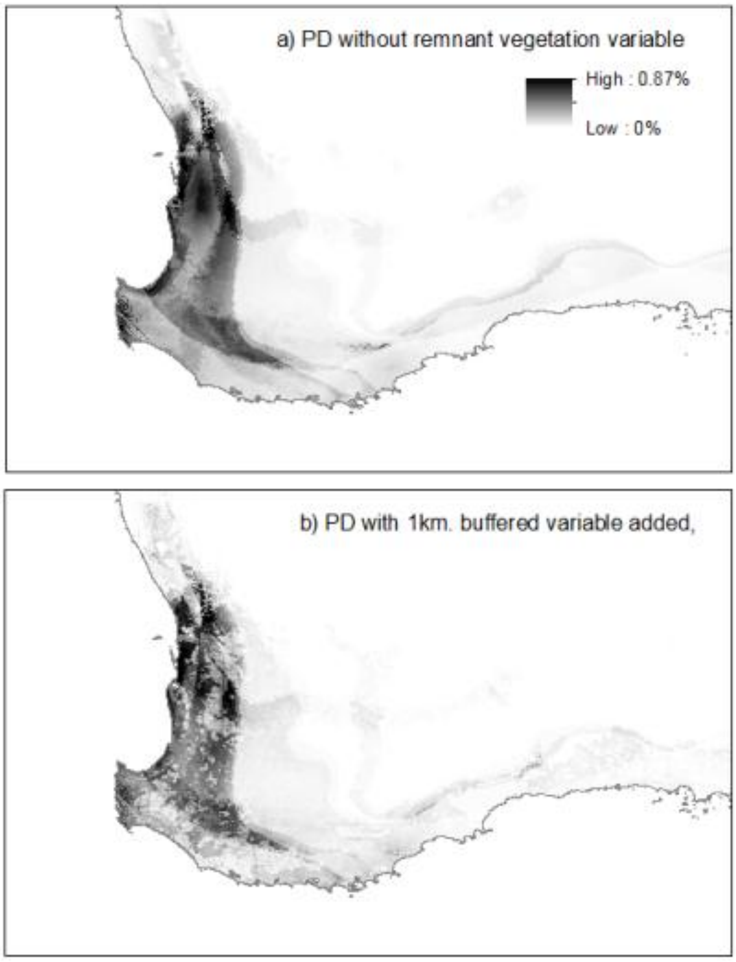

Figure 31: a) Post-1980 koomal PD using 5 selected bioclimatic variables alone and b) with 1 km buffered “koomal perspective” GIS layer included into the model as a predictive variable.

MaxEnt models using the five selected bioclimatic and the 1 km buffered variables were then run against the 3 selected GCMs. Core PD for each of the 2050 GCM scenarios were overlaid on Post 1980 core koomal PD and all 2050 scenario core distributions overlaid to produce a sum value given which shows the number of times each pixel has been identified as core PD (Figure 32). The difference in area between post-1980 PD and 2050 PD for all modelled GCMs was then quantified (Table 29). Each GCM scenario predicted, in comparison to the post 1980 PD, a reduction in koomal core PD of 56-86 % by 2050.

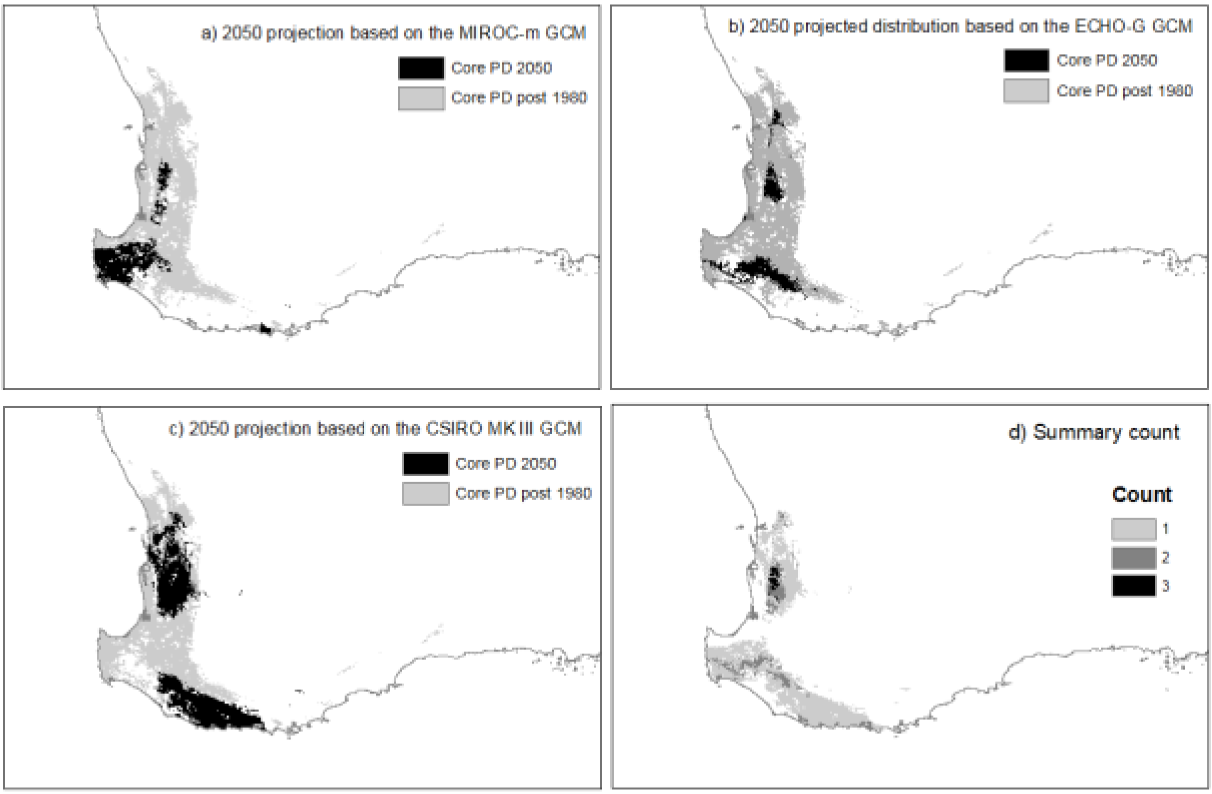

Figure 32: MaxEnt outputs incorporating 1 km buffered perspective. Post-1980 PD overlaid with 2050 GCM PDs overlaid (displayed as core areas) and a summary count (The number of times each pixel appears as core area).

Table 29: Change in core PD for each GCM and areas for sum values from 2050 overlays, as displayed in Figure 31.

Model	**Post 1980**	**MIROC-m**	**ECHO-G**	**CSIRO MKIII**
Area (ha.)	2,640,333	524,398	375,899	1,171,211
Change in PD at 2050 (%)	0.0	-80.1	-85.8	-55.6
Sum output	1	2	3	Total
Area (ha.)	1,467,985	239,042	42,084	1,749,111

6.3.5 Dieback overlay

Areas where dieback is, or is expected to be present, were overlaid over both the post-1980 model and 2050 sum overlay (Figure 33) and comparisons made to demonstrate the reductions in PD likely to arise from the application of this data (Table 30). This exercise shows that dieback significantly limits PD in the post 1980 model, its impact by 2050 GCMs, even at current level of infestation, will continue to increase and impacts will be much greater in those areas selected as potential distribution by the application of multiple GCMs.

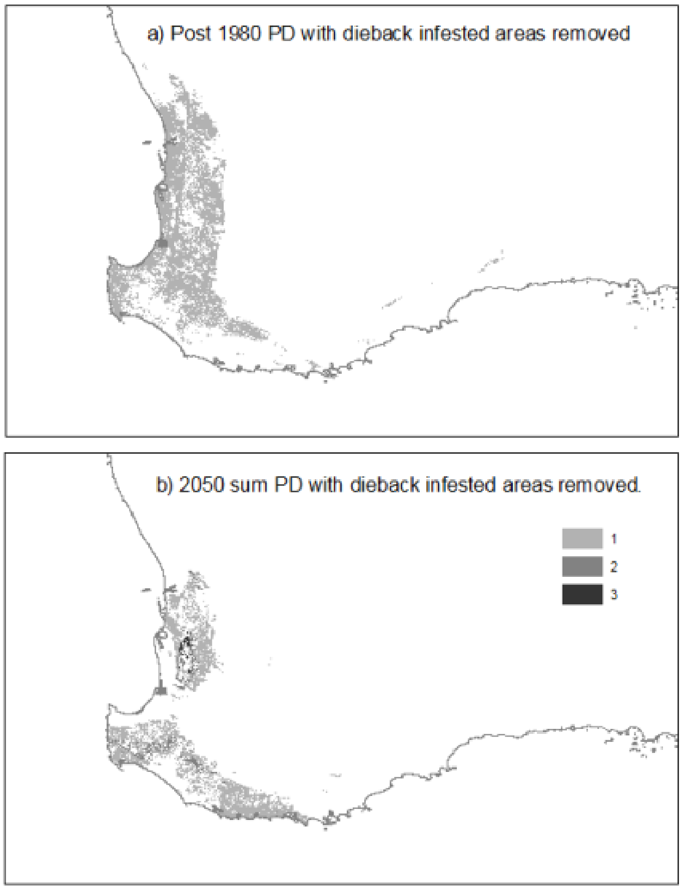

Figure 33: a) Post 1980 core PD and b) 2050 core PD sum overlay with dieback infested areas removed.

Table 30: Reduction in Post 1980 core PD and 2050 core PD sum overlay after the removal of dieback infested areas.

		Core PD 2050			
Model	**Total post 1980**	**1**	**2**	**3**	**Total (2050)**
Total area	2,640,333	1,467,985	239,042	42,084	1,749,111
Dieback present	481,735	385,928	85,530	21,622	493,080
Change 2050 (%)	-18	-26	-36	-51	-28

6.4 Discussion

6.4.1 Bioclimatic models

The MaxEnt koomal model using bioclimatic variables alone demonstrates a similar response in the contraction of PD as was predicted using the ngwayir model (ch.5). This is to be expected as both taxa share a common distribution and because both models are highly reliant on precipitation variables and share a landscape with a Mediterranean climate with a highly seasonal winter rainfall (Hearn *et al.* 2003; Gibson *et al.* 2010; Yates *et al.* 2010a). The 2050 GCM models show that koomal PD will be split into two distinct, northern and southern, populations, mirroring those predicted for marri *Corymbia calophylla* and jarrah *Eucalyptus marginata* in the previous chapter. This reflects the modelled reliance of all of these taxa on annual precipitation, a relatively low band of annual precipitation dividing the predicted PDs (Figure 34), and all of the GCMs predicting that precipitation in this low rainfall band will drop below habitat parameters.

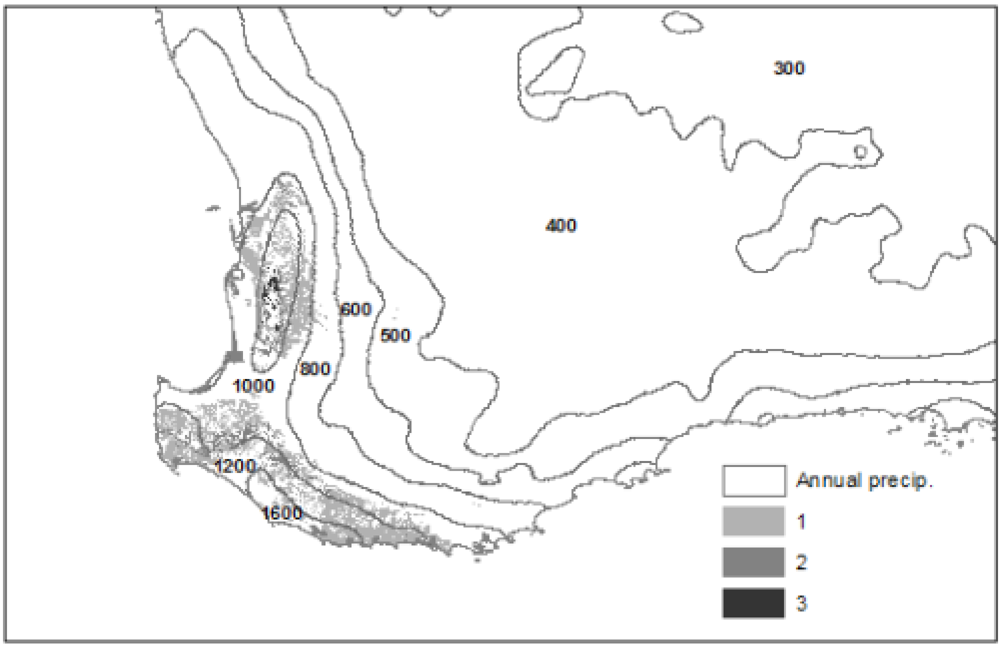

Figure 34: 2050 Sum PD (Figure 33b) with annual average precipitation (mm) overlaid.

6.4.2 Using a minimal set of bioclimatic variables

In ch.5 a full suite of 19 bioclimatic predictive variables were used and the MaxEnt SDM was allowed to calculate the level of contribution of all of these variables even though this represented a small danger of over-fitting (Fitzpatrick *et al.* 2008; Benito *et al.* 2009; Elith *et al.* 2011; Hijmans 2012). This was done because, in that exercise, the capacity of MaxEnt itself was being tested and because this model was being used to test the response of other species all of which may have had different bioclimatic requirements. In this exercise only one taxon was being modelled and the addition of habitat variables to the SDM model increased the probability of overfitting. The selection of the a suite of 5 bioclimatic variables by undertaking multiple model runs and removing the worst performing variables produced a koomal post-1980 PD model with very little visual or statistical difference from the model output where all 19 bioclimatic variables were used. Given the minimisation of potential over-fitting problems and the clarity arising from being able to better identify which variables are defining PD, the use of a minimal suite of bioclimatic variables was shown to be the more effective option in this exercise.

6.4.3 Including remnant vegetation data at the appropriate perspective

In ch.4 it was observed that koomal presence relied largely on remnant vegetation extent and that the gap crossing capacity of this taxon allowed it to persist within a fragmented landscape.

By applying remnant vegetation mapping at an effective scale/perspective to produce a predictive variable data set and incorporating it into the SDM, it was possible to take broad bioclimatic PDs and apply those onto actual landscape attributes. To do this, two issues had to be solved. The first required finding a quantifiable landscape parameter that reflected a koomal habitat preference, in this case remnant vegetation cover. The second was finding an appropriate perspective from which to view that habitat parameter. To do this, field observations were used to hypothesise a group of probable perspectives which could then be tested to determine which was the most suitable.

The 1 km buffered perspective proven to be the most useful within the context of defining habitat for this taxon in this landscape. Although, statistically, it appeared in some criteria to be marginally less effective than the 5 km x 5 km perspective it better addressed 2 of the criteria developed in ch.2, in that it did quantify a habitat value (Guisan & Thuiller

2005; Gontier *et al.* 2010) and, through providing better resolution, the model's utility value is enhanced (Broennimann *et al.* 2012; Šímová & Gdulová 2012).

The results of this exercise did not in any way detract from the bioclimatic modelling; instead it focussed bioclimatic parameters on landscapes where remnant vegetation cover met the koomal's habitat preferences. In so doing PDs was better defined and consequently, the potential for targeted application of model findings to management actions greatly enhanced.

6.4.4 Including dieback variables

In ch.4 it was observed that areas infested with dieback were not koomal habitat. By overlaying the dieback extent data set it was possible to eliminate areas that were, or probably were, not habitat from model outputs. This also helps to inform the delivery of targeted conservation management activities.

Of note in this exercise was the finding that dieback reduces the post 1980 core PD by 18% and the 2050 core PD by 28% (at current extent) and that areas highlighted as 2050 core PD twice will are reduced by 36% and areas identified as core PD by all three GCMs by 51%. This example shows how those areas most likely to provide core PD for the koomal in the future are the same areas at greatest risk from dieback. This suggests that these areas should not only be maintained as koomal habitat, but also that dieback management action planning be undertaken in these areas as a matter of priority.

6.4.5 Limitations

There is no available data predicting remnant vegetation extent or the potential extent of dieback circa 2050 for the modelled landscape. For this reason, post 1980 and 2050 models will run using the current data. Although this allows the benefits of including taxon specific data in PD models to be demonstrated, it does present a potential problem in applying the findings of this modelling exercise to conservation management. Therefore, it is recommended that the outputs of this exercise be viewed with this limitation acknowledged and that models be rerun with updated data as it comes to hand.

The impacts of climate change on dieback are also poorly understood. Given that the distribution, rate of dispersal and impact of this fungal pathogen are related to bioclimatic variables in general and precipitation in particular (Strelein *et al.* 2007; Anderson *et al.*

2010), it could be hypothesised that the changes predicted in many GCMs (Gibson *et al.* 2010; Yates *et al.* 2010b; Fordham *et al.* 2012; Prober *et al.* 2012), climate change may bring about a change in dispersal, or even a range contraction, for this pathogen.

6.5 Conclusions

This chapter demonstrates a means by which taxon specific observations, gathered through fieldwork, can be used to add resolution and robustness to a SDM. To achieve this, data obtained in the field for ch.4 has, with the aid of GIS software and statistical analyses techniques, been used to enhance the climate change modelling techniques trialled in ch.5. This exercise demonstrates how spatial modelling can be used to model a future PD for a taxon which has been shown to be vulnerable to the impacts of landscape fragmentation, a rapidly changing climate and dieback, a virulent plant pathogen which impacts negatively on koomal habitat.

In comparison to the simple bioclimatic model developed in ch.5, the incorporation of landscape data has enabled the development of a much more realistic PD as, by combining the habitat preferences of the koomal with bioclimatic parameters, areas which are not likely to be considered habitat by virtue of an unsuitable landscape matrix, or because of dieback infestation, are removed from the PD whilst largely retaining the habitat values of the bioclimatic-only model unchanged. A comparison between these two outputs will help to inform those areas where management activities such as dieback control, a change in tenure or revegetation could best be undertaken to help assure the persistence of this taxon. It also highlights those areas which, although not currently koomal habitat, may become so in the future.

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7 Discussion

The purpose of this thesis was to study how spatial modelling has been applied to conservation management in the fragmented landscapes of south-western Australia and to demonstrate means by which these tools and methodologies could be used more effectively. Given the broad and complicated nature of spatial modelling, its myriad potential applications and in seeking to develop practical outcomes from this study, a perspective on spatial modelling had to be made enabling spatial modelling to be put into the context of regional conservation management needs. It was therefore assumed that, for the purpose of this thesis, the objective of the spatial modelling exercise is to gather relevant data to inform and, where appropriate, drive conservation planning processes, identify and prioritise effective management actions and, in turn, deliver good conservation management outcomes.

Having set an objective for this study and given it context, it became necessary to find a way to compare and evaluate spatial modelling applications, thereby allowing a quantifiable means by which various methodologies can be evaluated and compared, in light of the degree to which they meet the needs of conservation managers. This required the development of a set of criteria, reflecting the needs of conservation managers, which could then be used as a yardstick by which the efficacy of various tools and methodologies could be measured.

A set of eight criteria were developed and applied to the five major spatial modelling tools which, at that time or writing, were being used by regional conservation managers and planners. In applying these criteria to these spatial modelling applications it was found that: although none of the spatial modelling tools used met all the criteria, the use of multiple tools in combination could meet manager's needs; tools were often used for purposes for which they were neither designed nor suited; and there was very low awareness of the existence and efficacy of the tools and methodologies that are available. Therefore the few tools employed were often used for applications for which they were not well suited, if used at all. To apply an appropriate axiom, "*When the only tool you've got is a hammer everything around you starts to look like a nail*." Consequently, much of the decision making in this region's environmental management has, and continues to be, based on assumption and inappropriate modelling. Having made this statement, I must also acknowledge that recent research within this region has provided some excellent examples of spatial modelling, particularly in regard to the potential impacts of climate change (Gibson *et al.* 2010; Yates *et al.* 2010a; Yates *et al.* 2010b; Fordham *et al.* 2012; Prober *et al.* 2012). However, there still seems to be a chasm between research findings and management actions, insomuch as it appears that the former have had little, if any, influence on the latter.

In setting criteria it became necessary to consider: firstly, the type and quality of information required by the conservation manager; secondly, the resources limitations of the conservation manager; and finally the capacity of the conservation manager to adequately comprehend and apply the outputs of the spatial modelling process through the development and delivery of effective management actions. The criteria of a successful spatial model and the means by which have been addressed in this thesis are listed below:

1. **Barriers to movement should be quantifiable:** In ch.4 it was shown that, through targeted fieldwork in a fragmented landscape, it was possible to broadly determine how gaps in habitat and landscape attributes impact or facilitate movement. Although this methodology can easily be adapted to examine how a target community reacts to a specific obstacle, this is of little use when looking at how fragmentation impacts on habitat value at the landscape scale. This is because, as the ch.4 exercise shows, habitat can be made up of a series of patches with varying gaps or obstacles between them. In this context habitat becomes defined by the individual’s capacity to use a group of patches for its own autecological requirements. Therefore, in regard to modelling the impacts of fragmentation, the landscape matrix, i.e. the manner in which patches of various sizes and shapes are positioned in the landscape, becomes a more useful perspective than that of modelling the single barrier impact. Furthermore, because of factors of scale, the larger the target landscape becomes, the less important the impact of a single barrier. Conversely, the larger the landscape the more important the matrix becomes to distribution models.

The ch.4 exercise did demonstrate how a taxon utilised resources within the landscape matrix. It thereby enabled some of the impacts of fragmentation, and hence barriers to movement, to be explicitly quantified in the form of population demographics, metapopulation movements, and responses to specific features within the landscape. Information of this type can then be useful in the development of mixed methods species distribution models, ch.6, and metapopulation modelling.

Incorporating barriers to movement through a variety of landscape matrices was also used in ch.3 which showed how predictive variables based on landscape matrices could be used to develop explicit models capable of quantifying the consequences of impacts or management actions on target species and communities.

In addressing this criterion, it was demonstrated that modelling the impacts of barriers to movement it is necessary to choose a perspective that will enable modelling at the required scale. By changing the modelling perspective from a simple response to an obstacle, or barrier to movement, to quantifying barriers to movement as a feature of the landscape matrix enables a more suitable input for modelling the impacts of fragmentation on a taxon or community.

2. **Habitat should be quantifiable:** In ch.3 the habitat perspective was taken from the patch and, like barriers to movement, put into the context of a landscape matrix. In this context habitat value became, like barriers to movement, quantifiable from a landscape perspective.

   In ch.5, landscape perspective was, temporarily, abandoned for a different perspective on habitat, that of potential distribution. This was a broad perspective relying solely on the application of bioclimatic variables which were used to implicitly identify and quantify a broad spatial envelope within which a taxon or community persist. This was done to show the potential impacts of climate change alone. As such this was another example of choosing a scale, or perspective, on habitat suitable for modelling a nominated impact on a specific taxon or community.

ch.4 exercise did lend itself to the development of some explicitly The quantifiable habitat parameters in that it found that dieback infected areas and shrublands were not habitat for the koomal, that trees with specific characteristics were required for nesting and that a home range could incorporate a patch matrix. Many of these observations were later applied in the mixed methods model, ch.6. To achieve this, a landscape fragmentation matrix was included into a bioclimatic potential distribution model and the resultant data set combined with simple explicit data to give a more effective species distribution model.

In addressing this criterion, as in modelling barriers to movement, it became necessary to choose a perspective, or group of perspectives, which will best enable the modeller to apply the best available, and most suitable, data to the task at hand.

3. **The response of species and communities to disturbance scenarios should be predictable:** The modelling exercises in chapters 3, 5 and 6 all demonstrated a means by which a target's response to a nominated disturbance could be predicted. In ch.3, a modelling tool was developed, which used logistic regression outputs based on existing survey data, which could predict the individual and collective responses of a group of indicator bird species to changes in vesting or vegetation extent. In ch.5, a series of species distribution models and global climate models were used to give an implicit insight into the possible impacts of climate change on the potential distribution of the ngwayir. In ch.6 a similar potential distribution model was combined with relevant data and landscape matrix perspectives chosen in response to field observations, ch.4, to provide a much more explicit potential distribution model for the koomal.

   For each of these examples a modelling methodology was selected to address a realistic conservation management. In each example, tools were selected, or developed, with the capacity to predict how a species or community will respond to a future disturbance scenario in a quantifiable manner. It should be noted that in each case tools were selected on the basis of their capacity to meet a modelling requirement, and requirements were not developed to meet the capacity of a given tool.

4. **Models should be able to demonstrate how change will happen over differing time frames, i.e. they have a multivariate capacity:** The modelling exercises in chapters 3, 5 and 6 all had a multivariate capacity as a central requirement of their selection. In each of these test scenarios, data taken from a historical baseline is compared with future scenarios with little limitation on the future scenarios used.

5. **Models should be able to make valid predictions based on data that is either currently held or can be obtained within a project's capacity, i.e. they can compensate for expected knowledge gaps:** All GIS data used in this thesis, along with all species data, was all made freely available upon approaching the appropriate custodians. During the course of this thesis the only data that was not freely available was the species specific data obtained in ch.4. As species specific data of this type is often not available, the ch.4 exercise was undertaken as an example of how data of this nature can be obtained while in ch.6 an example was given of how data obtained in this manner can enhance the spatial modelling process.

6. **The outputs of the model must be easily understood by a variety of stakeholders:** Although understanding many of the readouts of modelling exercises require a rudimentary understanding of statistics, this level of understanding is well within that expected of a graduate in a relevant discipline. Other than these basic statistical analyses, nearly all readouts are provided as simple graphics which can easily be understood by those with a rudimentary understanding of the nature of probabilities and, even where this is lacking, can be followed intuitively.

7. **Skill levels required to use the model effectively are accessible:** All modelling applications in this exercise required a basic understanding of GIS and statistical software operation. However, these standards too were of a level commensurate with those of a graduate in a relevant discipline. In the use of other modelling tools, those used, as are many more like them, are readily available online, as are tutorials on their use and, in most cases, online support networks and contacts.

   To test this criterion, all modelling tools used in this thesis, other than GIS and statistical software, were sourced online and used with no prior experience or training other than downloaded tutorials and literature. In so doing, it was found that required skill levels were also within those expected of a graduate in a relevant discipline.

8. **The model should be within a project's budget and resource constraints:** All data used in this project was obtained free of charge. Other than ArcMap® and SPSS® software, all other software used in this exercise were downloaded free of charge. Many other spatial modelling packages are also available online and free of charge.

   Although ArcMap® and SPSS® were purchased software, software packages of this type are usually in use with research, education and conservation management organisations and therefore, in most instances, do not represent an addition cost to the conservation manager. However, ESRI does offer heavily discounted ArcMap® to students and community organisations if required and there are GIS and statistical analysis software packages available freely online which will meet many spatial modelling requirements.

   As software and data costs for most spatial modelling applications are minimal, the resource cost then becomes one of person-hours. Without knowing the nature of a spatial modelling application or the skill levels available, no real guideline can be given as to how this cost will impact on a project. To best assess the true cost of a spatial modelling application one might ask, what is the potential cost of not adopting a spatial modelling application? In answer to this question I would put this is a case by case decision in which the following points should always be considered:

   - Undertaking effective spatial modelling builds skills and capacity within an organisation which, in turn, will make subsequent spatial modelling exercises easier to conduct, more effective and cheaper.

   - The cost of a failed project, e.g. revegetating a patch with plant species that will not survive in a changing climate, reintroducing a species into an area that does not meet its autecological needs, or establishing a linkage project

> that does not facilitate the movement of target species, will, over the long term represent a far greater cost in time, money and resources.

In summary, this thesis has demonstrated that spatial modelling is a proven and effective means of informing conservation planning and management processes. It has many applications and the ongoing development of tools and methodologies means that it will continue to grow in terms of potential applications, efficacy and amenity for the foreseeable future.

Through this thesis I have demonstrated the efficacy of spatial modelling in dealing with the conservation management requirements in south-western Australia. Exercises included: informing management activities, filling knowledge gaps and modelling the potential impacts of climate change within the context of a highly fragmented landscape, a set of circumstances confronting conservation managers in many regions throughout the world. All of this was done using data, tools and skills currently available to conservation managers. With this in mind I would assert that the use of assumption and the pleading of ignorance in conservation planning and management practices is becoming increasingly difficult to justify and even more difficult to accept.

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8 References

Adams-Hosking, C., Grantham, H. S., Rhodes, J. R., McAlpine, C. & Moss, P. T. (2011) Modelling climate-change-induced shifts in the distribution of the koala. *Wildlife Research* **38**(2): 122-130.

Adams-Hosking, C., McAlpine, C., Rhodes, J. R., Grantham, H. S. & Moss, P. T. (2012) Modelling changes in the distribution of the critical food resources of a specialist folivore in response to climate change. *Diversity and Distributions* **18**(9): 847-860.

Albert, S. v. J., Mervyn, W. M., Clarke, H. S., Stefanie, F., Steven, L. C., Caron, M., Stephanie, K., Heath, H., Chuck, B., Martin, K. & Sebastian, E.-Y. (1998) Biodiversity Assessment and Conservation Strategies. *Science* **279**(5359): 2106-2108.

Allen, C. D., Hogg, E. H., Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.-H., Allard, G., Running, S. W., Semerci, A., Macalady, A. K., Cobb, N., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A. & Breshears, D. D. (2010) A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *Forest Ecology and Management* **259**(4): 660-684.

Allison, I., Bindoff, N. L., Bindschadler, R. A., Cox, P. M., Noblet, N. d., England, M. H., Francis, J. E., Gruber, N., Haywood, A. M., Karoly, D. J., Kaser, G., Le Quéré, C., Lenton, T. M., Mann, M. E., McNeil, B. I., Pitman, A. J., Rahmstorf, S., Rignot, E., Schellnhuber, H. J., Schneider, S. H., Sherwood, S. C., Somerville, R. C. J., Steffen, K., Steig, E. J., Visbeck, M. & Weaver, A. J. (2009) *The Copenhagen Diagnosis, 2009: Updating the world on the Latest Climate Science.* Sydney, Australia: The University of New South Wales Climate Change Research Centre (CCRC).

Amarasekare, P. & Possingham, H. (2001) Patch dynamics and metapopulation theory: the case of successional species. *Journal of Theoretical Biology* **209**(3): 333-344.

Anderson, P., Brundrett, M., Grierson, P. & Robinson, R. (2010) Impact of severe forest dieback caused by Phytophthora cinnamomi on macrofungal diversity in the northern jarrah forest of Western Australia. *Forest Ecology and Management* **259**(5): 1033-1040.

ANZECC/MCFF. (1997) *Nationally agreed criteria for the establishment of a comprehensive, adequate and representative reserve system for forests in Australia.* Canberra: Australian and New Zealand Environment and Conservation Council Australia. Ministerial Council on Forestry Fisheries and Aquaculture.

Araujo, M. B., Pearson, R. G., Thuiller, W. & Erhard, M. (2005) Validation of species-climate impact models under climate change. *GLOBAL CHANGE BIOLOGY* **11**(9): 1504-1513.

Australian Government. (2001) *Australian native vegetation assessment 2001*. Turner, A.C.T: National Land & Water Resources Audit.

Ball, I. R. & Possingham, H. P. (2000) *MARXAN (V1.8.2): Marine Reserve Design Using Spatially Explicit Annealing. A Manual.* St Lucia Queensland: University of Queensland.

Ball, S. J., Ramsey, D., Nugent, G., Warburton, B. & Efford, M. (2005) A method for estimating wildlife detection probabilities in relation to home-range use: insights from a field study on the common brushtail possum (Trichosurus vulpecula). *Wildlife Research* **32**(3): 217-227.

Barrett, G., Silcocks, A., Barry, S., Cunningham, R. & Poulter, R. (2003) *The new atlas of Australian birds.* URL http://www.birdlife.org.au/projects/atlas-and-birdata.

Bascompte, J. & Solé, R. V. (1996) Habitat Fragmentation and Extinction Thresholds in Spatially Explicit Models. *Journal of Animal Ecology* **65**(4): 465-473.

Bateman, B. L., VanDerWal, J., Williams, S. E. & Johnson, C. N. (2012) Biotic interactions influence the projected distribution of a specialist mammal under climate change. *Diversity and Distributions* **18**(9): 861-872.

Beaumont, L. J., Hughes, L. & Poulsen, M. (2005) Predicting species distributions: use of climatic parameters in BIOCLIM and its impact on predictions of species' current and future distributions. *Ecological Modelling* **186**(2): 251-270.

Beaumont, L. J., Pitman, A. J., Poulsen, M. & Hughes, L. (2007) Where will species go? Incorporating new advances in climate modelling into projections of species distributions. *Global Change Biology* **13**(7): 1368-1385.

Beger, M., Linke, S., Watts, M., Game, E., Treml, E., Ball, I. & Possingham, H. P. (2010) Incorporating asymmetric connectivity into spatial decision making for conservation. *Conservation Letters* **3**(5): 359-368.

Beier, P., Majka, D. R. & Spencer, W. D. (2008) Forks in the road: choices in procedures for designing wildland linkages. *Conservation biology : The Journal of the Society for Conservation Biology* **22**(4): 836-851.

Belisle, M. & Desrochers, A. (2002) Gap-crossing decisions by forest birds: an empirical basis for parameterizing spatially-explicit, individual-based models. *Landscape Ecology* **17**(3): 219-231.

Benitez-Lopez, A., Alkemade, R. & Verweij, P. A. (2010) The impacts of roads and other infrastructure on mammal and bird populations: A meta-analysis. *Biological Conservation* **143**(6): 1307-1316.

Benito, B. M., Martinez-Ortega, M. M., Munoz, L. M., Lorite, J. & Penas, J. (2009) Assessing extinction-risk of endangered plants using species distribution models: a case study of habitat depletion caused by the spread of greenhouses. *Biodiversity and Conservation* **18**(9): 2509-2520.

Bennett, A. F., Lumsden, L. F. & Nicholls, A. O. (1994) Tree Hollows as a Resource for Wildlife in Remnant Woodlands: Spatial and Temporal Patterns across the Northern Plains of Victoria, Australia. *Pacific Conservation Biology* **1**(3): 222-235.

Bergman, B. (2003) Yellowstone to Yukon: A proposed 3,400 km wildlife corridor stirs up passions; for and against. *Maclean's* **116**(4): 37.

Bestelmeyer, B. T., Miller, J. R. & Wiens, J. A. (2003) Applying species diversity theory to land management. *Ecological Applications* **13**(6): 1750-1761.

Beyer, H. L. (2004) *Hawth's Analysis Tools for ArcGIS.* URL http://www.spatialecology.com/htools.

BOM. (2012) *Climate Online*. URL http://www.bom.gov.au/climate.

Bonn, A. & Schröder, B. (2001) Habitat models and their transfer for single and multi species groups: a case study of carabids in an alluvial forest. *Ecography* **24**(4): 483-496.

Brambilla, M., Casale, F., Bergero, V., Bogliani, G., Crovetto, G. M., Falco, R., Roati, M. & Negri, I. (2010) Glorious past, uncertain present, bad future? Assessing effects of land-use changes on habitat suitability for a threatened farmland bird species. *Biological Conservation* **143**(11): 2770-2778.

Brebbia, C. A. & Pascolo, P. (1998) *GIS technologies and their environmental applications : [First International Conference on Geographical Information Systems in the Next Millennium : GIS 98*. Southampton, England: WIT Press.

Bridle, K., Fitzgerald, M., Green, D., Smith, J., McQuillan, P. & Lefroy, T. (2009) Relationships between site characteristics, farming system and biodiversity on Australian mixed farms. *Animal Production Science* **49**(10): 869-882.

Broennimann, O., Zimmermann, N. E., Graham, C. H., Guisan, A., Fitzpatrick, M. C., Pearman, P. B., Petitpierre, B., Pellissier, L., Yoccoz, N. G., Thuiller, W., Fortin, M. J. & Randin, C. (2012) Measuring ecological niche overlap from occurrence and spatial environmental data. *Global Ecology and Biogeography* **21**(4): 481-497.

Brooker, L. & Brooker, M. (2002) Dispersal and population dynamics of the blue-breasted fairy-wren, Malurus pulcherrimus, in fragmented habitat in the Western Australian wheatbelt. *Wildlife Research* **29**(3): 225-233.

Brooker, L. & Brooker, M. (2003) Local distribution, metapopulation viability and conservation of the Blue-breasted Fairy-wren in fragmented habitat in the Western Australian wheatbelt. *Emu* **103**(3): 185-198.

Brouwers, N. C. & Newton, A. C. (2009a) Habitat requirements for the conservation of wood cricket (Nemobius sylvestris) (Orthoptera: Gryllidae) on the Isle of Wight, UK. *Journal of Insect Conservation* **13**(5): 529-541.

Brouwers, N. C. & Newton, A. C. (2009b) The influence of habitat availability and landscape structure on the distribution of wood cricket (Nemobius sylvestris) on the Isle of Wight, UK. *Landscape Ecology* **24**(2): 199-212.

Burbidge, A. (2010) Global hotspot under stress: while the south-west corner of Western Australia is recognised as a global biodiversity hotspot, its unique ecosystems have suffered land clearing, introduced pests and weeds, a changed fire regime, loss of water and salinisation. climate change may tip the balance for some species, unless effective action is taken. *Ecos* (153): 18-19.

Burns, C. E. & Grear, J. S. (2008) Effects of habitat loss on populations of white-footed mice: testing matrix model predictions with landscape-scale perturbation experiments. *Landscape Ecology* **23**(7): 817-831.

Burrows, N. D., Abbott, I., Western Australia. Dept. of, C. & Land, M. (2003) *Fire in ecosystems of south-west Western Australia: impacts and management*. Leiden: Backhuys Publishers.

Bystriakova, N., Peregrym, M., Erkens, R. H. J., Bezsmertna, O. & Schneider, H. (2012) Sampling bias in geographic and environmental space and its effect on the predictive power of species distribution models. *Systematics and Biodiversity* **10**(3): 305-315.

Cabeza, M. (2003) Habitat loss and connectivity of reserve networks in probability approaches to reserve design: Connectivity in reserve-network design. *Ecology Letters* **6**(7): 665-672.

Cairns, J., McCormick, P. V. & Niederlehner, B. R. (1993) A proposed framework for developing indicators of ecosystem health *Hydrobiologica* **263**(1): 1-44.

Carnaval, A. C. & Moritz, C. (2008) Historical climate modelling predicts patterns of current biodiversity in the Brazilian Atlantic forest. *Journal of Biogeography* **35**(7): 1187-1201.

Caro, T. M. (2010) *Conservation by proxy: indicator, umbrella, keystone, flagship, and other surrogate species*. Washington, DC: Island Press.

Carpenter, G., Gillison, A. N. & Winter, J. (1993) Domain - a Flexible Modeling Procedure for Mapping Potential Distributions of Plants and Animals. *Biodiversity and Conservation* **2**(6): 667-680.

Cassini, M. H. (2011) Ecological principles of species distribution models: the habitat matching rule. *Journal of Biogeography* **38**(11): 2057-2065.

Castro, H. F., Classen, A. T., Austin, E. E., Norby, R. J. & Schadt, C. W. (2010) Soil microbial community responses to multiple experimental climate change drivers. *Applied and environmental microbiology* **76**(4): 999-1007.

CCAFS. (2008) Downscaled GCM Data Portal. URL http://www.ccafs-climate.org/.

Chaturvedi, R. K., Gopalakrishnan, R., Jayaraman, M., Bala, G., Joshi, N. V., Sukumar, R. & Ravindranath, N. H. (2011) Impact of climate change on Indian forests: a dynamic vegetation modeling approach. *Mitigation and Adaptation Strategies for Global Change* **16**(2): 119-142.

Chetkiewicz, C.-L. B., St. Clair, C. C. & Boyce, M. S. (2006) Corridors for Conservation: Integrating Pattern and Process. *Annual Review of Ecology, Evolution, and Systematics* **37**(1): 317-342.

Collinge, S. K. (2009) *The Ecology of Fragmented Landscapes*. Baltimore: Johns Hopkins University Press.

Coops, N. C., Smith, M. L., Jacobsen, K. L., Martin, M. & Ollinger, S. (2004) Estimation of plant and leaf area index using three techniques in a mature native eucalypt canopy. *Austral Ecology* **29**(3): 332-332.

Cormont, A., Jochem, R., Malinowska, A., Verboom, J., WallisDeVries, M. F. & Opdam, P. (2012) Can phenological shifts compensate for adverse effects of climate change on butterfly metapopulation viability? *Ecological Modelling* **227**(Journal Article): 72-81.

Cowled, B. D., Giannini, F., Beckett, S.D., Woolnough, A., Barry, S., Randall, L., and Garner, G. (2009) Feral pigs: predicting future distributions. *Wildlife Research* **36**(3): 242-251.

Cowling, R. M., Lombard, A. T., Rouget, M., Kerley, G. I. H. & Knight, A. T. (2006) Designing Large-Scale Conservation Corridors for Pattern and Process. *Conservation Biology* **20**(2): 549-561.

Cristianini, N. & Scholkopf, B. (2002) Support vector machines and kernel methods - The new generation of learning machines. *AI Magazine* **23**(3): 31-41.

Crossman, N. D., Bryan, B. A. & Summers, D. M. (2012) Identifying priority areas for reducing species vulnerability to climate change. *Diversity and Distributions* **18**(1): 60-72.

Cruz, J., Sutherland, D. R., Martin, G. R. & Leung, L. K. P. (2012) Are smaller subspecies of common brushtail possums more omnivorous than larger ones? *Austral Ecology* **37**(8): 893-902.

Cserny, A., Domokos, E., Rédey, A. & Kovács, Z. (2009) Environmental information system for visualizing environmental impact assessment information. *Environmental science and pollution research international* **16**(1): 36-41.

CSIRO & BOM. (2007) *Climate change in Australia: technical report*. URL http://www.climatechangeinaustralia.gov.au/technical_report.php.

CSIRO & BOM. (2012) *State of the Climate 2012.* URL http://www.csiro.au/Outcomes/Climate/Understanding/State-of-the-Climate-2012.aspx.

Cunningham, M. A. & Johnson, D. H. (2011) Seeking Parsimony in Landscape Metrics. *The Journal of Wildlife Management* **75**(3): 692-701.

Dallmeier, F. & Comiskey, J. A. (1998) Forest biodiversity assessment, monitoring, and evaluation for adaptive management. *Forest Biodiversity Research, Monitoring and Modeling* **20**: 3-15.

Dang, E. K. F., Luk, R. W. P., Allan, J., Ho, K. S., Chan, S. C. F., Chung, K. F. L. & Lee, D. L. (2010) A new context-dependent term weight computed by boost and discount using relevance information. *Journal of the American Society for Information Science & Technology* **61**(12): 2514-2530.

Davis, R. A. (2004) *Metapopulation structure of the Western Spotted Frog (Heleioporus albopunctatus) in the fragmented landscape of the Western Australian wheatbelt. PhD Dissertation*, University of Western Australia. School of Animal Biology.

Davis, R. A., Gole, C. & Roberts, J. D. (2013) Impacts of urbanisation on the native avifauna of Perth, Western Australia. *Urban Ecosystems*: 427-452.

de Tores, P. J. (2008) Western Ringtail Possum. In: *The Mammals of Australia, 3rd Edition*, eds. S. Van Dyck & R. Strahan, pp. 253-255. Sydney: Reed New Holland.

de Tores, P. J. (2009) *A summary of research by Department of Environment and Conservation (DEC), Murdoch University and Curtin University on the western ringtail possum (Pseudocheirus occidentalis) on the southern Swan Coastal Plain and recommendations relevant to current research proposals.* Canberra: Prepared for the Commonwealth Department of Environment, water, Heritage and the Arts.

de Tores, P. J., Hayward, M. W. & Rosier, S. M. (2004) The western ringtail possum, *Pseudocheirus occidentalis* and the quokka, *Setonix brachyurus*, case studies: Western Shield review February 2003. *Conservation Science Western Australia* **5**(2): 235-257.

DEC. (2012) *Habitat for Nature Conservation - Revegetation.* URL http://www.dec.wa.gov.au/management-and-protection/land/salinity/revegetation.html?showall=&start=1.

DeGabriel, J. L., Wallis, I. R., Moore, B. D. & Foley, W. J. (2008) A simple, integrative assay to quantify nutritional quality of browses for herbivores. *Oecologia* **156**(1): 107-116.

Dell, B., Havel, J. J. & Malajczuk, N. (1989) *The Jarrah forest: a complex mediterranean ecosystem.* Dordrecht: Kluwer Academic Publishers.

Department of Environment and Conservation. (2007-2013*) NatureMap: Mapping Western Australia's Biodiversity.* Kensington Western Australia: Department of Environment and Conservation

Department of Environment and Conservation. (2007) *Buntine-Marchagee Natural Diversity Recovery Catchment : recovery plan 2007-2027*. Kensington Western Australia: Department of Environment and Conservation

Department of Sustainability, E., Water, Population and Communities. (2011) Maps: Australia's bioregions (IBRA) URLhttp://www.environment.gov.au/parks/nrs/science/bioregion-framework/ibra/index.html.

Dormann, C. F., Schymanski, S. J., Cabral, J., Chuine, I., Graham, C., Hartig, F., Kearney, M., Morin, X., Römermann, C., Schröder, B. & Singer, A. (2012) Correlation and process in species distribution models: bridging a dichotomy. *Journal of Biogeography* **39**(12): 2119-2131.

Duchesne, T., Fortin, D. & Courbin, N. (2010) Mixed conditional logistic regression for habitat selection studies. *The Journal of animal ecology* **79**(3): 548-555.

Dunlop, M. & Brown, P. R. (2008) Implications of climate change for Australia's national reserve system. In: *a preliminary assessment*, Canberra: Dept. of Climate Change.

Ebbers, M. J. H., Wallis, I. R., Dury, S., Floyd, R. & Foley, W. J. (2002) Spectrometric prediction of secondary metabolites and nitrogen in fresh Eucalyptus foliage: towards remote sensing of the nutritional quality of foliage for leaf-eating marsupials. *Australian Journal of Botany* **50**(6): 761-768.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E. & Yates, C. J. (2011) A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions* **17**(1): 43-57.

Environmental Protection Authority. (2006) *Guidance Statement No.10: Guidance for the Assessment of Environmental Factors - Level of assessment for proposals affecting areas within the System 6 region and Swan Coastal Plain portion of the System 1 region.* Perth: Environmental Protection Authority.

Environmental Protection Authority. (2007) *State of the environment report. Western Australia 2007 : overview*. Perth: Environmental Protection Authority.

Environmental Protection Authority. (2008) *Guidance Statement No. 33: Environmental guidance for planning and development*. Perth: Environmental Protection Authority.

Environmental Protection Authority. (2009*) Environmental Protection Bulletin No. 8: South West Regional Ecological Linkages.* Perth: Environmental Protection Authority.

Environmental Protection Authority. (2003) *Greater Bunbury Region Scheme: Western Australian Planning Commission : report and recommendations of the Environmental Protection Authority.* Perth, W.A: Environmental Protection Authority.

Erdbrügge, M., Kuhnt, S. & Rudak, N. (2011) Joint optimization of independent multiple responses. *Quality and Reliability Engineering International* **27**(5): 689-703.

ESRI Australia Pty. Ltd. (1999) *Understanding GIS: the ARC/INFO method : self-study workbook : version 7.2 for UNIX and Windows NT.* California: Environmental Systems Research Institute.

Evangelista, P. H., Kumar, S., Stohlgren, T. J. & Young, N. E. (2011) Assessing forest vulnerability and the potential distribution of pine beetles under current and future climate scenarios in the Interior West of the US. *Forest Ecology and Management* **262**(3): 307-316.

Fahrig, L. (2003) Effects of Habitat Fragmentation on Biodiversity. *Annual Review of Ecology, Evolution, and Systematics* **34**(Journal Article): 487-515.

Fahrig, L. (2007) Non-Optimal Animal Movement in Human-Altered Landscapes. *Functional Ecology* **21**(6): 1003-1015.

Fahrig, L. & Triantis, K. (2013) Rethinking patch size and isolation effects: the habitat amount hypothesis. *Journal of Biogeography* **40**(9): 1649-1663.

Favreau, J. M., Drew, C. A., Hess, G. R., Rubino, M. J., Koch, F. H. & Eschelbach, K. A. (2006) Recommendations for Assessing the Effectiveness of Surrogate Species Approaches. *Biodiversity and Conservation* **15**(12): 3949-3969.

Ferrier, S. (2002) Mapping Spatial Pattern in Biodiversity for Regional Conservation Planning: Where to from Here? *Systematic Biology* **51**(2): 331-363.

Ferrier, S. & Guisan, A. (2006) Spatial modelling of biodiversity at the community level. *Journal of Applied Ecology* **43**(3): 393.

Field, A. P. (2009) *Discovering statistics using SPSS*. London: SAGE.

Fischer, J. & Lindenmayer, D. B. (2007) Landscape modification and habitat fragmentation: a synthesis. *Global Ecology and Biogeography* **16**(3): 265-280.

Fischer, J., Lindenmayer, D. B. & Fazey, I. (2004) Appreciating Ecological Complexity: Habitat Contours as a Conceptual Landscape Model. *Conservation Biology* **18**(5): 1245-1253.

Fitzpatrick, M. C., Gove, A. D., Sanders, N. J. & Dunn, R. R. (2008) Climate change, plant migration, and range collapse in a global biodiversity hotspot: the Banksia (Proteaceae) of Western Australia. *Global Change Biology* **14**(6): 1337.

Foley, D. H., Weitzman, A. L., Miller, S. E., Faran, M. E., Rueda, L. M. & Wilkerson, R. C. (2008) The value of georeferenced collection records for predicting patterns of mosquito species richness and endemism in the Neotropics. *Ecological Entomology* **33**(1): 12-23.

Foley, W. J. & Moore, B. D. (2005) Plant secondary metabolites and vertebrate herbivores - from physiological regulation to ecosystem function. *Current Opinion in Plant Biology* **8**(4): 430-435.

Foody, G. M. (2008) GIS: biodiversity applications. *Progress in Physical Geography* **32**(2): 223-235.

Fordham, D. A., Regan, T. J., Tozer, M., Watts, M. J., White, M., Wintle, B. A., Yates, C., Brook, B. W., Resit Akçakaya, H., Araújo, M. B., Elith, J., Keith, D. A., Pearson, R., Auld, T. D., Mellin, C. & Morgan, J. W. (2012) Plant extinction risk under climate change: are forecast range shifts alone a good indicator of species vulnerability to global warming? *Global Change Biology* **18**(4): 1357-1371.

Foreman, D. (1999) The wildlands project and the rewilding of North America. *Denver University Law Review* **76**(2): 535-553.

Franklin, J. (2010) Moving beyond static species distribution models in support of conservation biogeography. *Diversity & Distributions* **16**(3): 321-321.

Freudenberger, D. & Brooker, L. (2004) Development of the focal species approach for biodiversity conservation in the temperate agricultural zones of Australia. *Biodiversity and Conservation* **13**(1): 253-274.

Gaia Resources. (2009) *Southwest Australia Ecoregion Initiative*. URL http://www.gaiaresources.com.au/website/gaiaresources/projects/swaei/.

Gibson, L., McNeill, A., de Tores, P., Wayne, A. & Yates, C. (2010) Will future climate change threaten a range restricted endemic species, the quokka (*Setonix brachyurus*), in south west Australia? *Biological Conservation* **143**(11): 2453-2461.

Gilman, R. T., Fabina, N. S., Abbott, K. C. & Rafferty, N. E. (2012) Evolution of plant–pollinator mutualisms in response to climate change. *Evolutionary Applications* **5**(1): 2-16.

Giovanelli, J. G. R., de Siqueira, M. F., Haddad, C. F. B. & Alexandrino, J. (2010) Modeling a spatially restricted distribution in the Neotropics: How the size of calibration area affects the performance of five presence-only methods. *Ecological Modelling* **221**(2): 215-224.

Gondwana Link. (2009) *Gondwana Link a landscape scale restoration project in south-west WA*. URL http://www.gondwanalink.org/GLink_GRNreport.pdf.

Gontier, M., Mortberg, U. & Balfors, B. (2010) Comparing GIS-based habitat models for applications in EIA and SEA. *Environmental Impact Assessment Review* **30**(1): 8-18.

Gougeon, D. J. (2009) Logistic regression: from introductory to advanced. *Choice: Current Reviews for Academic Libraries* **47**(1): 153-153.

Green, K., Stein, J. A. & Driessen, M. M. (2008) The projected distributions of Mastacomys fuscus and Rattus lutreolus in south-eastern Australia under a scenario of climate change: potential for increased competition? *Wildlife Research* **35**(2): 113-119.

Green Skills. (2007) *Peel Harvey Regional Ecological Linkages Project.* Bull Creek: Green Skills Inc.

Greg, J. H. & Andrew, F. B. (2009) Differing responses to landscape change: implications for small mammal assemblages in forest fragments. *Biodiversity & Conservation* **18**(11): 2997.

Gregory, R. D., van Strien, A., Vorisek, P., Gmelig Meyling, A. W., Noble, D. G., Foppen, R. P. B. & Gibbons, D. W. (2005) Developing indicators for European birds. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences* **360**(1454): 269-288.

Grimm, H. L. & De Tores, P. J. (2009) *Some aspects of the biology of the common brushtail possum (Trichosurus vulpecula) and the threatened western ringtail possum (Pseudocheirus occidentalis) in a pine plantation scheduled for harvesting and in adjacent turat and peppermint woodland near Busselton , Western Australia*. A report prepared for the Forest Products Commission, Perth: Government of Western Australia.

Gritti, E. S., Smith, B., Sykes, M. T., Lund, U., Dept of Physical, G., Ecosystems, A., Section of, B., Earth, S., Inst för naturgeografi och, e., Naturvetenskap, Biologisk-geovetenskapliga, v., Lunds, u., Geocentrum, II, Geocentre, II & Science. (2006) Vulnerability of Mediterranean Basin Ecosystems to Climate Change and Invasion by Exotic Plant Species. *Journal of Biogeography* **33**(1): 145-157.

Gross, L. (2011) Climate change could change rates of evolution. *PLoS Biology* **9**(2): e1001015.

Guerin, G. R. & Lowe, A. J. (2012) Multi-species distribution modelling highlights the Adelaide Geosyncline, South Australia, as an important continental-scale arid-zone refugium. *Austral Ecology* **1442-9985**.

Guisan, A. & Thuiller, W. (2005) Predicting species distribution: offering more than simple habitat models. *Ecology Letters* **8**(9): 993-1009.

Guo, Q. & Liu, Y. (2010) ModEco: an integrated software package for ecological niche modeling. *Ecography* **33**(4): 637-642.

Gurrutxaga, M., Lozano, P. J. & del Barrio, G. (2010) GIS-based approach for incorporating the connectivity of ecological networks into regional planning. *Journal for Nature Conservation* **18**(4): 318-326.

Hamish, F. (2008) Abandoned farm land to create green corridor. *7:30 Report - Australian Broadcasting Corporation* (Journal Article).

Hanski, K. & Ovaskainen, O. (2003) Metapopulation theory for fragmented landscapes. *Theoretical Population Biology* **64**(1): 119-127.

Harper, M. J. (2005) Home range and den use of common brushtail possums (*Trichosurus vulpecula*) in urban forest remnants. *Wildlife Research* **32**(8): 681-687.

Harper, M. J., McCarthy, M. A. & van der Ree, R. (2005) The use of nest boxes in urban natural vegetation remnants by vertebrate fauna. *Wildlife Research* **32**(6): 509-516.

Harper, M. J., McCarthy, M. A. & Van Der Ree, R. (2008) Resources at the landscape scale influence possum abundance. *Austral Ecology* **33**(3): 243-243.

Havel, J. J. & Mattiske, E. M. (2000) *Vegetation Mapping of South West Forest Regions of Western Australia*: *A report for the Department of Conservation and Land Management and Environment Australia*, Perth Western Australia. Department of Conservation and Land Managment

Hawkes, P. G. (2010) A new species of Asphinctopone (*Hymenoptera: Formicidae: Ponerinae*) from Tanzania. *Zootaxa* (2480): 27-36.

Hearn, R., Williams, K., Comer, S. & Beecham, B. (2003) JF2 -Southern Jarrah Forest subregion. In: *A biodiveristy audit of Western Australia's biogeographical subregions in 2002*, eds. N. McKenzie & J. May, pp. 382-403. Kensington, W.A.: Department of Conservation and Land Mangagment.

Heller, N. E. & Zavaleta, E. S. (2008) Biodiversity management in the face of climate change: A review of 22 years of recommendations. *Biological Conservation* **142**(1): 14-32.

Herman, P. M. J., Ysebaert, T., Hewitt, J. E. & Thrush, S. (2005) Multi-scale analysis of species-environment relationships. *Marine Ecology Progress Series* **302**(Journal Article): 13-26.

Herzog, F., Lausch, A., MÜLler, E., Thulke, H.-H., Steinhardt, U. T. A. & Lehmann, S. (2001) Landscape Metrics for Assessment of Landscape Destruction and Rehabilitation. *Environmental Management* **27**(1): 91-107.

Higgins, P. J., Ambrose, S. J. & Marchant, S. (2006) *Handbook of Australian, New Zealand and Antarctic birds*. Melbourne: Oxford University Press.

Hijmans, R. J. (2012) Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. *Ecology* **93**(3): 679-688.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* **25**(15): 1965-1978.

Hijmans, R. J. & Graham, C. H. (2006) The ability of climate envelope models to predict the effect of climate change on species distributions. *Global Change Biology* **12**(12): 2272-2281.

Hijmans, R. J., Luigi Guarino & Prem Mathur. (2012) *Diva-GIS Version 7.5 Manual.* URL http://www.diva-gis.org/.

Hobbs, R. J. (1993a) Effects of landscape fragmentation on ecosystem processes in the Western Australian wheatbelt. *Biological Conservation* **64**(3): 193-201.

Hobbs, R. J. (1993b) Fragmented landscapes in Western Australia: An Introduction. *Biological Conservation* **64**(3): 183-184.

Hobbs, R. J. & Saunders, D. A. (1991) Wildlife corridors in the wheatbelt. *Journal of agriculture, Western Australia* (4 ser v 32(2)): 46-47.

Hobbs, R. J., Saunders, D. A. & Main, A. R. (1993) *Conservation management in fragmented systems*. Dusseldorf: Springer-Verlag.

Hobbs, R. J. & Yates, C. J. (2003) Impacts of ecosystem fragmentation on plant populations: generalising the idiosyncratic. *Australian Journal of Botany* **51**(5): 471-488.

Hodgson, J. A., Thomas, C. D., Wintle, B. A. & Moilanen, A. (2009) Climate Change, Connectivity and Conservation Decision Making: Back to Basics. *Journal of Applied Ecology* **46**(5): 964-969.

Holland, G. J. & Bennett, A. F. (2009) Differing responses to landscape change: implications for small mammal assemblages in forest fragments. *Biodiversity and Conservation* **18**(11): 2997-3016.

Hopper, S. D. (2009) OCBIL theory: towards an integrated understanding of the evolution, ecology and conservation of biodiversity on old, climatically buffered, infertile landscapes. *Plant and Soil* **322**(1-2): 49.

Hopper, S. D. & Gioia, P. (2004) The Southwest Australian Floristic Region: Evolution and Conservation of a Global Hot Spot of Biodiversity. *Annual Review of Ecology, Evolution, and Systematics* **35**(1): 623-650.

Horne, J. S. & Garton, E. O. (2006) Likelihood Cross-Validation versus Least Squares Cross-Validation for Choosing the Smoothing Parameter in Kernel Home-Range Analysis. *The Journal of Wildlife Management* **70**(3): 641-648.

How, R. A. & Hillcox, S. J. (2000) Brushtail possum, , populations in south-western Australia: demography, diet and conservation status. *Wildlife Research* **27**(1): 81-89.

Huber, P. R., Greco, S. E. & Thorne, J. H. (2010) Spatial scale effects on conservation network design: trade-offs and omissions in regional versus local scale planning. *Landscape Ecology* **25**(5): 683-695.

Huck, M., Davison, J. & Roper, T. J. (2008) Predicting European badger Meles meles sett distribution in urban environments. *Wildlife Biology* **14**(2): 188-198.

Huggett, A. (2007) A review of the focal species approach in Australia. In: *Knowledge for managing Australian landscapes*, Canberra: Land & Water Australia.

Hughes, L. (2003) Climate change and Australia: Trends, projections and impacts. *Austral Ecology* **28**(4): 423-443.

Hughes, L. (2011) Climate change and Australia: key vulnerable regions. *Regional Environmental Change* **11**(1): 189-195.

Hui, C., McGeoch, M. A. & Warren, M. (2006) A Spatially Explicit Approach to Estimating Species Occupancy and Spatial Correlation. *Journal of Animal Ecology* **75**(1): 140-147.

Hutchinson, G. E. (1957) Concluding remarks. *Cold Spring Harbor Symposia on Quantitative Biology* **22**: 415-427.

Indian Ocean Climate Initiative. (2012) *Western Australia's Weather and Cimate: A Synthesis of Indian Ocean Climate Initiative Stage 3 Research*. Canberra: Commonwealth Scientific and Industrial Research Organisation and Bureau of Meteorology.

IPCC. (2007) Summary for policymakers. In: *Climate Change 2007: the Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, eds. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor & H. L. Miller, pp. 433-497. Cambridge and New York.: Cambridge University Press.

Januchowski, S., McAlpine, C. A., Callaghan, J. G., Griffin, C. B., Bowen, M., Mitchell, D. & Lunney, D. (2008) Identifying multiscale habitat factors influencing koala (Phascolarctos cinereus) occurrence and management in Ballarat, Victoria, Australia. *Ecological Management & Restoration* **9**(2): 134.

Ji, W., Sarre, S. D., Craig, J. L. & Clout, M. N. (2003) Denning Behavior of Common Brushtail Possums in Populations Recovering from Density Reduction. *Journal of Mammalogy* **84**(3): 1059-1067.

Jimenez-Valverde, A., Decae, A. E. & Arnedo, M. A. (2011) Environmental suitability of new reported localities of the funnelweb spider Macrothele calpeiana: an assessment using potential distribution modelling with presence-only techniques. *Journal of Biogeography* **38**(6): 1213-1223.

Jones, B. (2004) The Possum Fauna of Western Australia: Decline Persistence and Status. In: *The Biology of Australian Possums and Gliders*, pp. 149-160. Chipping Norton: Surrey Beatty & Sons.

Jones, B., Henry, J. & Francesconi, B. (2007) *An important local population of the Western Ringtail Possum Pseudocheirus occidentalis: a 2006 survey study of the population and habitat in the Busselton localities of Siesta Park and Kealy*. Busselton WA: Geocatch.

Jones, B. & Hillcox, S. (1995) A survey of the possums Trichosurus vulpecula and Pseudocheirus occidentalis ad their habitats at Ludlow, Western Australia. *Western Australian Naturalist* **20**(3): 139-150.

Jones, B., How, R. & Kitchener, D. (1994) A Field-Study of *Pseudocheirus-Occidentalis* (*Marsupialia, Petauridae*) .1. Distribution and Habitat. *Wildlife Research* **21**(2): 175-187.

Karanth, K. K., Curran, L. M. & Reuning-Scherer, J. D. (2006) Village size and forest disturbance in Bhadra Wildlife Sanctuary, western Ghats, India. *Biological Conservation* **128**(2): 147-157.

Karr, J. R. (1991) Biological Integrity: A Long-Neglected Aspect of Water Resource Management. *Ecological Applications* **1**(1): 66-84.

Kerle, J. A., Mckay, G. M. & Sharman, G. B. (1991) A Systematic Analysis of the *Brushtail Possum, Trichosurus-Vulpecula* (Kerr, 1792) (*Marsupialia, Phalangeridae*). *Australian Journal of Zoology* **39**(3): 313-331.

Khatchikian, C., Sangermano, F., Kendell, D. & Livdahl, T. (2011) Evaluation of species distribution model algorithms for fine-scale container-breeding mosquito risk prediction. *Medical and Veterinary Entomology* **25**(3): 268-275.

Kindlmann, P. & Burel, F. (2008) Connectivity measures: a review. *Landscape Ecology* **23**(8): 879-890.

Klausmeyer, K. R. & Shaw, M. R. (2009) Climate change, habitat loss, protected areas and the climate adaptation potential of species in mediterranean ecosystems worldwide. *PloS one* **4**(7): e6392.

Klenk, N. L. & Hickey, G. M. (2011) A virtual and anonymous, deliberative and analytic participation process for planning and evaluation: The Concept Mapping Policy Delphi. *International Journal of Forecasting* **27**(1): 152-165.

Kobayashi, T., Watanabe, K., Higuchi, T., Miyajima, T. & Otsu, N. (2009) Recognition of Dynamic Texture Patterns Using CHLAC Features and Linear Regression. *International Journal of Database Theory & Application* **2**(4): 13-26.

Kontic, D. & Kontic, B. (2009) Introduction of threat analysis into the land-use planning process. *Journal of Hazardous Materials* **163**(2-3): 683-700.

Kupfer, J. A. (2012) Landscape ecology and biogeography: Rethinking landscape metrics in a post-FRAGSTATS landscape. *Progress in Physical Geography* **36**(3): 400-420.

Lafortezza, R., Coomes, D. A., Kapos, V. & Ewers, R. M. (2010) Assessing the impacts of fragmentation on plant communities in New Zealand: scaling from survey plots to landscapes. *Global Ecology and Biogeography* **19**(5): 741-754.

Lambeck, R. J. (1997) Focal species: A multi-species umbrella for nature conservation. *Conservation Biology* **11**(4): 849-856.

Lambeck, R. J. (1999) *Landscape Planning for Biodiversity Conservation in Agricultural Regions: A case studey from the wheatbelt of Western Australia*. Canberra: CSIRO Press.

Landgate. (2011) *Shared Land Information Platform.* URL https://www2.landgate.wa.gov.au/web/guest.

Langford, W. T., Gordon, A. & Bastin, L. (2009) When do conservation planning methods deliver? Quantifying the consequences of uncertainty. *Ecological Informatics* **4**(3): 123-135.

Lawes, R. A. & Dodd, M. B. (2009) Does re-vegetating poor-performing patches in agricultural fields improve ecosystem function in the northern sandplain of the Western Australian wheatbelt? *Crop & Pasture Science* **60**(9): 912-920.

Lawler, J. J. & Edwards, T. C. (2002) Landscape patterns as habitat predictors: building and testing models for cavity-nesting birds in the Uinta Mountains of Utah, USA. *Landscape Ecology* **17**(3): 233-245.

Lawson, C. R., Bennie, J. J., Thomas, C. D., Hodgson, J. A. & Wilson, R. J. (2012) Local and landscape management of an expanding range margin under climate change. *Journal of Applied Ecology* **49**(3): 552-561.

le Mar, K. & McArthur, C. (2005) Habitat selection by common brushtail possums in a patchy eucalypt-forestry environment. *Australian Mammalogy* **27**(2): 119-127.

Lindenmayer, D. & Fischer, J. (2006) *Habitat fragmentation and landscape change : an ecological and conservation synthesis*. Collingwood, Vic.: CSIRO.

Lindenmayer, D., Hobbs, R. J., Montague-Drake, R., Alexandra, J., Bennett, A., Burgman, M., Cale, P., Calhoun, A., Cramer, V., Cullen, P., Driscoll, D., Fahrig, L., Fischer, J., Franklin, J., Haila, Y., Hunter, M., Gibbons, P., Lake, S., Luck, G., MacGregor, C., McIntyre, S., Mac Nally, R., Manning, A., Miller, J., Mooney, H., Noss, R., Possingham, H., Saunders, D., Schmiegelow, F., Scott, M., Simberloff, D., Sisk, T., Tabor, G., Walker, B., Wiens, J., Woinarski, J. & Zavaleta, E. (2008) A checklist for ecological management of landscapes for conservation. *Ecology Letters* **11**(1): 78-91.

Lindenmayer, D. B., Manning, A. D., Smith, P. L., Possingham, H. P., Fischer, J., Oliver, I. & McCarthy, M. A. (2002) The Focal-Species Approach and Landscape Restoration: A Critique. *Conservation Biology* **16**(2): 338-345.

Lindenmayer, D. B. & Nix, H. A. (1993) Ecological Principles for the Design of Wildlife Corridors. *Conservation Biology* **7**(3): 627-630.

Lindenmayer, D. B., Pope, M. L. & Cunningham, R. B. (2004) Patch use by the greater glider (Petauroides volans) in a fragmented forest ecosystem. II. Characteristics of den trees and preliminary data on den-use patterns. *Wildlife Research* **31**(6): 569-577.

Lindenmayer, D. B., Welsh, A. & Donnelly, C. F. (1997) Use of Nest Trees by the Mountain Brushtail Possum (*Trichosurus vulpecula*) (Phalangeridae : Marsupialia). III.

Spatial Configuration and Co-occupancy of Nest Trees. *Wildlife Research* **24**(6): 661-677.

Littell, J. S., Oneil, E. E., McKenzie, D., Hicke, J. A., Lutz, J. A., Norheim, R. A. & Elsner, M. M. (2010) Forest ecosystems, disturbance, and climatic change in Washington State, USA. *Climatic Change* **102**(1): 129-158.

Liu, I. & Suesse, T. (2008) The analysis of stratified multiple responses. *Biometrical journal. Biometrische Zeitschrift* **50**(1): 135-149.

Lovett, S., Lambert, J., Williams, J. E. & Price, P. (2008) *Restoring landscapes with confidence — an evaluation of the science, the methods and their on-ground application. Final Report*. Canberra: Land and Water Australia..

Lumpkin, S. & Seidensticker, J. (2006) Building an arc (Terai Arc). *Smithsonian* **37**(4): 56-63.

Luque, S., Saura, S. & Fortin, M.-J. (2012) Landscape connectivity analysis for conservation: insights from combining new methods with ecological and genetic data. *Landscape Ecology* **27**(2): 153-157.

Mac Nally, R. (2000) Regression and model-building in conservation biology, biogeography and ecology: The distinction between, and reconciliation of, ‘predictive’ and ‘explanatory’ models. *Biodiversity and Conservation* **9**(5): 655-671.

Macfarlane, C., Arndt, S. K., Livesley, S. J., Edgar, A. C., White, D. A., Adams, M. A. & Eamus, D. (2007) Estimation of leaf area index in eucalypt forest with vertical foliage, using cover and fullframe fisheye photography. *Forest Ecology and Management* **242**(2): 756-763.

Mackey, B., Watson, J., Worboys, G. L., ANU Enterprises (Firm), New South Wales. Dept. of Environment Climate Change and Water. & Interstate Agency Working Group (Alps to Atherton Connectivity Conservation Working Group). (2010) *Connectivity conservation and the Great Eastern Ranges corridor*. URL http://www.environment.nsw.gov.au/resources/nature/ccandger.pdf.

Majka, D. R., Spencer, W. D. & Beier, P. (2008) Forks in the Road: Choices in Procedures for Designing Wildland Linkages. *Conservation Biology* **22**(4): 836-851.

Malenovský, Z., Mishra, K. B., Zemek, F., Rascher, U. & Nedbal, L. (2009) Scientific and technical challenges in remote sensing of plant canopy reflectance and fluorescence. *Journal of experimental botany* **60**(11): 2987-3004.

Marcial, L. H. & Hemminger, B. M. (2010) Scientific data repositories on the Web: An initial survey. *Journal of the American Society for Information Science & Technology* **61**(10): 2029-2048.

Mateo, R. G., Croat, T. B., Felicisimo, A. M. & Munoz, J. (2010) Profile or group discriminative techniques? Generating reliable species distribution models using pseudo-absences and target-group absences from natural history collections. *Diversity and Distributions* **16**(1): 84-94.

Maxwell, S., Burbidge, A. A., Morris, K., Wildlife, A. & Endangered Species, P. (1996) *The 1996 action plan for Australian marsupials and monotremes / edited by Stephanie Maxwell, Andrew A. Burbidge and Keith Morris ; for the Australasian Marsupial and Monotreme Specialist Group, IUCN Species Survival Commission*. Canberra: Department of Environment and Conservation.

May, S. A. & Norton, T. W. (1996) Influence of fragmentation and disturbance on the potential impact of feral predators on native fauna in Australian forest ecosystems. *Wildlife Research* **23**(4): 387-400.

McCullagh, P. & Nelder, J. A. (1983) *Generalized linear models*. London; New York: Chapman and Hall.

McGarigal, K., Stafford, S. G. & Cushman, S. (2000) *Multivariate statistics for wildlife and ecology research*. New York: Springer.

McGarigal, K., Tagil, S. & Cushman, S. A. (2009) Surface metrics: an alternative to patch metrics for the quantification of landscape structure. *Landscape Ecology* **24**(3): 433-450.

McInerny, G. J., Turner, J. R. G., Wong, H. Y., Travis, J. M. J. & Benton, T. G. (2009) How range shifts induced by climate change affect neutral evolution. *Proceedings of the Royal Society B: Biological Sciences* **276**(1661): 1527-1534.

McKenzie, N. L. & May, J. E. (2003) *A biodiversity audit of Western Australia's biogeographical subregions in 2002*. Kensington, W.A.: Dept. of Conservation & Land Management.

McLane, A. J., Semeniuk, C., McDermid, G. J. & Marceau, D. J. (2011) The role of agent-based models in wildlife ecology and management. *Ecological Modelling* **222**(8): 1544-1556.

Melles S.J., D. Badzinski D, M.-J. Fortin, F. Csillag and K. Lindsay. (2009) Disentangling habitat and social drivers of nesting patterns in songbirds. *Landscape Ecology* **24**: 519-531.

Mersey, J. E., Millward, A. A. & Martinez, L. M. (2002) Realizing the potential of GIS in community-based management of protected areas. *International Journal of Sustainable Development and World Ecology* **9**(3): 208-222.

Metzger, K. L., Sinclair, A. R. E., Hilborn, R., Hopcraft, J. G. C. & Mduma, S. A. R. (2010) Evaluating the protection of wildlife in parks: the case of African buffalo in Serengeti. *Biodiversity and Conservation* **19**(12): 3431-3444.

Milad, M., Schaich, H., Bürgi, M. & Konold, W. (2011) Climate change and nature conservation in Central European forests: A review of consequences, concepts and challenges. *Forest Ecology and Management* **261**(4): 829-843.

Molloy, S., O'Connor, T., Wood, J. & Wallrodt, S. (2007) *Local government biodiversity planning guidelines for the Perth metropolitan region : addendum for the South West Biodiversity Project area*. Perth: Western Australian Local Government Association.

Molloy, S., Wood, J., Hall, S., Wallrodt, S. & Whisson, G. (2009) *South West Regional Ecological Linkages Technical Report*. Perth: Western Australian Local Government Association and Western Australian Department of Environment and Conservation.

Monk, J., Ierodiaconou, D., Versace, V. L., Bellgrove, A., Harvey, E., Rattray, A., Laurenson, L. & Quinn, G. P. (2010) Habitat suitability for marine fishes using presence-only modelling and multibeam sonar. *Marine Ecology-Progress Series* **420**: 157-174.

Moore, B. D., Wallis, I. R., Pala-Paul, J., Brophy, J. J., Willis, R. H. & Foley, W. J. (2004) Antiherbivore chemistry of Eucalyptus - Cues and deterrents for marsupial folivores. *Journal of Chemical Ecology* **30**(9): 1743-1769.

Moore, J. E. & Swihart, R. K. (2005) Modeling Patch Occupancy by Forest Rodents: Incorporating detectability and spatial autocorreltation with hierarchically structured data. *Journal of Wildlife Management* **69**(3): 933.

Morris, K., Burbidge, A. & Friend, T. (2008) *Pseudocheirus occidentalis*. In: IUCN 2012. IUCN Red List of Threatened Species. Version 2012.1. URL www.iucnredlist.org.

Myers, N., Mittermeier, R. A., Mittermeier, C. G., da Fonseca, G. A. B. & Kent, J. (2000) Biodiversity hotspots for conservation priorities. *Nature* **403**(6772): 853-858.

National Biodiversity Strategy Review Task Group. (2009) *Australia's Biodiversity Conservation Strategy 2010–2020 Consultation draft*. Perth: Department of Environment, Water, Heritage and the Arts.

Navarro-Cerrillo, R. M., Hernandez-Bermejo, J. E. & Hernandez-Clemente, R. (2011) Evaluating models to assess the distribution of *Buxus balearica* in southern Spain. *Applied Vegetation Science* **14**(2): 256-267.

Nersesian, C. L., Banks, P. B. & McArthur, C. (2012) Behavioural responses to indirect and direct predator cues by a mammalian herbivore, the common brushtail possum. *Behavioral Ecology and Sociobiology* **66**(1): 47-55.

New South Wales. Dept. of Environment and Climate Change, New South Wales. Dept. of Environment Climate Change and Water & Environmental Trust (N.S.W.). (2007) *Alps to Atherton Initiative : a continental-scale lifeline to engage people with nature : NSW business plan, 2007-2010*. Sydney South, N.S.W.: Dept. of Environment and Climate Change.

Opdam, P., Luque, S. & Jones, K. B. (2009) Changing landscapes to accommodate for climate change impacts: a call for landscape ecology. *Landscape Ecology* **24**(6): 715-721.

Oreskes, N., Shrader-Frechette, K. & Belitz, K. (1994) Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences. *Science* **263**(5147): 641-646.

Patt, M. (1995) *The free-ranging population of the brush-tail possum, Trichosurus vulpecula Kerr, in the urban enrionment of the Perth Zoo; population estimates and managment implications*. B.Sc. Honours B.Sc. Honours, Edith Cowan University.

Paull, D. J. (2003) *Habitat fragmentation and the southern brown bandicoot Isoodon obesulus at multiple spatial scales.* PhD, Doctoral Thesis, University of New South Wales - Australian Defence Force Academy. School of Physical, Environmental and Mathematical Sciences.

Pearson, R. G. (2004) *Modelling the potential impacts of climate change and landscape fragmentation on the distribution of species*. United Kingdom: Oxford University.

Pearson, R. G. & Dawson, T. P. (2003) Predicting the Impacts of Climate Change on the Distribution of Species: Are Bioclimate Envelope Models Useful? *Global Ecology and Biogeography* **12**(5): 361-371.

Pearson, R. G. & Dawson, T. P. (2005) Long-distance plant dispersal and habitat fragmentation: identifying conservation targets for spatial landscape planning under climate change. *Biological Conservation* **123**(3): 389-401.

Peeters, E. T. H. M., Gardeniers & Jean, J. P. (1998) Logistic regression as a tool for defining habitat requirements of two common gammarids. *Freshwater Biology* **39**(4): 605-615.

Perkins, S. E., Pitman, A. J., Holbrook, N. J. & McAneney, J. (2007) Evaluation of the AR4 Climate Models' Simulated Daily Maximum Temperature, Minimum Temperature, and Precipitation over Australia Using Probability Density Functions. *Journal of Climate* **20**(17): 4356-4376.

Phillips, S. J., Anderson, R. P. & Schapire, R. E. (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* **190**(3): 231-259.

Phillips, S. J. & Dudík, M. (2008) Modeling of Species Distributions with Maxent: New Extensions and a Comprehensive Evaluation. *Ecography* **31**(2): 161-175.

Possingham, H., Ball, I. & Andelman, S. (1998) Mathematical methods for identifying representative reserve networks. *Quantitative Methods for Conservation Biology*: 291-306.

Possingham, H., Kearns, A., Jarman, P., Start, A. N., Mawson, P. R. & Western Australia. Dept. of Conservation and Land Management. (2004) *A review of Western Shield program*. Como. W.A.: Dept. of Conservation and Land Management.

Potvin, F., K. Lowell, M.-J. Fortin and L. Belanger. (2001) How to test habitat selection at the home range scale: a resampling random windows technique. Ecoscience **8**: 399-406.

Pressey, R. L. & Bottrill, M. C. (2008) Opportunism, threats, and the evolution of systematic conservation planning. *Conservation Biology* **22**(5): 1340-1345.

Prober, S. M., Lemson, K., Lyons, T., Macfarlane, C., O’Connor, M. H., Scott, J. K., Standish, R. J., Stock, W. D., van Etten, E. J. B., Wardell-Johnson, G. W., Watson, A., Thiele, K. R., Rundel, P. W., Yates, C. J., Berry, S. L., Byrne, M., Christidis, L., Gosper, C. R. & Grierson, P. F. (2012) Facilitating adaptation of biodiversity to climate change: a conceptual framework applied to the world’s largest Mediterranean-climate woodland. *Climatic Change* **110**(1): 227-248.

Pryor, K. J. (2003) *Habitat fragmentation*. South Yarra, Vic.: Macmillan Education.

Ramachandra, T. V. & Uttam, K. (2011) Characterisation of Landscape with Forest Fragmentation Dynamics. *Journal of Geographic Information System* **3**(3): 234-246.

Ramakrishna, A. & Ravishankar, G. A. (2011) Influence of abiotic stress signals on secondary metabolites in plants. *Plant Signaling & Behavior* **6**(11): 1720-1731

Ramirez, J. & Jarvis, A. (2008) *High Resolution Statistically Downscaled Future Climate Surfaces*. URL http://www.ccafs-climate.org/about/.

Randin, C. F., Dirnböck, T., Dullinger, S., Zimmermann, N. E., Zappa, M. & Guisan, A. (2006) Are Niche-Based Species Distribution Models Transferable in Space? *Journal of Biogeography* **33**(10): 1689-1703.

Rastetter, E. B. (2003) The collision of hypotheses: What can be learned from comparisons of ecosystem models? pp. 211-224 In: Canham, C.D., J.J. Cole, and W.K. Lauenroth, editors. *Models in Ecosystem Science.* Princeton (NJ): Princeton University Press.

Reiss, H., Cunze, S., Konig, K., Neumann, H. & Kroncke, I. (2011) Species distribution modelling of marine benthos: a North Sea case study. *Marine Ecology-Progress Series* **442**: 71-86.

Richardson, K., Steffen, W. L. & Liverman, D. (2011) *Climate change: global risks, challenges and decisions*. New York: Cambridge University Press.

Richardson, R. G. (2007) Western weeds: a guide to the weeds of Western Australia - 2nd edition. *Plant Protection Quarterly* **22**(4): 160.

Rijavec, F., Harrison, N. & Bradby, K. (2002*) A million acres a year*. Sydney, N.S.W Film Australia.

Robertson, O. J. & Radford, J. Q. (2009) Gap-crossing decisions of forest birds in a fragmented landscape. *Austral Ecology* **34**(4): 435-446.

Robinson, N., Siewert, R., Horwitz, P. & Conservation Council of Western, A. (1993) *Impact and control of feral animals in South-Western Australia: proceedings of a seminar with workshops held at Edith Cowan University, Churchlands Campus.* Perth, Western Australia, 29 and 30 November, 1993. Perth, W.A: Conservation Council of Westen Australia.

Rodrigues, A. S. L. & Brooks, T. M. (2007) Shortcuts for Biodiversity Conservation Planning: The Effectiveness of Surrogates. *Annual Review of Ecology, Evolution, and Systematics* **38**(Journal Article): 713-737.

Rouget, M., Cowling, R. M., Lombard, A. T., Knight, A. T. & Kerley, G. I. H. (2006) Designing large-scale conservation corridors for pattern and process. *Conservation Biology* **20**(2): 549-561.

Ruggiero, L. F., Hayward, G. D. & Squires, J. R. (1994) Viability Analysis in Biological Evaluations - Concepts of Population Viability Analysis, Biological Population, and Ecological Scale. *Conservation Biology* **8**(2): 364-372.

Sampson, J. C. (1971) *The biology of Bettongia penicillata Gray,* 1837. Ph.D. Dissertation, University of Western Australia.

Santika, T. & Hutchinson, M. F. (2009) The effect of species response form on species distribution model prediction and inference. *Ecological Modelling* **220**(19): 2365-2379.

Saunders, D. A. (1990) Problems of survival in an extensively cultivated landscape: the case of Carnaby's cockatoo Calyptorhynchus funereus latirostris. *Biological Conservation* **54**(3): 277-290.

Saura, S. & Rubio, L. (2010) A common currency for the different ways in which patches and links can contribute to habitat availability and connectivity in the landscape. *Ecography* **33**(3): 523-537.

Schmolke, A., Thorbek, P., DeAngelis, D. L. & Grimm, V. (2010) Ecological models supporting environmental decision making: a strategy for the future. *Trends in Ecology & Evolution* **25**(8): 479-486.

Schooley, R. L. & Branch, L. C. (2011) Habitat quality of source patches and connectivity in fragmented landscapes. *Biodiversity and Conservation* **20**(8): 1611-1623.

Schuurman, N. (2004) *GIS: a Short Introduction.* Oxford UK.: Blackwell Publishing Ltd.

Scrivener, N. J., Johnson, C. N., Wallis, I. R., Takasaki, M., Foley, W. J. & Krockenberger, A. K. (2004) Which trees do wild common brushtail possums (*Trichosurus vulpecula*) prefer? Problems and solutions in scaling laboratory findings to diet selection in the field. *Evolutionary Ecology Research* **6**(1): 77-87.

Sgrò, C. M., Lowe, A. J. & Hoffmann, A. A. (2011) Building evolutionary resilience for conserving biodiversity under climate change. *Evolutionary Applications* **4**(2): 326-337.

Shaw, M. R., Daily, G. C., Cameron, D. R., Chan, K. M. A. & Underwood, E. C. (2006) Conservation Planning for Ecosystem Services. *PLoS Biology* **4**(11): e379-2152.

Shimodaira, H. (1998) An Application of Multiple Comparison Techniques to Model Selection. *Annals of the Institute of Statistical Mathematics* **50**(1): 1-13.

Shoo, L., Hoffmann, A., Garnett, S., Pressey, R., Williams, Y., Taylor, M., Falconi, L., Yates, C., Scott, J., Alagador, D. & Williams, S. (2013) Making decisions to conserve species under climate change. *Climatic Change* **119**(2): 239-246.

Shortridge, G. C. (1909) An account of the geographical distribuion of the marsupials and monotremes of south-west Australia, having special reference to the specimens collected during the Balston Expedition of 1904-1907. *Proceedings of the Zoological Society* **55**: 803-848.

Shova, T. & Hubacek, K. (2011) Drivers of illegal resource extraction An analysis of Bardia National Park, Nepal. *Journal of Environmental Management* **92**(1): 156-164.

Šímová, P. & Gdulová, K. (2012) Landscape indices behavior: A review of scale effects. *Applied Geography* **34**(Journal Article): 385-394.

Simpson, R. D. (1999) The price of biodiversity. *Issues in Science and Technology* **15**(3): 65.

Sitzia, T., Semenzato, P. & Trentanovi, G. (2010) Natural reforestation is changing spatial patterns of rural mountain and hill landscapes: A global overview. *Forest Ecology and Management* **259**(8): 1354-1362.

Skidmore, A. (2002) *Environmental modelling with GIS and remote sensing*. New York: Taylor & Francis.

Smith, A., Lambeck, R. J. & Greening Australia (W.A.). (2004) *Living landscapes : the story of a successful landcare program in Western Australia*. Fremantle, W.A.: Greening Australia (WA) Inc.

Smith, C. S., Howes, A. L., Price, B. & McAlpine, C. A. (2007) Using a Bayesian belief network to predict suitable habitat of an endangered mammal - The Julia Creek dunnart (*Sminthopsis douglasi*). *Biological Conservation* **139**(3-4): 333-347.

Smith, F. P. (2008) Who's planting what, where and why - and who's paying? An analysis of farmland revegetation in the central wheatbelt of Western Australia. *Landscape and Urban Planning* **86**(1): 66-78.

Smith, R. J., Goodman, P. S. & Matthews, W. S. (2006) Systematic conservation planning: a review of perceived limitations and an illustration of the benefits, using a case study from Maputaland, South Africa. *Oryx* **40**(4): 400-410.

Stankowski, P. A. & Parker, W. H. (2010) Species distribution modelling: Does one size fit all? A phytogeographic analysis of Salix in Ontario. *Ecological Modelling* **221**(13-14): 1655-1664.

Stow, A. J., Minarovic, N., Eymann, J., Cooper, D. W. & Webley, L. S. (2006) Genetic structure infers generally high philopatry and male-biased dispersal of brushtail possums (*Trichosurus vulpecula*) in urban Australia. *Wildlife Research* **33**(5): 409-415.

Strelein, G., Swain, D., Miller, J., Ball, S. & Green, M. (2007) SCRIPT *Dieback Risk Analysis. Pytophthora cinnamomi: Mapping the Threats and Building the Capacity to Manage Them*. Perth: Department of Conservation and Land Management Western Australia.

Tattoni, C., Ciolli, M. & Ferretti, F. (2011) The Fate of Priority Areas for Conservation in Protected Areas: A Fine-Scale Markov Chain Approach. *Environmental Management* **47**(2): 263-278.

Tattoni, C., Ciolli, M., Ferretti, F. & Cantiani, M. G. (2010) Monitoring spatial and temporal pattern of Paneveggio forest (northern Italy) from 1859 to 2006. *Biogeosciences and Forestry* **3**(1): 72-80.

Thackway, R. M. & Cresswell, I. D. (1995) *An interim bio-geographic regionalisation for Australia: a framework for setting priorities in the national reserves system cooperative program.* Canberra: Australian Nature Conservation Agency.

Tischendorf, L. & Fahrig, L. (2000a) How should we measure landscape connectivity? *Landscape Ecology* **15**(7): 633-641.

Tischendorf, L. & Fahrig, L. (2000b) On the usage and measurement of landscape connectivity. *Oikos* **90**(1): 7-19.

Tjørve, E. (2002) Habitat size and number in multi-habitat landscapes: a model approach based on species-area curves. *Ecography* **25**(1): 17-24.

TNC. (2007) *Conservation Action Planning Handbook: Developing Strategies, Taking Action and Measuring Success at Any Scale.* Arlington Va.: The Nature Conservancy.

Tognelli, M. F., Roig-Junent, S. A., Marvaldi, A. E., Flores, G. E. & Lobo, J. M. (2009) An evaluation of methods for modelling distribution of Patagonian insects. *Revista Chilena De Historia Natural* **82**(3): 347-360.

Turner, M. G., Arthaud, G. J., Engstrom, R. T., Hejl, S. J., Liu, J. G., Loeb, S. & Mckelvey, K. (1995) Usefulness of Spatially Explicit Population-Models in Land Management. *Ecological Applications* **5**(1): 12-16.

UCMERCED. (2011) ModEco Homepage. URL http://gis.ucmerced.edu/ModEco/.

Urban, D. L., Minor, E. S., Treml, E. A. & Schick, R. S. (2009) Graph models of habitat mosaics. *Ecology Letters* **12**(3): 260-273.

Van Horne, B. (1983) Density as a Misleading Indicator of Habitat Quality. *The Journal of Wildlife Management* **47**(4): 893-901.

Vapnik, V. N. (1995) *The nature of statistical learning theory*. New York: Springer.

Vasconcelos, T. S., Rodríguez, M. Á. & Hawkins, B. A. (2012) Species distribution modelling as a macroecological tool: a case study using New World amphibians. *Ecography* **35**(6): 539-548.

Voelk, F. H., Woess, M. & Grillmayer, R. (2002) Green bridges and wildlife corridors in Austria Grünbrücken und Wildkorridore in österreich. *Zeitschrift für Jagdwissenschaft* **48**(1): 25-32.

Vos, C. C., Berry, P., Opdam, P., Baveco, H., Nijhof, B., O'Hanley, J., Bell, C., Kuipers, H. & Nijho, B. (2008) Adapting Landscapes to Climate Change: Examples of Climate-Proof Ecosystem Networks and Priority Adaptation Zones. *Journal of Applied Ecology* **45**(6): 1722-1731.

Wallace, K. J. (1998) *Dongolocking pilot planning project for remnant vegetation. Phase 1., Final report*. Como, W.A.: Dept. of Conservation and Land Management and Environment Australia.

Wallis, I. R., Watson, M. L. & Foley, W. J. (2002) Secondary metabolites in Eucalyptus melliodora: field distribution and laboratory feeding choices by a generalist herbivore, the common brushtail possum. *Australian Journal of Zoology* **50**(5): 507-519.

Wathern, P. (1988) *Environmental impact assessment: theory and practice*. London: Routledge.

Watson, A., Judd, S., Watson, J., Lam, A. & McKenzie, D. (2008) *The Extraordinary Nature of the Great Western Woodlands.* Perth: The Wildlife Society of WA Inc.

Watson, I. (2003) *Fragmented futures : new challenges in working life*. Annandale, N.S.W.: Federation Press.

Watson, J., Freudenberger, D. & Paull, D. (2001) An Assessment of the Focal-Species Approach for Conserving Birds in Variegated Landscapes in Southeastern Australia. *Conservation Biology* **15**(5): 1364-1373.

Watson, J. E. M., Whittaker, R. J. & Freudenberger, D. (2005) Bird community responses to habitat fragmentation: how consistent are they across landscapes? *Journal of Biogeography* **32**(8): 1353-1370.

Watts, M. E., Ball, I. R., Stewart, R. S., Klein, C. J., Wilson, K., Steinback, C., Lourival, R., Kircher, L. & Possingham, H. P. (2009) Marxan with Zones: Software for optimal conservation based land- and sea-use zoning. *Environmental Modelling & Software* **24**(12): 1513-1521.

Wayne, A. (2009) New Conservation Initiative to Save the Woylie from Extinction in the Wild. *Pacific Conservation Biology* **15**(4).

Wayne, A. F., Cowling, A., Lindenmayer, D. B., Ward, C. G., Vellios, C. V., Donnelly, C. F. & Calvey, M. C. (2006) The abundance of a threatened arboreal marsupial in relation to anthropogenic disturbances at local and landscape scales in Mediterranean-type forests in south-western Australia. *Biological Conservation* **127**(4): 463-476.

Wayne, A. F., Rooney, J. F., Ward, C. G., Vellios, C. V. & Lindenmayer, D. B. (2005a) The life history of *Pseudocheirus occidentalis* (Pseudocheiridae) in the jarrah forest of south-western Australia. *Australian Journal of Zoology* **53**(5): 325-337.

Wayne, A. F., Ward, C. G., Rooney, J. F., Vellios, C. V. & Lindenmayer, D. B. (2005b) The life history of *Trichosurus vulpecula hypoleucus* (Phalangeridae) in the jarrah forest of south-western Australia. *Australian Journal of Zoology* **53**(4): 265-278.

Welsh, A. H., Lindenmayer, D. B. & Donnelly, C. F. (2013) Fitting and interpreting occupancy models. *PLoS One, 01/2013, Volume 8, Issue 1* **8**(1): e52015.

White, G. C. & Burnham, K. P. (1999) Program MARK: survival estimation from populations of marked animals. *Bird Study* **46 Suppl 1**(Journal Article): 120-139.

Williams, S. E., Shoo, L. P., Isaac, J. L., Hoffmann, A. A. & Langham, G. (2008) Towards an integrated framework for assessing the vulnerability of species to climate change. *PLoS Biology* **6**(12): 2621.

Wilson, A. M. & Lindenmayer, D. (1995) *Wildlife corridors and the conservation of biodiversity : a review*. Canberra: Centre for Resource and Environmental Studies, Australian National University.

Wilson, K. J. (2009) *Quantifying the Genetic Effects of Habitat Fragmentation on the Western Ringtail Possums (Pseudocheirus occidentalis) in South-West Western Australia.* Honours Thesis. Murdoch University.

WorldClim. (2012) Global Climate Data Base. URL http://worldclim.org/.

Wormington, K. R., Lamb, D., McCallum, H. I. & Moloney, D. J. (2005) The Status of Hollow-bearing Trees Required for the Conservation of Arboreal Marsupials in the Dry Sclerophyll Forests of South-east Queensland, Australia. *Pacific Conservation Biology* **11**(1): 38-49.

Yates, C. J., Elith, J., Latimer, A. M., Le Maitre, D., Midgley, G. F., Schurr, F. M. & West, A. G. (2010a) Projecting climate change impacts on species distributions in megadiverse South African Cape and Southwest Australian Floristic Regions: Opportunities and challenges. *Austral Ecology* **35**(4): 374-374.

Yates, C. J., McNeill, A., Elith, J. & Midgley, G. F. (2010b) Assessing the impacts of climate change and land transformation on Banksia in the South West Australian Floristic Region. *Diversity and Distributions* **16**(1): 187-201.

Yin, H. K. (2006) *The metabolic and hygric physiology of the western ringtail possum (Pseudocheirus occidentalis).* Honours Thesis, Curtin University.

Zafra-Calvo, N., Cerro, R., Fuller, T., Lobo, J. M., Rodriguez, M. A. & Sarkar, S. (2010) Prioritizing areas for conservation and vegetation restoration in post-agricultural landscapes: A Biosphere Reserve plan for Bioko, Equatorial Guinea. *Biological Conservation* **143**(3): 787-794.

Zielinski, W. J., Carroll, C. & Dunk, J. R. (2006) Using landscape suitability models to reconcile conservation planning for two key forest predators. *Biological Conservation* **133**(4): 409-430.

Ziska, L. H., Blumenthal, D. M., Runion, G. B., Hunt Jr, E. R. & Diaz-Soltero, H. (2011) Invasive species and climate change: an agronomic perspective. *Climatic Change* **105**(1): 13-42.