

The current distribution of the Striped Legless Lizard, *Delma impar*, in south western Victoria: predicting habitat associations at a landscape scale

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DECLARATION

This thesis is my original work and has not been presented in any other degree or at any other university. To the best of my knowledge this work does not contain the works or ideas of others, except where this is referenced within the text.

A handwritten signature in black ink, appearing to read "Gemma Candy".

Gemma Candy, July 2008

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ABSTRACT

This thesis is concerned with the distribution of the Striped Legless Lizard, *Delma impar*, in south western Victoria. The Striped Legless Lizard is a small grassland reptile, which is reported to be declining within its range in south eastern Australia. It is listed as an endangered species under the national Environment Protection and Biodiversity Conservation Act 1999, and is recognised by protective state and territory legislation in South Australia, Victoria, New South Wales and the Australian Capital Territory. The species is associated with temperate tussock grasslands which have been extensively lost or modified since European settlement, with only small disjunct remnants remaining. Clarification of the current distribution of *D. impar* is an urgent priority due to the continued loss of native grasslands.

South western Victoria covers a significant part of the species known range and contains a large number of established monitoring sites. Habitat and microhabitat characteristics have been studied at these sites previously, but broad scale spatial analysis of sites has not been investigated until now.

This study analysed the species presence/absence data from monitoring sites in south western Victoria along with broadly mapped environmental variables in order to identify which attributes could be used to predict the current distribution of *D. impar* in the region. Using logistic regression modelling *D. impar* presence/absence was found to be strongly associated with the current extent of native grassy vegetation, and temperature and geology also contributed to explaining differences between sites where the species was found and sites with no *D. impar* records.

A distribution map was generated from the model predictions, which identifies areas with the highest likelihood of the species occurring. The map highlights priority areas which should be the focus of future survey effort to identify as yet unknown populations that continue to persist in this extensively modified landscape. The statistical model and predictive distribution map should be updated as new survey data becomes available.

INTRODUCTION

Over the last few decades awareness of world-wide species decline resulting from habitat loss and fragmentation has increased (Lindenmayer & Burgman 2005). Single species habitat studies often only consider habitat at a single spatial scale, but it is now recognised that species distribution is influenced by habitat characteristics and fragmentation at multiple scales. The factors responsible for species presence or absence in an area are not always obvious at a single spatial scale and it can be difficult to determine why a species is absent from what appears to be suitable habitat.

Habitat studies have benefited from technological advances in Geographical Information Systems (GIS), and coupled with statistical modelling these are progressively being used to collect, store, analyse and display spatial data (Paull 2003; Wintle et al. 2005). This approach allows available species survey data to be used to predict the distribution of the species over an entire region. This study considers the current distribution of, *Delma impar*, a rare grassland reptile persisting in a highly modified agricultural landscape in south western Victoria. The species has been surveyed over a large area and a number of studies have looked at habitat associations at the site scale, but the findings of these studies cannot explain the observed discrepancies of *D. impar* absence from seemingly suitable areas.

If the observed distribution of *D. impar* within the landscape is found to be associated with the distribution of broadly mapped environmental attributes, this may contribute to a better understanding of what does and does not constitute habitat for this species. This is because patterns and habitat attributes observable at a broader scale might not be evident, or might not have been considered at a finer scale of enquiry.

By increasing awareness of the factors and processes likely to be influencing the current distribution of *D. impar* we may be in a better position to assess the threats to extant populations and ultimately the long-term viability of the species.

Aims and objectives

This study aims to use existing biological and spatial data to predict the current distribution of *Delma impar* in south western Victoria, in an attempt to reduce extraneous time spent on future field surveys by directing efforts to areas likely to support populations. The following objectives have been identified to achieve this aim:

- Identify variables that can be related to *D. impar* distribution at a landscape scale across south western Victoria.
- Determine which one, or combination of influential variables can be used to quantify predictions of *D. impar* occurrence.
- Produce a distribution map of predicted habitat for this species across south western Victoria, highlighting locations with the highest likelihood of occurrence.

1985 p884). Subsequently, research fields within conservation biology, landscape ecology and natural resource management are attempting to mitigate these processes to slow rates of species loss (Lindenmayer & Fischer 2006).

Landscape scale fragmentation, as a concept, has evolved through early associations with island biogeography theory (MacArthur & Wilson 1967, cited in Haila 2002) to recognition that the 'matrix' (the area surrounding fragments) is a very important element to consider. Characteristics of the matrix can influence the distribution and population dynamics of species occurring within habitat fragments (Saunders *et al.* 1991; Lindenmayer *et al.* 2001; Haila 2002).

McIntyre and Hobbs (1999) suggest a scheme which places a range of landscape configurations on a continuum representing the degree of habitat destruction, ranging from intact (least disturbed) to relict (most altered). Landscape variegation and habitat contours introduce alternative ways to conceptualise human modified landscapes, which avoid the habitat (fragment) versus non-habitat (matrix) approach (Fischer *et al.* 2004). These alternatives address the neglect of small habitat patches, and habitat elements such as gradients not readily recognised by the simplified fragment/matrix view of landscapes (Haila 2002). The variegation concept proposes that in some landscapes, while having been variously modified, gradual boundaries exist between undisturbed habitat remnants and the surrounding modified land (McIntyre & Barrett 1992; McIntyre & Hobbs 1999). Habitat contours, on the other hand, adopts a species-oriented approach, rather than a pattern-oriented landscape view (Fischer & Lindenmayer 2007). Habitat contours are described as a conceptual approach, which involves thinking about landscapes as overlaid species-specific habitat contour maps, with one recognised benefit being a high potential for considering both multiple species and multiple scales (Fischer *et al.* 2004).

The approach most suitable to the ecological problem to be investigated will depend on the species and the context. Haila (2002) argues that, regardless of the approach adopted, research on the effects of human-caused fragmentation should be species specific, considering habitat at spatial and temporal scales relevant to the species. This might include the dispersion (spatial arrangement) of fragments, size, shape

and position of the fragment/s within the landscape, and the degree of connectivity between these fragments (Lord & Norton 1990; Saunders *et al.* 1991; Haila 2002).

Historical patterns of land use

To understand ecological patterns in fragmented agricultural landscapes, researching the history of anthropogenic disturbance regimes can be important (Lunt & Spooner 2005). Patterns of historical land use specific to an area have been shown to correlate with current distribution patterns of native species (Dorrough & Ash 1999; Spooner & Lunt 2004). Furthermore, it is thought that previous patterns of land use can be just as important as past ecological processes in explaining species distributions (Drake 1989) and it is argued that these anthropogenic patterns are not random, but rather, are arranged in logical ways within a landscape (Lunt & Spooner 2005). In south eastern Australia, for example, post-European settlement land clearance would often occur on a selective basis (Saunders *et al.* 1991) evident in many rural areas where rocky ridgelines retain trees, and lower slopes and plains are extensively cleared. Similarly, selective bias is evident in western Victoria (in south eastern Australia), where the fertile clay soils were considered excellent for sheep-grazing, and as a result this region was one of the first in the state to be extensively settled and farmed (Gibbons & Rowan 1993). Following this approach, an understanding of historical patterns of land use may be helpful when attempting to understand species distribution resulting from habitat fragmentation at a landscape scale.

Species distribution, habitat loss and fragmentation

Although 'fragmentation' in this context is generally assumed to mean landscape fragmentation resulting from human land use, it should be acknowledged that human induced habitat fragmentation patterns have been imprinted over natural fragmentation patterns, and these jointly influence species' distribution (Rees & Paull 2000; Haila 2002). For example, changes in geology, soils, and vegetation occur naturally over time and space, fragmenting the distribution of species populations

(Paull 2003; Lindenmayer & Fischer 2006). How individual species respond to subsequent human imposed landscape alteration will depend on the scale at which they perceive their environment (McIntyre and Hobbs 1999) and their life history strategies (Ewers & Didham 2005).

Several studies on single species distributions found that influential factors were apparent at more than one scale, emphasising the importance of considering multiple spatial scales in habitat analyses (Balcom & Yahner 1996; Carroll *et al.* 1999; Lindenmayer 2000; Paull 2003). This is considered particularly important when working on threatened species management, where populations continue to decline and critical habitat components are still not well understood (Lindenmayer & Fischer 2006). It is also reported that there is a depauperate number of studies on the effects of habitat fragmentation on reptiles compared to birds, mammals and insects (McNally & Brown 2001).

Ewers and Didham (2005) provide a cautionary conclusion to their study of species responses to habitat fragmentation; they emphasise that anthropogenic fragmentation is such a recent phenomenon on an evolutionary time scale, it is likely that the final, long-term impacts of human-induced habitat fragmentation are yet to be seen. The 'extinction debt' concept described by Lindenmayer and Fischer (2006) further supports this idea of delayed responses, suggesting that populations may become extinct well after landscape change has taken place. Therefore, a species under study may be responding to a change in circumstance which is no longer evident to the researcher as a direct cause and effect relationship (Lindenmayer & Fischer 2006). This suggests that researchers may need to be wary of reporting spurious correlations when investigating species responses to habitat components.

Threatening processes and extinction proneness

Fischer and Lindenmayer (2007) provide a summary of threatening processes for species in modified landscapes. They are described broadly as either *deterministic* (predictably lead to declines) or *stochastic* (dependent on chance events) and can be further categorised as *exogenous* or *endogenous*, relating to whether or not the threat arises as part of the species biological attributes. For example habitat loss is

an *exogenous deterministic* process because it is occurring externally to the species biology, and will predictably lead to population declines. On the other hand an *endogenous stochastic* event might be the birth of only one sex in a small population in one year (examples adapted from Lindenmayer & Fischer 2006). These processes might also become confounding factors, such as habitat loss leading to smaller populations, thereby increasing the chances of uneven sex ratios.

One of the major questions in conservation biology is “What makes some species in modified landscapes more vulnerable to extinction than others?”. Ewers and Didham (2005) identify five species traits, from their review of current theoretical understandings of fragmentation effects, which might be used to predict species responses to different spatial components of fragmentation. These factors were trophic level, dispersal ability, body size, niche breadth (generalist/specialist) and rarity. The authors found that generally, in response to patch isolation (as one component of fragmentation), species more likely to be adversely affected were consumers rather than producers, sedentary rather than dispersive, smaller rather than larger, rare rather than abundant, and exhibited a high level of habitat specialisation (see Ewers & Didham 2005 for trait-based responses to other spatial components of habitat fragmentation).

Considering niche breadth on a continuum, it is found that species towards the generalist end of the spectrum are more likely to be able to utilise areas surrounding habitat fragments, and are therefore less susceptible to spatial isolation (Lord & Norton 1990; Lawton & Woodroffe 1991; McNally & Brown 2001). Conversely, species which display a higher level of habitat specialisation will generally be more extinction-prone in highly modified landscapes. However, if we don't know much about the ecological traits and population dynamics of a species, it is difficult to predict the effects of habitat fragmentation, and this is considered especially true for highly cryptic species (Tischendorf & Fahrig 2000).

A reasonable conclusion from the available literature might be that, at this stage, only generalisations can be made about the susceptibility of different species to human-induced habitat fragmentation based on life history traits. However, investigating biological aspects of each species can, to some degree, provide

explanations for the distribution of species in the landscape (Huggett 1998). Furthermore, landscape scale fragmentation is often the only scale considered, yet fragmentation effects are likely at a range of scales, and an attempt should be made to consider scale from the species perspective (Weins & Milne 1989).

Modelling species distribution: a GIS and GLM approach

Biological surveys attempting to cover whole regions are generally restricted by the time and cost involved (Nicholls 1989; Manel *et al.* 1999). One solution to this problem is the use of habitat modelling techniques, which are increasing in popularity, coinciding with improvements in multivariate statistical methods (Ewers & Didham 2005). It should be acknowledged that there are a number of statistical methods available for predictive habitat modelling (see Guisan & Zimmermann 2000, Table 1, for a summary of techniques). Generalised linear models (GLMs) are a popular choice for modelling species distribution (Guisan & Zimmerman 2000). GLMs have proven to be robust in a number of predictive habitat distribution modelling examples (Manel *et al.* 1999; Pearce & Ferrier 2000b; Hirzel *et al.* 2001; Brotons *et al.* 2004). Some GLMs can be used to predict and map the probability of the presence or absence of a species or community at unsampled locations (Delaney & Van Niel 2007), potentially highlighting priority areas for future surveys. GLMs can be complimented by the use of Geographic Information Systems (GIS) to compile spatial data for analysis, as well as to display model predictions.

Generalised Linear Models

Fundamentally, GLMs consist of a *random component* (response variable), a *systematic component* (predictor variables), and a *link* which describes the functional relationship between them (Agresti 1990). GLMs are based on an assumed relationship between the response variable and a linear combination of predictor (explanatory) variables (McCullagh & Nelder 1989; Guisan *et al.* 2002).

GLMs are not only a statistical analysis method in ecological related fields of research, but are often used in medical and social sciences. The predictive capability of GLMs is frequently reported to be low in ecology (Pearce & Ferrier 2000a), but due to the uncertainty inherent in ecology, Soulé (1985) suggests that, in general, a greater level of uncertainty may be expected, and accepted, within this discipline. Generally, attempts should not be made to apply models to locations outside the sampled region (Guisan *et al.* 2002). One reason being that the data used to fit the model could be influenced by local historic factors affecting the distribution/character of environmental variables in that area (Guisan & Zimmermann 2000). Furthermore, an ecological assumption of these models is that of environmental equilibrium (Guisan & Zimmermann 2000), which of course is not always true in naturally changing environments. Dynamic elements, such as dispersion, competition and predation, that are not incorporated into modelling can be influencing actual occurrence of the species on the ground, and might therefore result in reducing the accuracy of predictive distribution maps (Austin 2002; Fischer *et al.* 2004). Austin (2002) recommends greater consideration be given to incorporating biotic and environmental processes into these statistical models in the future.

For categorical response variables with only two categories (e.g. presence/absence), and both continuous and categorical predictor variables, binary logistic regression is a recommended GLM approach (following Agresti 1990; McCullagh & Nelder 1989; Guisan & Zimmermann 2000; Garson 2008) and will be adopted for this study.

Considerations of GLM use

Data quality is likely to be a key issue affecting the reliability of model predictions (Stockwell & Peterson 2002; Brotons *et al.* 2004). Ideally, sampling will be evenly distributed across the study area, and incorporate representative samples of all combinations of environmental variables available within the environmental space (Nicholls 1989). However, due to the problem of limited resource allocation to field surveys, which is often reported (Nicholls 1989; Stockwell & Peterson 2002; Carroll *et al.* 1999), data used for predictive habitat distribution modelling can often be reliant on only a small sample size and/or irregularly spaced or clustered

observations across the study area. Uneven sampling design can lead to data being affected by spatial autocorrelation, where the values or attributes of samples close together are more likely to be similar than samples further apart (Johnston 1998). Spatial autocorrelation can violate the assumption of independent observations required for tests of statistical significance, yet this problem can be difficult to avoid when observational or retrospective data are used (Carroll *et al.* 1999). Adjusting the effective sample size in the model is one method which has been suggested to overcome autocorrelation problems (Carroll *et al.* 1999).

A sample unit for species distribution modelling will generally consist of an independent monitoring location with geographic co-ordinates, and each sample will be described by the attributes (predictor variables) at that location (Carroll *et al.* 1999; Guisan & Hofer 2003). Careful consideration should be given to sample size when preparing to use GLMs. Comparative studies investigating the influence of sample size on the accuracy of model predictions have produced inconsistent results. Pearce and Ferrier (2000a) recommend a sample size of at least 250 as a result of a comprehensive study comparing the discrimination performance of GLMs fit with data on a range of species. It was found that lower sample sizes produced less accurate models, particularly when the ratio of species presence to absence was low (Pearce & Ferrier 2000a). Comparatively, Stockwell and Peterson (2002) found maximum model prediction accuracy of GLMs to be achieved with 100 data points, based on their study of a large number of different avian fauna. This discrepancy can be explained, at least partially, by consistent use of even proportions of presence and absence data for all species by Stockwell and Peterson (2002).

Limited life history information and basic distribution data for rare and cryptic species can be a problem for researchers wishing to undertake predictive habitat distribution modelling (Paull 2003). This is unfortunate as conservation management, and accurate habitat modelling, is often most critical for rare species (Manel *et al.* 1999). Species rarity has been shown to reduce the accuracy of model predictions and lower the proportion of positive predictions (Manel *et al.* 1999; Pearce & Ferrier 2000a). Yet, positive predictions may be increased at the expense of accepting more false positive predictions, which for rare species might be acceptable. This is

because it may be considered more important to accurately identify locations where a rare species does occur and accept more false predictions of presence, compared to the alternative which would be to predict a species as absent where it is in fact present, effectively overlooking populations (Wuensch 2008).

Geographic Information Systems

Geographic Information Systems (GIS) are integrated systems of computer software and hardware, designed to capture, store, analyse and display spatially distributed data (Johnston 1998). Using a GIS computer program, it is possible to map any object or entity (e.g. road, river, building, tree), as long as it has a spatial location (Delaney & Van Niel 2007). Mapped features of the same type (i.e. points, lines, polygons or grid cells) are stored and displayed as a layer, which may be overlaid with other layers to produce a complete map.

GIS layers map the spatial attributes of environmental variables which can be used to sample locations remotely, and the data can then be used for multivariate statistical analysis, as demonstrated by broad scale species habitat analyses (Paull 2003; Wintle *et al.* 2005). The results of these analyses can also be displayed as GIS layers, for example GLM predictions can be used to display the probability of species occurrence over a large area (Guisan & Zimmermann 2000; Pearce & Ferrier 2000a). GIS spatial predictions can show where the species is most likely to occur, directing field studies (Ferrier 1991) or highlighting important areas for protection (Carroll *et al.* 1999), effectively optimising limited conservation resources.

South western Victoria: volcanic plains grassland

Native grassland decline in south eastern Australia

European settlement in Australia heralded the introduction of intensive agriculture, which has dramatically modified the quality and extent of native vegetation (Lunt & Spooner 2005). Among the most severely depleted ecosystems in Australia are the lowland temperate grasslands, with the few examples that remain generally limited to

small, isolated remnants (Lunt 1991; DNRE 1997). Prior to European settlement, large tracts of south eastern Australia are thought to have been covered by native grasslands (Kirkpatrick *et al.* 1995) and it is estimated that over 99 percent have been destroyed or highly modified for agricultural purposes (Lunt & Morgan 2002).

Their treeless nature, fertile soils and flat to gently undulating topography made the temperate grasslands attractive for early agricultural settlement (Lunt & Morgan 2002; Eddy 2007). As a result, grazing, fertiliser application, cultivation, introduced flora and fauna, and changed fire regimes have altered the structure and floristic composition of these native grasslands (Lines 1991; McIntyre & Lavorel 1994; Dorrough & Ash 1999).

In rural landscapes of south eastern Australia today, intact native grassland remnants generally occur on public land such as roadsides, rail reserves and cemeteries, with some remnants on private land where disturbance has not been intense or prolonged (Willis 1964; Stuwe & Parsons 1977; Stuwe 1986; Jefferson *et al.* 1991; Lunt 1991; Lunt *et al.* 1998). These small fragments of native-dominated grassland persisting in the landscape are considered by some to be critically important, both as representative remnants of Australia's temperate lowland grasslands and as a component of habitat for some indigenous fauna (Lunt 1995; Kirkpatrick *et al.* 1995; Lunt & Morgan 2002; Williams 2007). South western Victoria is a prime example of rapid and widespread land cover change which has resulted in altered habitat availability and quality for many native fauna species (Kirkpatrick *et al.* 1995).

The Western Plains of Victoria: natural history

The dominant geology of western Victoria is volcanic in origin (Jones 1999) and the young basalts form one of the largest geological units recognised in Victoria (Rosengren 1999). It is thought that the young basalt derived soils have strongly influenced the distribution of grasslands in western Victoria (Jones 1999) in conjunction with other factors, namely topography, climate and fire regimes (Willis 1964; Stuwe & Parsons 1977; Jones 1999).

The soils supporting native grasslands in south western Victoria are typically characterised by high proportion of clay in the subsoil, high fertility, and can be prone to waterlogging (Gibbons & Rowan 1993; Dahlhaus *et al.* 2003). Floristic surveys on remnant grassy vegetation in the region suggest that the native grass species which once dominated these volcanic soils were *Themeda triandra* (Kangaroo Grass) in dryer areas, and *Poa labillardieri* (Common Tussock Grass) at wetter sites (Willis 1964; Stuwe 1986).

It has been suggested that the deep cracking of the clay soils can disrupt the taproot system of establishing trees, limiting tree distribution across the volcanic plains (Gibbons & Rowan 1993). Other explanations for the treelessness on the plains are: exclusion of tree seedlings caused by a thick grass root mat, mortality of tree seedlings by frequent fire events, and lack of available soil moisture (Kirkpatrick *et al.* 1995). Tree and shrub cover is restricted to the better drained soils (Jones 1999) or along streams and in depressions, where stunted trees, predominantly River Red Gum (*Eucalyptus camaldulensis*) can survive (Willis 1964).

Most of the area receives on average 500 to 700mm of annual rainfall, with most occurring in winter months (Bureau of Meteorology & Walsh 1993). Wetlands are another feature of the volcanic plains, attributed to the low relief and altered drainage patterns that are a result of the activity of over 300 volcanoes in the region, erupting over the last four to five million years (Jones 1999; Rosengren 1999). Basalt boulders, both at the surface and embedded, are common in this landscape (Conley & Dennis 1984). It is also suggested that fire, natural and Aboriginal-lit, played an important role in influencing the structure of these native grasslands prior to European settlement (Gott 1993; Kirkpatrick *et al.* 1995; Lunt & Morgan 2002).

The Western Plains of Victoria: an agricultural landscape

The original grassy landscapes of south western Victoria were one of the first areas settled for agriculture (Gibbons & Rowan 1993; Williams 2007), and the fertile grassy plains were crucial to the success of early pastoralists who arrived in the late 1830s (Lang 2000). Large numbers of sheep grazed on the native perennial grasses and herbaceous vegetation of the plains for one hundred years (Gibbons & Rowan 1993)

until around the 1940s and 1950s when many farmers converted their paddocks to exotic annual and perennial pasture grasses and clovers (Conn 1993; Gibbons & Rowan 1993). Recently, crop production has increased exponentially in south western Victoria. For example, between 1990 and 2000 the Institute of Land and Food Resources (2000) reported that cropping in the region increased from 62,000 to 205,000 hectares. Changing farming practices is thought to be driven by economic factors (Lang 2000; Taylor *et al.* cited in Williams 2007), the introduction of raised bed cropping techniques (Institute of Land and Food Resources 2000; Dahlhaus *et al.* 2003) and the availability of new crop varieties (Lang 2000). Fertiliser and chemical use has also increased in the region with the increase in cereal crops and sown exotic pasture grasses (Institute of Land and Food Resources 2000).

There has been research undertaken on the impacts of agricultural land use on grassland plants in other parts of south east Australia. In temperate grassy vegetation in northern NSW, native plant species richness was found to be higher at sites with no history of cultivation or fertiliser use and little to no grazing, while increased grazing intensity and fertiliser inputs significantly increased exotic species richness (Reseigh *et al.* 2003). This work supports previous research conducted in the same region, which found that native and rare native species showed a negative response to increased nutrients and soil disturbance, while exotics showed the reverse trend (McIntyre & Lavorel 1994). Similarly, a study of central Queensland grasslands along a grazing disturbance gradient, found that native species declined and exotics increased as grazing intensified (Fensham *et al.* 1999). The situation in south western Victoria appears to support this trend, where grassland sites that are still dominated by native species are generally areas which have experienced minimal disturbance (Stuwe & Parsons 1977), with the exception of fire (to be discussed).

Management of remnant grasslands in south western Victoria

Some native grasslands in south western Victoria and other rural areas of Victoria are regularly burnt along roadsides and rail easements, with the primary aim of reducing the risk of wildfire to adjacent privately owned properties (Kirkpatrick *et al.*

1995; Williams 2007). Regular burning of some of the remaining native dominated grasslands is considered beneficial to maintaining floristic diversity (Kirkpatrick *et al.* 1995). This is because regular burning can expose inter-tussock spaces, which are found to be important for herbaceous species that do not survive constant competition from the dominant perennial grasses (Fensham *et al.* 1999). Furthermore, it was found that *Themeda triandra*, the dominant tussock grass species of Victoria's western plains, requires inter-fire intervals of no longer than five years to maintain maximum health and vigour (Morgan & Lunt 1999). Higher faunal species richness has also been found in grasslands with complex floristic diversity and an open structure, compared to sites with dense biomass and few plant species (Hadden 1998). It appears that fire management to maintain biodiversity of grassland communities is an area requiring further research, as the implications of variables such as frequency, extent, intensity and season on different plant and animal species is currently limited (Lunt & Morgan 2002; Lindenmayer & Fischer 2006).

There is no set management plan available for grassland conservation, and sometimes the only prescription is to maintain the same regime of burning, grazing, or no active management, that has allowed the grassland to survive thus far (Lunt 2005). For example, livestock are used as a management tool for achieving conservation outcomes by reducing the biomass of dominant grass species in some public reserves in south eastern Australia (Lunt 2005; Lunt *et al.* 2007). A recent study in western Victoria highlighted the potential implications of changing a long-term grassland management regime (Williams 2007). Altering roadside fire prevention techniques from controlled burning to herbicide spraying was found to be the most likely explanation for remnant native grassland loss in the area (Williams 2007).

The conservation of grasslands on private property is considered troublesome, because it is recognised that native grasslands are often not highly valued for conservation by farmers (Fischer *et al.* 2004). A study in south eastern Australia exploring perceptions of native grasslands highlighted a lack of perceived ecological value of these environments, finding that respondents more often valued native grasslands for agricultural or aesthetic reasons (Williams & Cary 2001). Furthermore, native grassland on private property is thought to be under continual threat as

landowners alter land use in response to economic pressures (Lang 2000; Williams 2007). While there have been recent attempts to provide market based incentives for landholders to manage native vegetation on their property in south western Victoria (e.g. Bush Broker, Bush Tender and Plains Tender – see www.dse.vic.gov.au), the schemes rely on landholders taking the initiative.

Decline of grassland fauna

Naturally treed landscapes are generally better recognised for their importance to the conservation of native fauna and are perceived as being ‘more natural’ and more appealing than native grasslands (Lamb & Purcell 1990). Grassland ecosystems may appear structurally simple, and are therefore not well recognised for their biological conservation significance, yet Victoria’s native grasslands are found to support a diverse composition of flora and fauna (Lunt 1991; Kirkpatrick *et al.* 1995; Morgan 1994). With an estimated one percent of native plains grassland vegetation remaining in south western Victoria (Lunt *et al.* 1998), there is little doubt that habitat loss is the primary determining cause of grassland species decline. The quality of remnants, the isolation of habitat patches, and increased risk of predation, are just a few of the confounding factors which may threaten faunal grassland species further (Kirkpatrick *et al.* 1995).

It should be recognised that some native fauna, for example Galahs (*Cacatua roseicapilla*) and Little Ravens (*Corvus mellori*), have responded positively to agricultural landscapes, and have extended their range and population sizes, (Lunt *et al.* 1998). Yet grassland species such as the Plains Wanderer (*Pedionomus torquatus*), Eastern Barred Bandicoot (*Perameles gunnii*), the Golden Sun-moth (*Syrophorus plana*) as well as the Striped Legless Lizard (*Delma impar*), provide examples of some well-documented species which have been adversely affected by the loss of habitat resulting from extensive agricultural landscapes (Lunt *et al.* 1998). Lang (2000) recognises some immediate threats to remaining native grassland fauna in south western Victoria, including cropping (soil disturbance, reduced heterogeneity of plant diversity), rock removal (an important habitat element for many species), and herbicide use (eliminates native flora) (Williams 2007). What remains of Victoria’s

western plains grasslands continues to diminish in both quality and extent (Williams 2007), highlighting the importance of active conservation management

The Striped Legless Lizard – *Delma impar*

Species Description

Delma impar, also referred to as the Striped Legless Lizard, is a member of Pygopodidae, a family of legless lizards found only in Australia and New Guinea (Jenkins & Bartell 1980; Cogger 1986; Zug 1993). Pygopodids share similar morphology and habits with their closest relatives, geckos (Greer 1989), such as fused eyelids, the ability to vocalise and face-wiping with the tongue (Patchell & Shine 1986; Greer 1989). However, they demonstrate vastly different external morphology; geckos show no evidence of limb reduction, whereas the ‘legless’ lizards retain only remnant hind limbs and have comparatively elongate and attenuate bodies (Greer 1989).

D. impar exhibits variation in colour and markings (Smith & Robertson 1999), but generally individuals display characteristic longitudinal brown lines running from the tympanum (ear) to just beyond the vent, where these distinct markings change to diagonal stripes continuing down the tail (Coulson 1990). Vestigial hind limbs, or flaps, are evident on either side of the vent (Cogger 1986). The dorsum is generally pale brown, the head darker brown, and the underside of the lizard cream to white (Jenkins & Bartell 1980; Coulson 1990). The majority of live specimens display a yellow colouration of the throat, extending from the lower lip scales to the tympanum (Coulson 1990). Maximum length is approximately 300mm, of which about two thirds is tail (Smith & Robertson 1999).

Rauhala & Andrew (1998) found cloacal spurs were a feature of adult male *D. impar*, that are consistently absent in adult females, and therefore a determinant of sex. Hatchlings and juveniles of this species lack the prominent striped markings of adults, and have dark brown to black heads (Coulson 1990). The sex of juveniles cannot be confidently determined from the external cloacal spurs used to sex adult specimens (Rauhala & Andrew 1998).

Distribution

D. impar is the most southerly distributed Pygopodid (Coulson 1990). The western-most extent of known distribution of *D. impar*, presently and historically, is far south east South Australia (Stratman 2007). Extant populations are found across western and central Victoria, through southern NSW to the ACT, and slightly north there of (Coulson 1990; Hadden 1995; Dorrough 1995) (Figure 2.1). Spatial distribution appears to be patchy across the known range (Smith & Robertson 1999). Predictive distribution modelling based on climate related variables has revealed further potential habitat including north of the ACT, around Cowra (Coulson 1990), and an isolated patch in Gippsland, south east Victoria (Hadden 1995). However, the species has never been recorded at either of these potential locations.

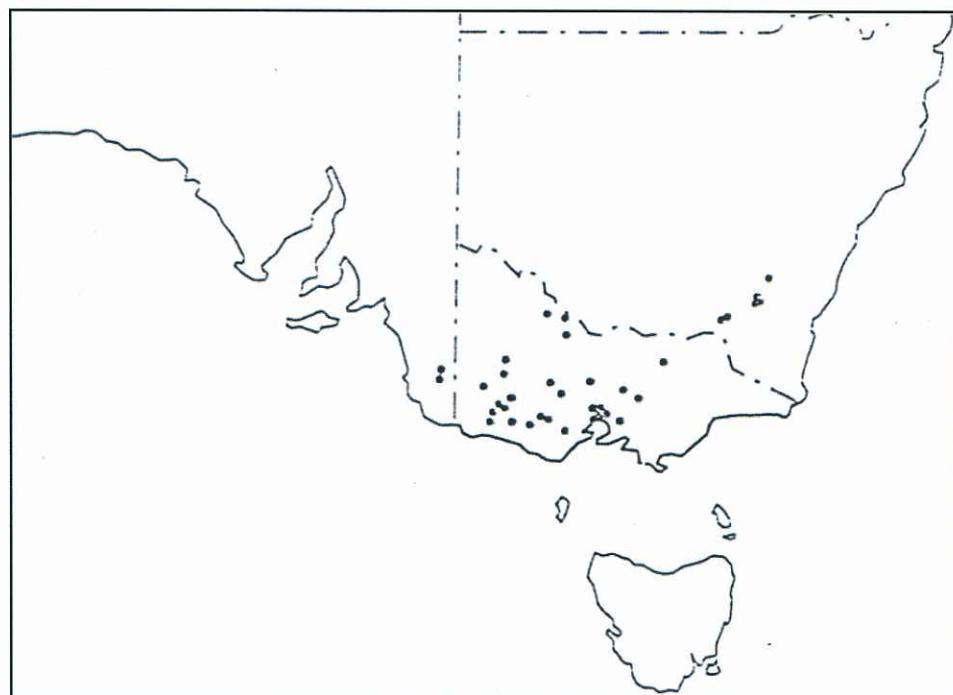


Figure 2.1 Distribution of *Delma impar* in SE Australia
(source: Dorrough 1995)

An initial investigation into the distribution and ecological requirements of *D. impar* in 1989 (Coulson 1990) was inspired by concerns for the future security of the species, due to a perceived decline in numbers (Coulson 1990; Kutt 1992). The degree of decline is difficult to gauge because knowledge of previous extent is limited to a small number of early records (O'Shea 2005). Over the last two decades, survey efforts in South Australia, Victoria, NSW and the ACT have contributed records of new locations within the species known range, as well as rediscoveries at historic locations (Dorrough & Ash 1999; Rohr & Peterson 2003; Koehler 2004; Stratman 2007; pers. obs. 2007). Further targeted surveys of potential habitat within south eastern South Australia, western and central Victoria, and southern NSW are warranted to locate further potential extant populations (Smith & Robertson 1999).

Behaviour, Movement and Diet

Initially reported as nocturnal (Jenkins & Bartell 1980), more recent observations suggest that *D. impar* is active during the day (diurnal) over a wide range of temperatures (Coulson 1990; Kutt 1992; O'Shea 1996). Considered a thigmotherm, *D. impar* also displays some heliothermic behaviour, with a number of observations of individuals basking (Kutt 1992; Turner 2007). Like most pygopods, *D. impar* is oviparous (egg laying), with a clutch size of two (Patchell & Shine 1986) and a variable incubation period spanning from 30 days (Kutt 1992) to 50 days (Dorrough 1995). It has been reported that members of the genus *Delma* ovulate between spring and early summer, followed by oviposition in mid summer (Patchell & Shine 1986).

The social systems of *D. impar* are relatively unknown, although communal behaviour is suggested by the discovery of communal egg laying sites (Kutt 1992; Green 2008; G. Peterson, pers. comm. 2008). Clustered spatial arrangements, rather than random patterns, have been observed when trapping individuals supporting suggestions of communal behaviour (Kutt 1992; O'Shea 1996; Dorrough & Ash 1999). However the spatial clustering that has been observed is not necessarily due to communal behaviour, but could instead be influenced by heterogeneity of habitat quality or availability (Kutt 1992).

Movement patterns are not well known for this species. The longest distances recorded when individuals have been recapturing in pitfall trap studies are relatively short: 25m within three months (Coulson 1990), 36m within two months (O'Shea 1996) and 60m within two days (Kukolic *et al.* cited in O'Shea 2005). While experimenting with a fluorescent tracking technique, Kutt (1992) measured one individual moving 20m in a night. In another study, Dorrough and Ash (1999) calculated an annual dispersal distance of approximately 12 metres, based on the distance individuals were found from primary grassland habitat. These finding suggests that the species has relatively low dispersal ability.

D. impar has been described as a selective arthropod feeder (Nunan 1995). Spiders, moth larvae (Lepidoptera), crickets and cockroaches have been recorded as common prey items (Nunan 1995; Kutt *et al.* 1998). The diet of *D. impar* has been shown to vary between native dominated grassland and adjacent exotic dominated grassland habitat types (O'Shea 2005), and seasonal variation in diet has also been found (Kutt *et al.* 1998). Generally little information is available on the trophic relationships of this species with both predators and prey.

Species habitat

D. impar is restricted to temperate tussock grasslands in south eastern Australia (Smith & Robertson 1999). Some field guides have suggested that the species may inhabit forest and woodland environments (Jenkins & Bartell 1980; Cogger 1986), yet all notable research on the species since these early publications support the idea that *D. impar* is a grassland specialist (Smith & Robertson 1999).

There is consensus that, while not reliant on any particular floristic species, *D. impar* does require tussock vegetation as a component of habitat (Dorrough & Ash 1999; Hadden 1998). The species is most often found where vegetation cover is dominated by *Themeda triandra* (Kangaroo Grass) in Victoria, and *Austrostipa bigeniculata* (Tall Spear Grass) in the ACT (Hadden 1995), yet there are many accounts of *D. impar* inhabiting grasslands dominated by exotic perennial tussock grasses (Coulson 1990; Kutt 1992; Hadden 1995; O'Shea 1996; Dorrough & Ash 1999; Koehler 2004; Stratman 2007). It is not understood whether grasslands dominated by introduced

species can support *D. impar* in the long term, but there is evidence to suggest that they do reproduce in these environments (Smith & Robertson 1999). O'Shea (1996) found *D. impar* in exotic dominated grassland to a distance of 80 metres from native dominated grassland. However, in the same study, more individuals were found in native dominated habitat than in adjacent exotic dominated grassland, and this was consistent across samples, although the trend was not statistically significant (O'Shea 1996). These results lend support to the idea of introduced grasslands providing potentially viable habitat for this species. Whether exotic dominated grasslands close to native grasslands provide good habitat for *D. impar*, or are only inhabited due to their proximity, is unknown, but Tyre *et al.* (2001) reports that bad habitat close to good habitat may be more often occupied than good habitat far away.

In Victoria, sites where *D. impar* has been recorded are most often characterised by flat to gently undulating plains with cracking clay soils and rocks, either on the surface or lightly embedded (Coulson 1990; Hadden 1995; Koehler 2004). It is thought that soil cracks may be used for overwintering (Smith & Robertson 1999) and as refuge sites during fire events and other unsuitable conditions such as intense grazing and drought (Hadden 1995; Smith & Robertson 1999). Conversely, cracking clays and surface rocks are not usually features of *D. impar* sites in the ACT (Dorrough 1995), indicating that these characteristics are not critical habitat components of the species, but will be used if available (Hadden 1995).

In the ACT, Dorrough & Ash (1999) found clay content (as an indicator of the soils potential to form cracks) was not a significant predictor of *D. impar* presence or abundance, yet all sample sites were reported to be clay-rich. The authors report that numerous invertebrate burrows were observed at sites in their study, and go on to suggest that spider/invertebrate burrows may be used by *D. impar* in the absence of soil cracks. A stronger reliance on tussocks for protection and as torpor sites where soil cracks are uncommon, as suggested by Smith and Robertson (1999), may also explain the apparent differences between habitat components at Victorian and ACT sites.

The geology associated with *D. impar* in Victoria is most often basalt, with relatively fewer sites on sedimentary geology, yet the soil types at all sites are consistently characterised by moderate to high proportions of clay (Hadden 1995). A recent survey effort in the Mosquito Creek Catchment (spans the border between Victoria and South Australia), characterised by predominantly sandy soils, did not record *D. impar*, however extent populations exist nearby on clay soils (Stratman 2007).

The importance of rocks as a habitat component is not completely understood. The species has been found under deeply embedded boulders (removed for housing developments), under surface rocks (Coulson 1990), and on top of rocks - apparently basking (Turner 2007). The majority of *D. impar* sites in the ACT contain no rocks, yet the species is found more often at sites where rocks are present over its known range (Hadden 1995; Koehler 2004). Therefore, the presence of rocks might be an indication of minimal disturbance at a site, and act as an indirect indicator of habitat quality for *D. impar* (Coulson 1990) rather than being a critical component of habitat.

Conservation status

The decline and potential extinction of Australian fauna species is acknowledged by protective legislation nationally and globally at a number of levels. *D. impar* is recognised internationally as a 'vulnerable' species by the IUCN (2007). Commonwealth legislation considers the species 'vulnerable' under the *Environment Protection and Biodiversity Conservation Act 1999*, and at state and territory level *D. impar* has the following status:

Victoria – endangered (*Flora and Fauna Guarantee Act 1988*)

ACT – vulnerable (*Nature Conservation Act 1980*)

NSW – vulnerable (*Threatened Species Conservation Act 1995*)

South Australia – endangered (*National Parks and Wildlife Act 1972*)

Threats

Loss and degradation of remaining habitat are considered to be the main threats to the long-term survival of extant *D. impar* populations (Smith & Robertson 1999). Agricultural activities such as ploughing, fertiliser application and prolonged heavy grazing are considered to be serious threats, while roads and cleared fire breaks may dissect otherwise continuous habitat and effectively pose barriers to movement (Coulson 1990; Hadden 1995; Dorrough & Ash 1999; O'Shea 2005).

Fire has been considered a threat to *D. impar* populations, due to observed mortality immediately following fire events (Coulson 1990; Walton 1995; O'Shea 2005). There are also predicted indirect impacts such as increased predation risk, decreased food availability and lower recruitment as a result of habitat loss (ARAZPA 1996). Although, in some trapping and monitoring programs, *D. impar* has been found in recently burnt sites (within 12 months of fire event) more often than unburnt sites (Koehler 2004; O'Shea 2005). In addition, *D. impar* has been found to persist at some sites under an annual burn regime (Hadden 1995). The findings suggest that the effects of fire alone may not be a significant threat, but combined with other factors (eg. suitability of nearby habitat, availability of refuge sites, season of burn) could potentially be deleterious to the species (Coulson 1990; O'Shea 2005). There is consensus that more work is required to understand the implications of frequency, time of year, scale and intensity of fire events on the long-term survival of this species (Hadden 1995; Koehler 2004; O'Shea 2005).

In south western Victoria remnant native grassland patches on roadsides provide habitat for *D. impar* (Coulson 1990; Koehler 2004) and are recognised generally for their wildlife conservation potential (Bennet 1991), yet these important habitat patches are found to be declining in extent and quality (Williams 2007). Altering roadside fire prevention techniques, from controlled burning to herbicide spraying, is thought to be contributing to the loss (Williams 2007).

METHODS

The South West Striped Legless Lizard Project

In response to the decline of *Delma impar*, a National Recovery Plan was prepared to determine priority recovery actions and objectives for the long-term survival of the species in the wild (Smith & Robertson 1999). The South West Striped Legless Lizard Project (SWSLLP) was established through the directive of the Recovery Plan, and involves the implementation of numerous recovery actions for the species across south western Victoria. The initial phase of the SWSLLP has involved undertaking large scale targeted surveys to determine the current distribution and status of the species. As part of this ongoing project, the Department of Sustainability and Environment (DSE) have worked collaboratively with the Victorian Striped Legless Lizard Working Group, catchment management authorities, universities, consultants, community groups and individuals to establish and maintain monitoring sites since 2003 (G. Peterson, pers. comm. 2008). DSE are the stewards of the SWSLLP monitoring data, which has been made available for use in this predictive habitat analysis.

Project area

The project is within the Glenelg Hopkins Catchment Management Authority (GHCMA) region, which covers about 27 000²km, representing around twelve percent of Victoria (Department of Primary Industries 2008b), as well as the Corangamite Catchment Management Authority (CCMA) region, which covers 13 000²km, approximately six percent of Victoria (Department of Primary Industries 2008a) (Figure 3.1). The Wimmera Catchment Management Authority (WCMA) region also contains monitoring sites established as part of the SWSLLP, but has been omitted from this study due to limitations of time and resources and comparatively few records of *D. impar* in the region (G. Peterson, pers. comm. 2007).

The monitoring sites are located in a wide band orientated east-west across south western Victoria; from the edge of the Central Victorian Uplands bioregion in the

east, to the Dundas Tablelands in the west, with most sites on the Victorian Volcanic Plains (Figure 3.1).

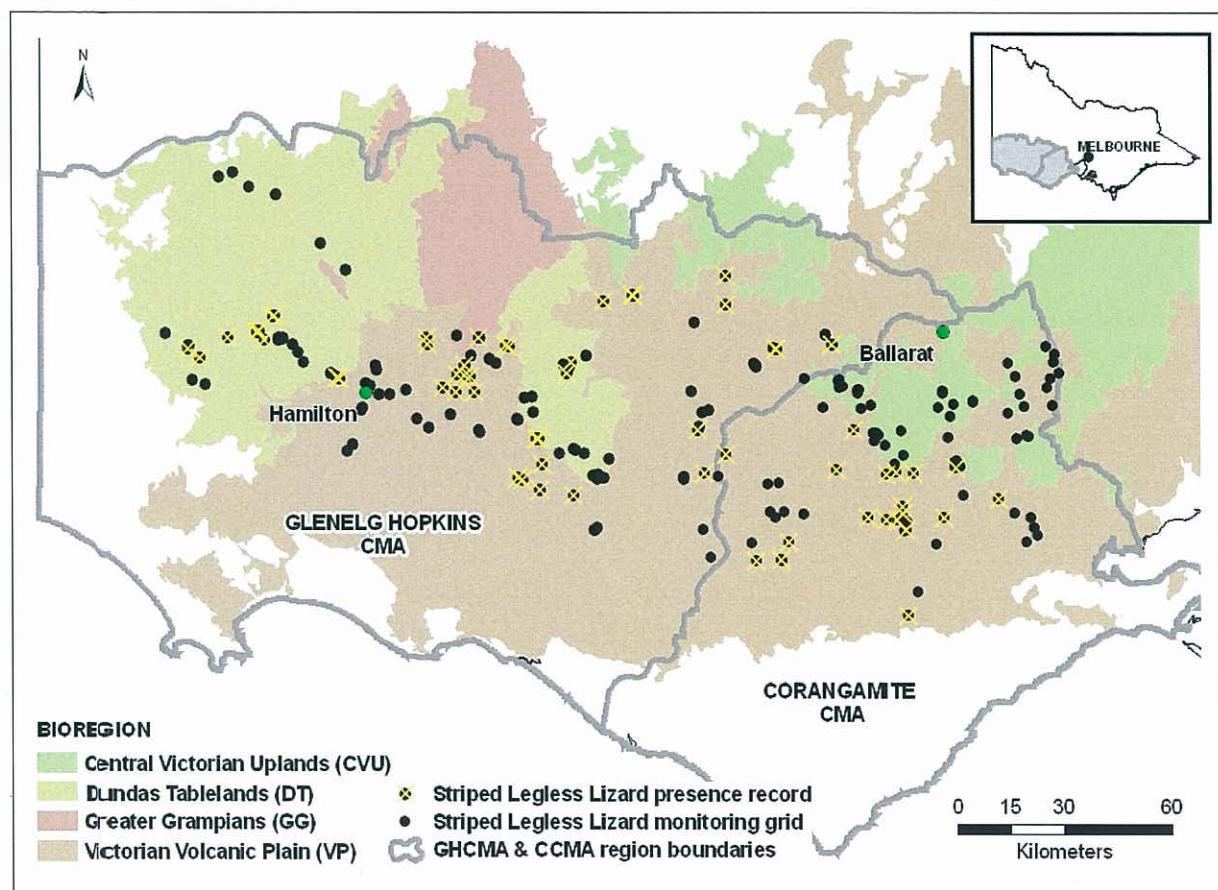


Figure 3.1 Location of SWSLLP monitoring sites within GHCMA and CCMA regions in south western Victoria, shown here with bioregions relevant to the study area.

Site selection

Site selection for the establishment of monitoring grids generally followed a process of identifying sites from DSE's native vegetation and biodiversity maps, followed by ground-truthing to confirm site suitability (Koehler 2004). The Ecological Vegetation Classes (EVCs) targeted were Plains Grassland and Plains Grassy Woodland (and later Plains Grassland/Plains Grassy Woodland Mosaic). These were the vegetation types highlighted by Coulson (1990), and later Hadden (1995), as most often associated with *D. impar* observations.

Some monitoring sites were selected based on close proximity to historical *D. impar* record sites (Koehler 2004) and others were established in response to

landholders/managers contacting DSE with information on the species following media releases (newspaper articles, radio interviews, fliers, etc). The suitability of the sites was subsequently assessed by DSE biodiversity staff (G. Peterson, pers. comm. 2007). The majority of survey sites were established between May and June 2004 in the GHCMA region (Koehler 2004) and between July and September 2004 in the CCMA region (C. Grant, pers. comm. 2007).

Survey technique and monitoring regime

Each survey site consists of fifty roof tiles (both concrete and terracotta) arranged in a 45x20 metre grid formation, with 5 metres between tiles in each direction, covering a total area of 900m² (Figure 3.2). Tiles are thought to be utilised by *D. impar* for refuge, thermoregulation and possibly prey foraging (Thompson 2006). Tile grid monitoring has been adopted as an alternative to pit-fall trapping, with some recognised advantages being a reduction in site disturbance, lower equipment costs, and less time and labour required for installation (Koehler 2004; O'Shea 2005; Thompson 2006). Tiles have the added advantage of not restricting individuals - requiring less frequent monitoring, and they can also be used to monitor other small vertebrate and invertebrate species which have been found to use them (detailed coverage of issues surrounding the tile survey method can be found in Thompson 2006).

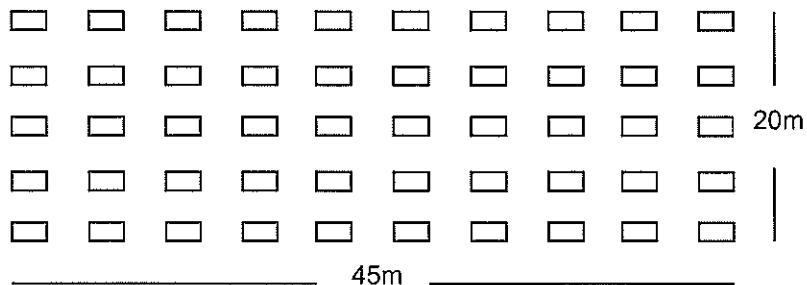


Figure 3.2 Diagram representing the arrangement of roof tiles which form sampling grids for the Striped Legless Lizard project.

Regular monitoring and record keeping commenced at the majority of sites in spring 2004 and is conducted four times a year for GHCMA sites (spring, summer, autumn, winter), and three times per year for CCMA sites covering the known surface active period of this species, i.e. spring, summer and autumn. Twenty monitoring grid sites were checked more intensively (between nine and eighteen times over summer 2005/2006) as part of a previous study of *D. impar* microhabitat and local-scale site characteristics (Thompson 2006). Checking grids involves turning each tile and recording *D. impar*, or any other vertebrate species observed. Skins shed by *D. impar* can be found under tiles, are readily identifiable and are therefore considered evidence of this species occurrence at a site.

The presence/absence records from the SWSLLP monitoring that will be used in the current investigation relate to monitoring data updated to spring 2007 for CCMA sites (approximately 10 surveys per site in total) and summer 2007/08 for GHCMA sites (approximately 14 surveys per site).

Predictive distribution modelling

Binary logistic regression was the statistical approach used to predict *D. impar* occurrence using broadly mapped habitat indicators (predictor variables) and the observed presence/absence data (binary response variable) from the SWSLLP monitoring. Both categorical and continuous predictor variables were included in modelling, which is one of the benefits of logistic regression (McCullagh & Nelder 1989; Guisan & Zimmermann 2000; Garson 2008). An automated forward stepwise model fitting procedure was used (forward LR) in the statistical program SPSS[®] (Version 16) to identify the predictor variables which best explain the response variable. Figure 3.3 introduces the approach taken in this study to develop the model for *D. impar* and outlines the steps involved, each of which will then be explained in further detail.

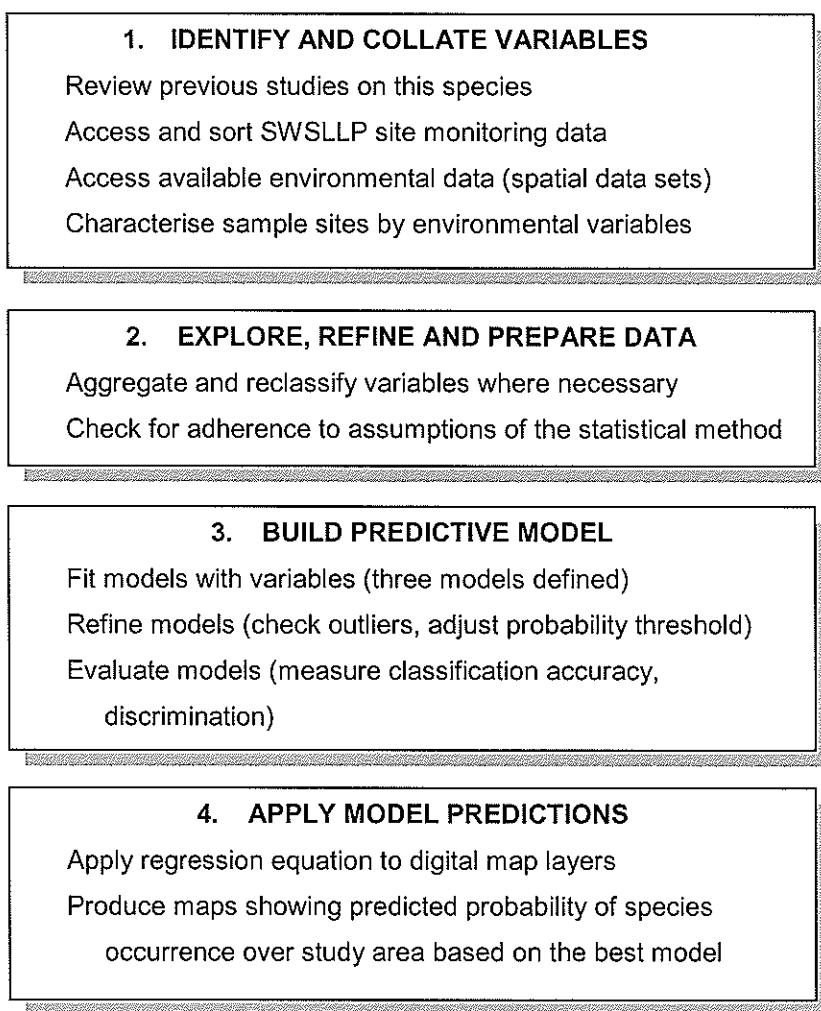


Figure 3.3 Overview of major steps involved in developing predictive distribution modelling and mapping for *D. impar*, as undertaken in this study.

Identify and collate variables

In order to determine which environmental attributes performed best at predicting the locations of extant *D. impar* populations across south western Victoria, it was necessary to first identify possible predictive variables. As recommended by Wintle *et al.* (2005) careful consideration was given to the biology of the target species when compiling a list of environmental variables for habitat modelling. The list of variables was guided by what is known about *D. impar* habitat, the availability of GIS spatial data characterising environmental attributes over the study area and SWSLP site data (Table 3.1).

Table 3.1 Compiled list of potential predictor variables and their form of availability for modelling *D. impar* habitat.

Variables identified	Form of availability
Geology	GIS spatial data
Soil texture (clay content)	GIS spatial data *
Historic vegetation structure	GIS spatial data
Current vegetation extent	GIS spatial data
Climate – temperature, rainfall	GIS spatial data
Altitude	GIS spatial data
Dominant land use	SWSLLP site data
Fire frequency	SWSLLP site data
Habitat patch size	Not available

* Available for GHCMA region only

The size of habitat patches surrounding monitoring grid sites was not available as GIS spatial data or from site data, but could be measured through interpretation of aerial photography. Polygons (patches) were created to represent the extent of potential habitat surrounding grid sites using the mapping program ArcGIS[®] (Version 9). To reduce variation in interpretation and achieve consistent boundary delineation, all patches were assessed by one individual, following predetermined guidelines. Guidelines were based on considerations such as: what are likely barriers to *D. impar* movement, and what evidence is there to suggest incompatible land use based on what is known about threats to this species (Appendix A details the specific guidelines for determining patch boundaries). The digitised spatial patches were then verified by DSE field officers who are familiar with sites, and updated in response to their recommendations. The area within polygons (patches) was calculated in hectares using the Field Calculator tool in ArcGIS[®] (Version 9) and then patches were sorted into four different size classes (Table 3.3).

All other environmental variables were either accessible as GIS spatial map layers or were available through DSE from the SWSLLP site monitoring data. Environmental attributes mapped over the study region and available as digital map layers (Table 3.2) were overlayed with the tile grid sites using the GIS program ArcGIS[®] (Version 9). All layers were checked for spatial compatibility and map projections were changed where necessary to insure accurate overlay. Each *D. impar* survey site was

characterised by the environmental attributes occurring at that location. Through this process a data set was created with each row representing a grid site (total of approximately 200), coded with "0" for *D. impar* absence and "1" for *D. impar* presence (the dependent variable), and all other columns representing each of the environmental variables.

For the native vegetation (modelled current extent) spatial data, 'highly likely native vegetation – grassy' was the variable used. Due to the level of detail within this spatial data set (25m grid cells) these variables were classified as either present or absent within a 50 metre circular buffer of *D. impar* survey sites (Table 3.4).

Table 3.2 Environmental attributes sourced from digital map layers which were used to characterise *Delma impar* survey grid sites in south western Victoria.

Spatial environmental data	Source	Scale
Geology - geological unit names and lithology descriptions	Department of Primary Industries (DPI), Geoscientific Data DVD (Version July 2007) (map tiles - Ballarat, Colac, Hamilton & Melbourne)	1:250 000
Soil Texture – surface clay content, subsurface clay content (GHCMA region only)	Department of Primary Industries (DPI), Glenelg Hopkins Land Resource Assessment (GHLRA) Baxter & Robinson (2001)	1:100 000
Historic vegetation – pre-1750 Ecological Vegetation Classes (EVCs) by bioregion	Department of Sustainability and Environment (DSE) Native Vegetation – Pre-1750s EVC mapping for Victoria	1:100 000
Current native vegetation extent – four different categories (classified as present if occurring within 50m of grid)	Department of Sustainability and Environment (DSE) Native Vegetation – Modelled Extent 2005 dataset	25 metre cell size (raster)
Climatic variables – average annual temperatures and rainfall	Australian Bureau of Meteorology (based on data between 1961 and 1990)	2500 metre cell size (raster)
Altitude – Digital Elevation Model (DEM)	Department of Primary Industries (DPI) Glenelg Hopkins Land Resource Assessment (GHLRA) Baxter & Robinson (2001)	20 metre cell size (raster)

Variables derived from site monitoring data (land use and fire frequency) were not mapped for the whole region and therefore could not be practically applied to landscape scale predictive mapping. This was also true for patch size. However, while not included in the logistic regression modelling, these variables (Table 3.3) were still considered to be potentially related to *D. impar* presence. Each of these three variables was analysed in relation to *D. impar* presence/absence with Chi-square contingency tests of independence to test if relationship might be detected. These three variables were also cross-tabulated with each other and tested using a Chi-square test of independence to identify potential relationships between them. Sites occurring within the roadside/rail reserve land use category (Figure 3.3) were analysed further as a stratified subsample, due to the high representation of sites within habitat patches in the five hectare and under size class and a high representation of burnt sites. This data set was tested again using a Chi-square test of independence to identify possible relationships between patch size and *D. impar* presence/absence, and fire frequency and *D. impar* presence/absence.

Table 3.3 Categorical environmental variables characterising grid sites and potentially related to *Delma impar* occurrence, but not mapped for the entire region. These variables were analysed in relation to *D. impar* presence/absence using Chi-square tests of independence.

Variable description	Category descriptions
Dominant land use	1 – roadside/ rail reserve (active) 2 – grazing & conservation 3 – grazing 4 – conservation/ reserve/ cemetery/ rail reserve (not active)
Patch size class	1 – \leq 5ha 2 – 6ha - 50ha 3 – 51ha – 200ha 4 – \geq 201ha
Fire frequency (controlled burns)	0 – unburnt 1 – burnt once 2 – burnt twice or more

Data exploration and preparation for model-fitting

Reducing the number of raw categories where there were too few monitoring sites represented per category for qualitative predictor variables was undertaken (approximately five or less was considered too few). Careful consideration was required when aggregating categories and an effort was made to maintain differences that were meaningful to the species biology and known habitat associations. For example, the historic vegetation variable initially consisted of sixteen vegetation classes, which were aggregated according to dominant structural components into four categories. Table 3.4 lists the final candidate predictors chosen and their category descriptions. Further details outlining the process and reasoning for complex aggregations can be found in Appendix B for soil clay content of the A and B horizons (A/BCLAY) and Appendix C for Pre-1750 EVCs (HVS).

While logistic regression does not require that predictor variables be normally distributed, transformed continuous variables may produce a better fit model (Garson 2008). For this reason continuous variables were log transformed, yet no significant difference was detected in preliminary modelling outcomes, and these variables were used in subsequent model fitting in their untransformed state.

Table 3.4 Code names, descriptions and category levels or ranges for the 9 candidate predictor variables used in logistic regression model fitting.

Model Code	Variable description	Category descriptions / range
GEOL	Geology	1 – basalt 2 – sedimentary (marine) 3 – sedimentary (non-marine)
ACLAY	Clay content of soil A horizon (GHCMA only)	1 – <20% clay 2 – 20-30% clay 3 – 30-40% clay 4 – >40% clay
BCLAY	Clay content of soil B horizon (GHCMA only)	1 – 20-30% clay 2 – 30-40% clay 3 – >40% clay
A/BCLAY	Clay content of the soil A and B horizons (GHCMA only)	1 – (H) high clay both horizons 2 – (C) contrast between horizons 3 – (L/M) low /medium clay both horizons
HVS	Historic vegetation structure (based on EVC benchmarks and pre-1750 cover extent)	1 – grass dominated 2 – high grass component woodland 3 – low grass component woodland 4 – forest/shrubby/wetland
CENVG	Current extent native grassy vegetation	0 – absent 1 – present
TEMPMAX	Average annual maximum temperature	17 – 20.4 C*
ANNRAIN	Average annual rainfall	523 – 824 mm*
ALT	Altitude	55 – 526 m (asl)*

* Ranges are relevant to reduced dependent variable data set (n=166)

While not always possible when relying on pre-existing species observations, survey sites should be distributed systematically over the study area following a stratified design, in order to sample the range of environmental combinations or geographical gradients (Paull 2003; Wintle *et al.* 2005). Due to the retrospective nature of the SWSLLP survey data, some environmental combinations were sampled much more frequently, than others. In this study, for example, geology was initially categorised by lithology descriptions, but there were a number of categories with minimal representation (less than five cases) therefore geology was eventually grouped by broad types (Table 3.4).

Another consideration with retrospective data is the independence of observations. Spatial autocorrelation (the closer things are the more likely they are to be similar) can violate the assumption of independent observations required for statistical significance tests (Carroll *et al.* 1999). The presence/absence data from the SWSLLP used in this study was potentially spatially autocorrelated due to the strategy that was used to determine sampling site locations. Survey sites were obviously clustered in some locations (e.g. areas where the species was historically recorded), while other areas were largely devoid of sampling sites over the study region (refer to map - Figure 3.1). Two sources of spatial dependence are identified in Fortin and Dale (2005), one is endogenous spatial autocorrelation (e.g. mobility and dispersal could dictate the distance individuals/populations are influencing each other), and the other source is related to exogenous processes, where the species has a functional relationship with another variable that is itself spatially autocorrelated. To reduce the risk of spatial autocorrelation and non-independent samples for this study the data was thinned, the process of which is outlined below.

Survey grids occurring within the same contiguous habitat patch (as defined previously for the predictor variable patch size), or survey grids within 500m of one another were considered at risk of statistically problematic spatial autocorrelation and were separated from the dataset for closer consideration. Sites within the same patch were considered to potentially be sampling the same population, and 500m was nominated as the minimum separation distance between observations following similar habitat modelling studies targeting small vertebrate species (Paull 2003; Wintle *et al.* 2005).

When deciding which grids to retain in the analysis, presence records were chosen over absence where the two occurred together (within 500m or in the same patch). This was based on the idea that in biological surveys false-negatives (failing to record a species when it is present) are more prevalent than false-positives (recording a species as present when it is absent) (Tyre *et al.* 2003; Wintle *et al.* 2005) especially for cryptic or elusive species (Ottaviani *et al.* 2004) such as *D. impar*. Where a pair or cluster of sites all had records of species absence, one site was randomly chosen to be retained, unless two or more environmental variables

were considerably different, in which case both sites, or those that were considered different (if more than two) were retained. Where two or more presence records occurred together, the one with the most recent *D. impar* observation was retained, or where two or more environmental variables were different both (or the two most different) were retained.

As a result of this process, the adjusted sample size available for analysis was reduced to 166 (32.5 % species presence, 67.5% species absence). Methods for incorporating spatial autocorrelation into habitat analyses, rather than thinning the data as was done here, have been described (Carroll *et al.* 1999) and successfully implemented (for example see Augustin *et al.* 1996). However, these alternative processes are considered technically demanding to implement and are not readily available in most statistical software (Wintle *et al.* 2005). Furthermore, the time constraints of this study limited thorough exploration of alternative methods for dealing with spatial autocorrelation.

Statistical models

Three models were chosen to investigate the species-habitat relationship of *D. impar* at a landscape scale in south western Victoria. Model 1 ($n = 166$) considered the predictive strength of the variables GEOL, HVS, ALT, TEMPMAX, ANNRAIN and CENVG (refer to Table 3.4) to explain the dependent variable (species presence/absence). The same predictor variables offered in the model fitting process for model 1 were also used for model 2. Model 2 represented a subset of monitoring sites that occurred on either roadsides or rail reserves ($n = 79$). Sites within this land use category constitute almost half of all sites, and were considered worthy of separate analysis due to their similar management history, as well as a higher prevalence of *D. impar* presence compared to the full data set. Model 3 considered the soil texture variables ACLAY, BCLAY and A/BCLAY as well as all other predictor variables in Table 3.4, but only analysed sites within the GHCMA region ($n = 86$) because soil mapping between the GHCMA and CCMA regions was found to be incompatible. Clay content of soil has been identified in previous studies on *D. impar* to potentially be an important indicator of habitat, and therefore was considered

worth of investigating even on a reduced data set, which might be considered too small to produce reliable, robust predictions.

Each binary logistic regression model was fit using a forward stepwise procedure. The automated forward stepwise procedure (Forward LR in SPSS[®]) for selection of variables begins with no predictors in the model (null model), then adds the one with the smallest significance value (p-value) based on the likelihood ratio (LR) statistic. The likelihood ratio test is measured by Chi-square difference (Garson 2008). The next step calculates the significance of each of the remaining variables based on the LR statistic while accounting for the variable already explaining some of the variance within the model. The variable found to be the most significant in this step is then added to the model. The process is continued until no more variables contribute significantly ($p < 0.05$) to explaining the dependent variable (explanation adapted from Quinn and Keogh 2002, and Garson 2008).

The statistical relationship between p (the probability of species presence) and the predictor variables takes the form:

$$z = \text{logit} (p) = \log (p/1 - p) = b_0 + b_1x_1 + b_2x_2 + \dots + b_nx_n$$

where z is the linear combination of predictor variables, b_0 is the constant (slope intercept), $b_1 - b_n$ are the coefficients (or weightings) for the explanatory variables, and each x is an observed, predictor variable that may explain p (following Legendre & Legendre 1998; Quinn & Keough 2002; Lindenmayer & Burgman 2005). In this way, the logistic regression equation with the final predictors retained in the model, and their coefficients (parameter estimates), can be used to predict the probability (p) of species occurrence at unsampled locations, within the sampled study region (Guisan *et al.* 2002).

A probability threshold (cut-point) was determined for each model separately. The threshold determines the probability value between 0 and 1, above which cases will be classified as presence predictions, and below which species absence will be predicted by the model (the default threshold in SPSS is 0.5). Due to the dependent variable (observed presence/absence) being disproportionate for all *D. impar*

models, a cut-point based on species prevalence (proportion of presence observations) was used, as recommended by Carroll *et al.* (1999). The cut-points for models 2 and 3 were adjusted further, as a result of considering the effect of false-negative and false-positive errors on model predictions (Wilson *et al.* 2005; Wuensch 2008). A false-negative error occurs when an observed presence is predicted as an absence, and alternatively a false-positive error results from an absence being predicted as a presence (Tyre *et al.* 2003). In the case of the endangered *D. impar*, it was considered more important to have a high rate of correct presence predictions (i.e. low false-negative rate) than to be highly accurate at predicting species absence (i.e. low false-positive rate).

Evaluation of models

Standardised residuals and Cook's leverage values for each case were saved for all models, and were inspected for outliers. Where a small number of cases were identified to be outliers, models were run again without them. Where the influence of these outliers on model predictions was found to be minimal (i.e. did not result in significant changes to parameter estimates or their standard errors) they were retained in the dataset.

Due to the relatively low number of survey sites available for analysis, a subset of the data was not withheld from model fitting for the purpose of cross-validating model predictions. However, the models were evaluated using the following quantitative methods.

Model fit was assessed using Hosmer and Lemeshow's goodness of fit test in SPSS[®], which groups predictions into ten probability classes and computes a Chi-square statistic from comparing observed and expected frequencies of presence and absence.

A Receiver Operating Characteristic (ROC) curve plot was used to summarise the predictive performance of the final models. A ROC curve plots the relative proportion of correct predictions of presence (model sensitivity) against the false positive fraction, or 1 – specificity (where specificity is the proportion of observations correctly predicted as absence by the model) (Fielding & Bell 1997; Lindenmayer & Burgman

2005). The ROC curve plots probabilities over all possible threshold levels, and can therefore be reported as a threshold independent assessment of a models discriminatory power (Pearce & Ferrier 2000b; Ottaviani *et al.* 2004).

Assessing prediction accuracy in relation to the threshold value was achieved by exploring classification tables which compared predicted presence/absence to observed presence/absence. False-positive and false-negative rates were also calculated from the classification tables of each model and compared within and between models.

One model was chosen as the best model overall. This was done on the basis of sample size, ROC curve plots, classification accuracy, variance explained and 95 percent confidence intervals of prediction parameters. The model chosen was used for probability predictions of species occurrence over the study area, by using the parameter estimates of environmental predictors. Validation of the model will ultimately require new field data to be collected at locations previously unsampled within the prediction region.

Predictive distribution mapping

The model that best explained the distribution of *D. impar* was used to map probabilities of species occurrence over the region. The relevant map layers (spatial data) were overlayed using the union tool in ArcGIS[®], which combined the environmental variables to be used for prediction. The parameter estimates for each predictor variable included in the final model were used to calculate probability values for the relevant combinations of the predictor variables mapped over the study area. The predicted distribution of occurrence was then thematically displayed using increments of predicted probability between 0 and 1. This process followed similar species distribution modelling studies (e.g. Carroll *et al.* 1999; Guisan & Hofer 2003; Paull 2003; Wintle *et al.* 2005), but in the current study predicted probabilities were calculated and displayed using vector data (in the form of polygons) rather than raster data (equally sized and spaced grid cells). Vector data was chosen due to limited computer processing capacity and predictor variables mapped at very different scales to one other.

RESULTS

Variables recorded on site

Patch size

Of the 166 survey sites analysed, 123 (74%) were estimated to be within habitat patches equal to or less than 50ha in size, and of the 54 presence sites 27 (50%) were in the ≤ 5 ha size class (Table 4.1; Figure 4.1). A test of independence found *D. impar* presence/absence was significantly related to patch size class (Table 4.1). Sites occurring within patches between 6 and 50 hectares were found to have species presence recorded much less often than expected, contributing most to the Chi-square statistic. The second highest contribution to the Chi-square statistic was from sites occurring within patches between 51 and 200 hectares, which saw presence observed more often than expected.

Table 4.1 Number of sites within each patch size class for all sites *D. impar* recorded absent, for all sites *D. impar* recorded present, and number of sites within patch size class for all survey sites (percentages in brackets), with result of Chi-square test of independence for patch size classes by presence/absence.

Patch size (ha)	Absence sites	Presence sites	All sites
≤ 5	53 (47%)	27 (50%)	80 (48%)
6 - 50	36 (32%)	7 (13%)	43 (26%)
51 - 200	12 (11%)	12 (22%)	24 (15%)
≥ 201	11 (10%)	8 (15%)	19 (11%)

Chi-square test of patch size X presence/absence $\chi^2 = 9.3$ df = 3 P = 0.025

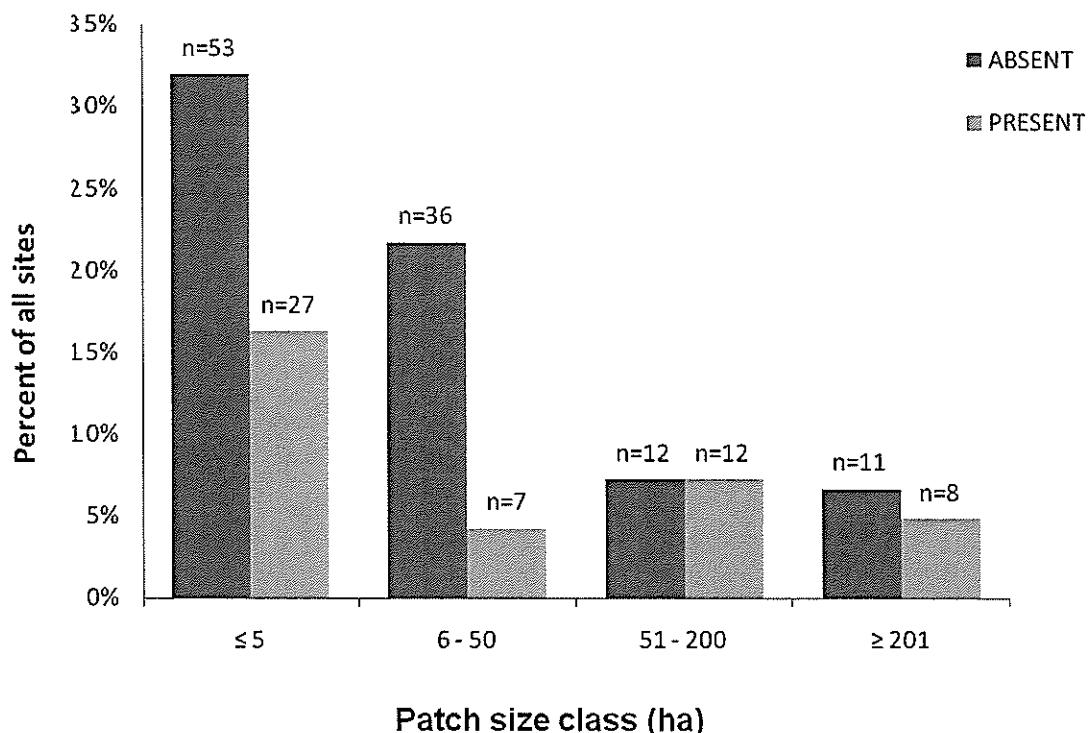


Figure 4.1 Percentage of all sites ($n = 166$) in each size class, shown here by presence and absence of *Delma impar*, with the number of cases displayed above bars (all bars combined equal 100%).

Land use

Of the 166 survey sites, 79 (47%) occurred on roadsides or active rail reserves (non-active rail reserves were included in the conservation/reserve land use category) (Table 4.2; Figure 4.2). Of the 54 sites where *D. impar* was recorded, 33 (61%) were in the roadside/rail reserve land use category (Table 4.2). The variable land use was not found to be related to *D. impar* presence/absence ($P = 0.052$) yet is close enough to the 0.05 significance level to suggest results might not be conclusive (Table 4.2). Figure 4.2 shows sites in the roadside/rail reserve category and the grazing & conservation category display noticeably higher proportions of *D. impar* presence compared to absence than sites in the grazing or conservation/reserve land use categories.

Table 4.2 Number of sites within each land use category for all sites *D. impar* recorded absent, for all sites *D. impar* recorded present, and total number of sites within each land use category for all survey sites (percentages in brackets), with result of Chi-square test of independence for land use categories by presence/absence.

Land use	Absence sites	Presence sites	All sites
Roadside/rail reserve	46 (41%)	33 (61%)	79 (47%)
Grazing & conservation	13 (11%)	8 (15%)	21 (13%)
Grazing	12 (11%)	3 (6%)	15 (9%)
Conservation/reserve	41 (37%)	10 (18%)	51 (31%)

Chi-square test of land use X presence/absence $\chi^2 = 7.7$, df = 3, P = 0.052

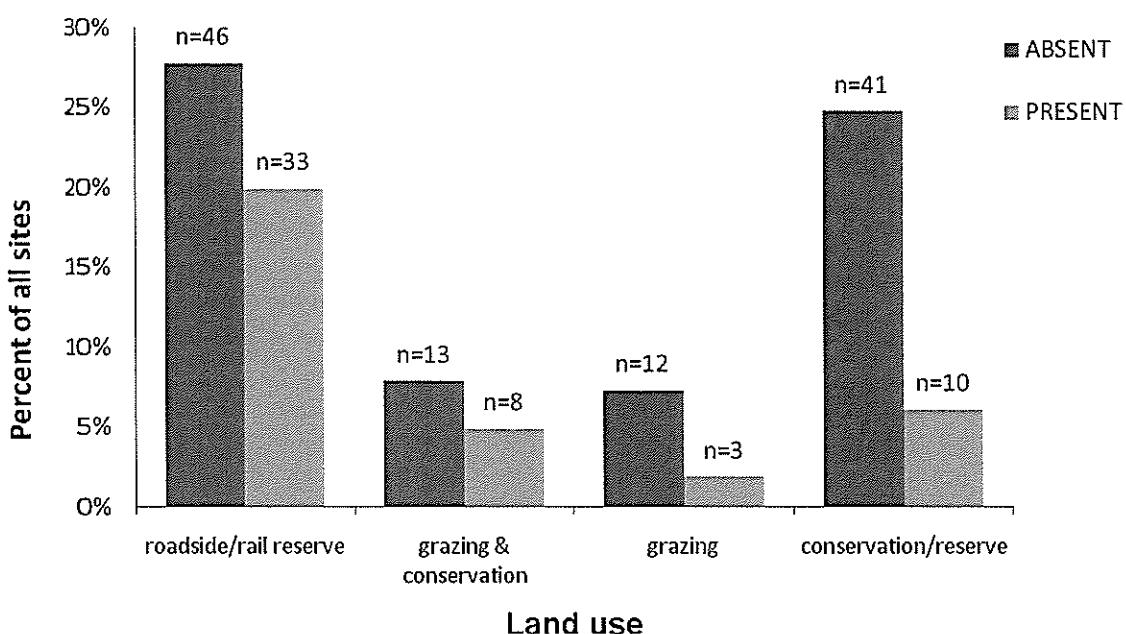


Figure 4.2 Percentage of all sites (n = 166) within each land use category, shown here by presence and absence of *D. impar*, with the number of cases displayed above bars (all bars combined equal 100%).

Fire frequency

Of all 166 sites, the majority 118 (71%) were not influenced by any fire events between spring 2004 and spring 2008 (the period for which the data relates) (Table 4.3; Figure 4.3). Sites burnt once, and sites burnt more than once accounted for only 20 (12%), and 28 (17%) respectively, of the total 166 sites (Table 4.3). The group of 118 sites where no burning was recorded had the lowest proportion of *D. impar* presence records compared to absence (Figure 4.4). Sites burnt more than once had a higher proportion of presence compared to absence, and an overall trend can be seen in Figure 4.4 of the increased proportions of *D. impar* occurrence as the number of fire events increased. The results of the Chi-square test indicate that there is a relationship between fire frequency and *D. impar* presence/absence (Table 4.3).

Table 4.3 Number of sites within each fire frequency category for all sites *D. impar* recorded absent, for all sites *D. impar* recorded present, and the total number of sites within each fire frequency category for all survey sites (percentages in brackets), with result of Chi-square test of independence for fire frequency categories by presence/absence.

Fire frequency	Absence sites	Presence sites	All sites
0	89 (79%)	29 (54%)	118 (71%)
1	11 (10%)	9 (17%)	20 (12%)
>1	12 (11%)	16 (29%)	28 (17%)

Chi-square test of fire frequency X presence/absence $\chi^2 = 12.5$, df = 2, P = 0.002

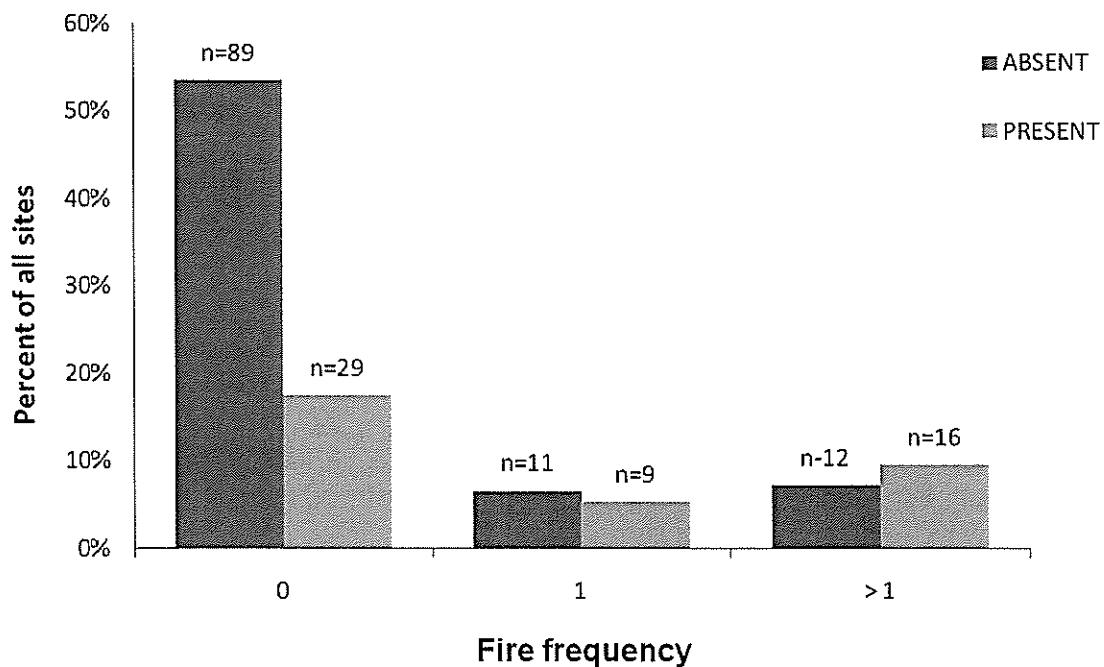


Figure 4.3 Percentage of all sites ($n = 166$) within each fire category, shown here by presence and absence of *D. impar*, with the number of cases displayed above bars (all bars combined equal 100%).

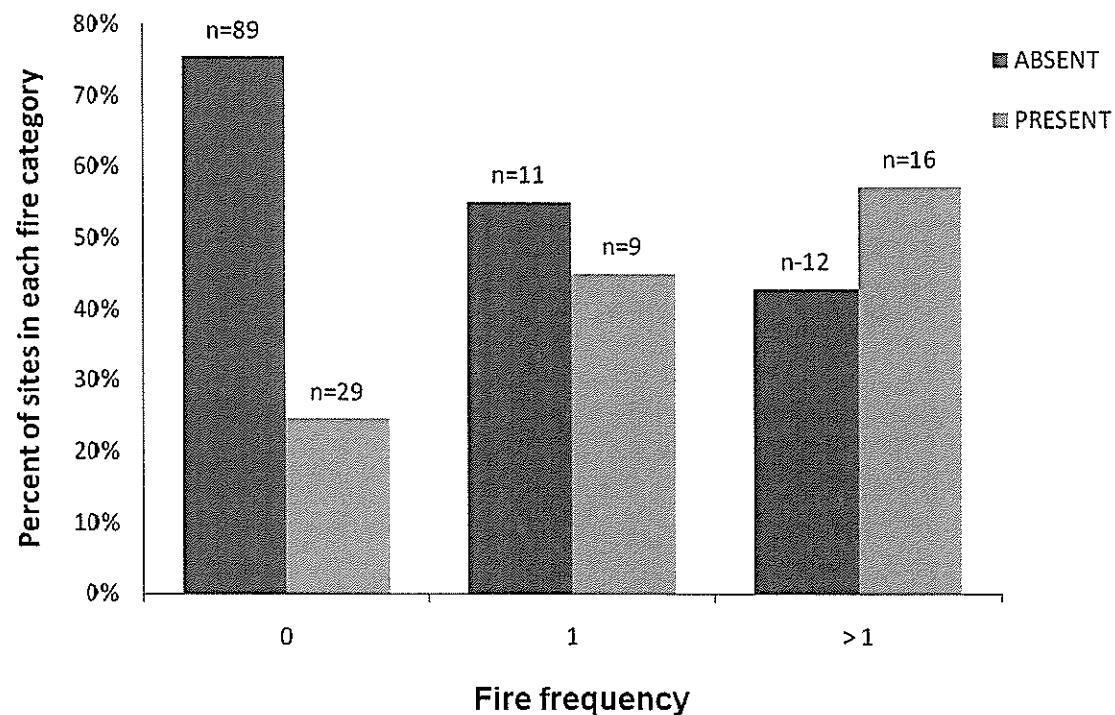


Figure 4.4 Percentage of *D. impar* presence and absence within each fire category (each pair of presence/absence bars equal 100%), with number of cases (total $n = 166$) displayed above bars.

Site variables compared

Land use, fire frequency and patch size were found to all be related to one another (Table 4.4).

Table 4.4 The results of Chi-square independence tests of variables recorded at grid sites.

Variables tested	χ^2 statistic	df	p-value
Land use X Fire frequency	49.9	6	< 0.001
Land use X Patch size	52.9	9	< 0.001
Fire frequency X Patch size	34.5	6	< 0.001

Inspection of the contingency tables for each of these tests revealed that of the total 80 sites within patches ≤ 5 ha in size, 59 (72%) were within the roadside/rail reserve land use category. In addition, of the total 48 burnt sites, 40 (83%) occurred within the ≤ 5 ha patch size class, and 43 (89%) of burnt sites were on roadsides or active rail reserves. Subsequently, sites within the roadside/rail reserve land use category ($n=79$) were tested as a separate subset of data for a relationship with *D. impar* presence/absence.

As presented above, *D. impar* occurrence was found to be related to the number of fire events and patch size in the full data set ($n=166$) (Table 4.3 and Table 4.1), however, for the sample of only roadside/rail reserve sites, fire frequency was still found to be significant ($\chi^2 = 8$, df = 2, P = 0.018) but patch size was not ($\chi^2 = 0.4$, df = 3, P = 0.935).

Logistic Regression Models

Model 1 – all variables (except soil texture) (n=166)

Logistic regression identified three independent variables to be significant predictors of *D. impar* presence/absence for model 1. Step one of model fitting included current extent native vegetation - grassy (CENVG $\chi^2 = 20.39$, df = 1, P < 0.001), step two selected average annual maximum temperature (TEMPMAX $\chi^2 = 13.46$, df = 1, P < 0.001), and finally geology type (GEOL $\chi^2 = 6.856$, df = 2, P = 0.032) was added, after which no other variables improved the model significantly. Predicted probabilities were split by a 0.32 cut-point, resulting in correct classification of *D. impar* presence and absence 70.5% of the time (67% correct classification of observed absence, 77.8% correct classification of observed presence – Table 4.6).

The Hosmer and Lemeshow goodness of fit test statistic calculated for model 1 was not significant ($\chi^2 = 5.609$, df = 8, P = 0.586) therefore the null hypothesis (no difference between observed and model-predicted values) could be accepted. This result indicated that the model fit the data at an acceptable level (P > 0.05). It is important to remember that while this statistic tests whether the variance in the dependent explained by the model is significant, it does not measure how much of the variance is explained (Garson 2008).

Table 4.5 shows the parameter estimates and significance level of each variable when entered into the model, as well as the relative significance contributed to the final model (step 3) and the odds ratios for each factor. Odds ratios for the final model can be interpreted as the likelihood that *D. impar* will be present at sites characterised by those particular environmental attributes. For categorical variables the odds ratio is related to the reference category within that variable, whereas continuous variables relate to a single unit increase. Therefore, the odds ratios for the geology type indicate that *D. impar* is 2.628 times more likely to be present at sites characterised by basalt than if the geology was sedimentary non-marine, holding all other variables constant. Yet *D. impar* is less likely (0.653) to be present at sites characterised by sedimentary marine geology when compared with sedimentary non-marine geology. The likelihood of *D. impar* occurrence increases 3.381 times with the presence of native grassy vegetation, and by 5.044 for each

degree increase in average annual maximum temperature (within the temperature range sampled).

Table 4.5 Model 1 showing changes to the model as variables are entered at each step. Step 3 shows all variables included in the final model. Parameter estimates and significance level are given at each step of model fitting. The odds ratios and their corresponding confidence intervals have also been calculated.

Step	Variables in model	Parameter estimate	P value	Odds ratios	95% C.I. for odds ratios	
					Lower	Upper
1	Current extent native veg – grassy	1.653	<0.001	5.222	2.506	10.881
	Constant	-1.247	<0.001	0.287		
2	Maximum average annual temperature	1.288	0.001	3.627	1.651	7.965
	Current extent native veg – grassy	1.547	<0.001	4.696	2.196	10.041
	Constant	-25.453	0.001	0.000		
3	Geology – Sedimentary (non-marine)		0.043			
	Geology – Basalt	0.966	0.044	2.628	1.028	6.721
	Geology – Sedimentary (marine)	-0.427	0.576	0.653	0.146	2.916
	Maximum average annual temperature	1.618	0.001	5.044	1.980	12.848
	Current extent native veg – grassy	1.218	0.003	3.381	1.526	7.491
	Constant	-32.113	<0.001	0.000		

Geology – Sedimentary (non-marine) is the reference category for the geology variable

Correctly and incorrectly classified cases are presented as an assessment of the model's prediction accuracy based on the cut-point (Table 4.6). Step 1 of the model shows that, alone, the variable CENVG is used to correctly classify presence and absence of *D. impar* in 72.9% of cases. Total prediction accuracy of the final model with CENVG, TEMPMAX and GEOL is 70.5%, and therefore less than the total prediction accuracy at step 1. Although, while the final model (step 3) has slightly less overall classification accuracy, it correctly predicts the presence of *D. impar* in more cases as additional variables are included (step1 – 50%, step 2 – 61.1%, step 3 – 77.8%). As correct classification of presence increase the false negative rate decreases. Correspondingly, correct classification of species absence decreases at each step within the model (Table 4.6), effectively increasing false positives. This is related to the cut-point which has been adjusted (from the 0.5 default to 0.32) to

reflect the ratio of presence/absence in the observed data (binary response variable), and also to reduce false negative predictions.

Table 4.6 Classification table for model 1 showing how accurate the model is at correctly predicting presence or absence of *Delma impar*, as each variable is added. Step 3 shows the proportion of correct predictions for absence, presence and overall of the final model.

Variables in the model	<i>D. impar</i> (recorded at site)	<i>D. impar</i> predicted by model		Percent correctly predicted by model
		absent	present	
Step 1 CENVG	absent	94	18	83.9
	present	27	27	50.0
				Total 72.9
Step 2 CENVG TEMPMAX	absent	80	32	71.4
	present	21	33	61.1
				Total 68.1
Step 3 CENVG TEMPMAX GEOL	absent	75	37	67.0
	present	12	42	77.8
				Total 70.5

The cut-point was set at 0.32, therefore probabilities under this value have been predicted as absence of the species, and probabilities over 0.32 predicted as presence. The shaded columns are the number of predicted presence/absence, and the shaded rows are the observed (actual) presence/absence of the species.

Model 2– subset of sites on road and rail reserves (cases, n=79)

Model 2 represented all sites within the land use category 'roadside/rail reserve'. This subset of data was found to be characterised by more frequent burning than any other land use category and most sites were estimated to be within habitat patches less than or equal to 5ha in size. Stepwise selection for model 2 produced the same predictors as model 1 (CENVG $\chi^2 = 20.8$, df = 1, P < 0.001, TEMPMAX $\chi^2 = 6.489$, df = 1, P = 0.011, GEOL $\chi^2 = 7.159$, df = 2, P = 0.028), and with a 0.35 cut-point, the model classified presence and absence correctly at a rate of 75.9% (67% correct classification of observed absence, 87.9% correct classification of observed presence – Table 4.8). Table 4.7 shows the parameter estimates and significance level of each variable when entered into the model, as well as the relative significance contributed to the final model (step 3). Results for model 2 are similar to model 1, but the confidence intervals for the odds are noticeably wider.

Table 4.7 Model 2 showing changes to the model as variables are entered at each step. Step 3 shows all variables included in the final model. Parameter estimates and significance level are given at each step of model fitting. The odds ratios and their corresponding confidence intervals have also been calculated.

Step	Variables in model	Parameter estimate	P value	Odds ratios	95% C.I. for odds ratios	
					Lower	Upper
1	Current extent native veg – grassy	2.534	<0.001	12.600	3.670	43.255
	Constant	-1.030	0.001	0.357		
2	Maximum average annual temperature	1.259	0.030	3.521	1.133	10.940
	Current extent native veg – grassy	2.400	<0.001	11.024	3.134	38.773
	Constant	-24.705	0.024	0.000		
3	Geology – Sedimentary (non-marine)		0.062			
	Geology – Basalt	1.403	0.078	4.068	0.856	19.324
	Geology – Sedimentary (marine)	-1.338	0.332	0.262	0.018	3.923
	Maximum average annual temperature	2.033	0.008	7.638	1.686	34.604
	Current extent native veg – grassy	2.153	0.002	8.618	2.257	32.863
	Constant	-40.158	0.007	0.000		

Geology – Sedimentary (non-marine) is the reference category for the geology variable

Inspection of the classification table shows how the correct positive prediction rate increases at each step (Table 4.8). The threshold (cut-point) for model 2 was 0.35, which was chosen based on the ratio of presence to absence in the observed data and inspection of the Receiver Operating Characteristic (ROC) curve in an attempt to reduce the false negative classifications.

Table 4.8 Classification table for model 2 showing how accurate the model is at correctly predicting presence or absence of *Delma impar*, as each variable is added. Step 3 shows the proportion of correct predictions for absence, presence and overall of the final model.

Variables in the model	<i>D. impar</i> (recorded at site)	<i>D. impar</i> predicted by model		Percent correctly predicted by model
		absent	present	
Step 1 CENVG	absent	42	4	91.3
	present	15	18	54.5
			Total	75.9
Step 2 CENVG TEMPMAX	absent	33	13	71.7
	present	12	21	63.6
			Total	68.4
Step 3 CENVG TEMPMAX GEOL	absent	31	15	67.4
	present	4	29	87.9
			Total	75.9

The cut-point was set at 0.35, therefore probabilities under this value have been predicted as absence of the species, and probabilities over 0.35 predicted as presence. The shaded columns are the number of predicted presence/absence, and the shaded rows are the observed (actual) presence/absence of the species.

The Hosmer and Lemeshow test result is not reported for model 2 because predicted probabilities, when divided into deciles, did not meet the recommended 95% with expected frequencies greater than 5, indicating potential sample inadequacy for this test (Garson 2008). The Hosmer and Lemeshow significance test for goodness of fit is therefore not reliable as a measure of difference between the predicted probabilities and the observed data for this model.

Model 3 – subset of sites in GHCMA region (cases, n=86)

Soil texture variables (measuring clay content), horizon A, horizon B and the variable representing the clay content of both horizons (ACLAY, BCLAY and A/BCLAY) were included for selection in logistic regression model 3. The model fitting process ceased after the inclusion of only one variable, because no other predictor variables were found to contribute to produce a significantly better model. The final model contained the soil texture variable A/BCLAY, which revealed a significant association with the variance in the dependent variable ($\chi^2 = 9.4$, df = 2, P = 0.009). The final model revealed that the likelihood of *D. impar* being present was highest where soil clay content was high, because when compared to the high clay category (reference category) the other two categories have negative parameter estimates (Table 4.9). The likelihood of *D. impar* presence was lower for contrasting soil texture, and the odds were lowest when soil clay content of the A and B horizons was categorised as medium to low. The current extent native grassy vegetation variable (CENVG) chosen in the first step of models 1 and 2, was an available predictor for model 3, but was not found to explain as much of the variance in the dependent variable as an indicator of soil clay content.

Table 4.9 Step 1 for model 3 represents the final model. Parameter estimates and significance level are given for each category of the variable A/BCLAY. The odds ratios and their corresponding confidence intervals have also been calculated.

Step	Variables in model	Parameter estimate	P value	Odds ratios	95% C.I. for odds ratios	
					Lower	Upper
1	Soil texture A/B horizon clay – High		0.023			
	Soil texture A/B horizon clay – Contrast	-1.079	0.040	0.340	0.122	0.952
	Soil texture A/B horizon clay – Medium/low	-2.277	0.037	0.103	0.012	0.871
	Constant	0.080	0.777	1.083		

Soil texture A/B horizon clay – High is the reference category for the soil texture A/B variable

With one predictor variable, model 3 had a correct overall classification rate of 62.8% (53.8% correct classification of observed absence, 76.5% correct classification of observed presence) (Table 4.10). The cut-point was set at the 0.5 default, to maximised correct predictions of species presence for this model.

Table 4.10 Classification table for model 3 showing how accurate the model is at correctly predicting presence or absence of *Delma impar*, at step one, which is the final model.

Variables in the model	<i>D. impar</i> (recorded at site)	<i>D. impar</i> predicted by model		Percent correctly predicted by model
		absent	present	
Step 1 A/BCLAY	absent	28	24	53.8
	present	8	26	76.5
		Total		62.8

The cut-point was set at 0.5, therefore probabilities under this value have been predicted as absence of the species, and probabilities over 0.5 predicted as presence. The shaded columns are the number of predicted presence/absence, and the shaded rows are the observed (actual) presence/absence of the species.

The Hosmer and Lemeshow goodness of fit test was not appropriate for model 3 because there was only one predictor variable in the final model.

Summary and comparison of predictive models

Model 2 shows the highest overall classification accuracy, the lowest error rates and is the most improved on the null model when all models are compared (Table 4.11 – null model is explained in the footnote of the table). Model 1 appears to only perform better at explaining more of the variance in the observed data (Table 4.11) using the same predictors as model 2 but calculated on a sample twice the size. The 95 percent confidence intervals are comparatively narrower for model 1 also (Table 4.5 and Table 4.7). Compared to the other models, model 3 explains little of the variance in the response variable, as shown by the comparatively small change in model log likelihood (table 4.11). This model also has the highest false negative rate and the lowest overall prediction accuracy. Yet model 3 found A/BCLAY to be a better single predictor of *D. impar* presence/absence than CENVG, suggesting that for the sites in the GHCMA region CENVG explains less of the variance than A/BCLAY.

For all models, the improvement made to null models appears relatively low, yet should be considered in relation to false-negative and false-positive rates. This is because the null model for all three models would have predicted more false negatives than false positives, yet these rates are now reversed as a result of altering the model prediction thresholds.

Table 4.11 Summary of all 3 logistic regression models with evaluation measures.

Model	Overall classification accuracy	False-negative rate	False-positive rate	Percent improved on null model*	Change in model log likelihood (deviance)
1	70.5	0.14	0.47	3	40.709
2	75.9	0.11	0.34	17.7	34.453
3	62.8	0.22	0.48	2.3	9.4

* the null model (or intercept-only model) is based on predicting the most numerous category of the dependent variable for all cases, for example, the intercept-only predictions for all 3 models presented here would predict absence for all cases, as it is the more prevalent of the two categories of the dependent variable. For example, in the case of model 1, the null model would predicted absence for all sites and would be correct 67.5% of the time, because this is the proportion of observed absence.

A comparison of a threshold independent measure of each models predictive performance can be seen in the Receiver Operating Characteristic (ROC) plots (Figure 4.5) showed much the same as the other quantitative evaluation measures in Table 4.11. Model 2 has the highest area under the curve (AUC) score indicating that it has the best predictive power, followed by model 1. Model 1 shows a smoother curve than model 2 with fewer abrupt fluctuations, which could be the influence of the smaller sample size and higher variance of model 2. The three simple plot lines forming the curve in model 3 represent the three categories within the predictor variable (A/BCLAY)

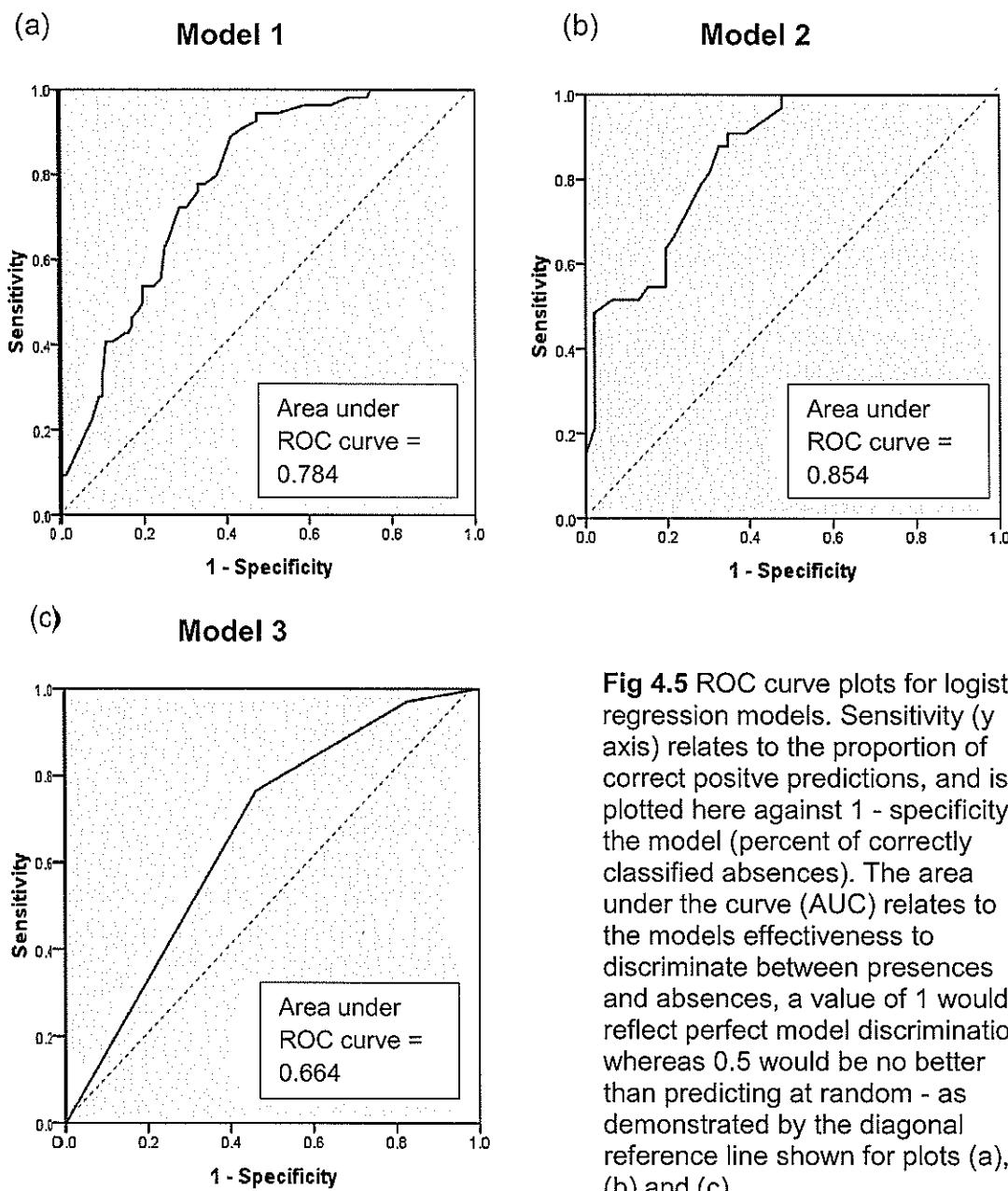


Fig 4.5 ROC curve plots for logistic regression models. Sensitivity (y axis) relates to the proportion of correct positive predictions, and is plotted here against 1 - specificity of the model (percent of correctly classified absences). The area under the curve (AUC) relates to the models effectiveness to discriminate between presences and absences, a value of 1 would reflect perfect model discrimination, whereas 0.5 would be no better than predicting at random - as demonstrated by the diagonal reference line shown for plots (a), (b) and (c).

Practical application of the statistical model

Model 1 was chosen to map predictive distribution for this species over the study region. In the comparison of quantitative model evaluation measures, model 2 appeared to performed better than model 1, yet model 2 only analyses sites in one land use category (roadside/rail reserve), whereas model 1 incorporates all land use data. Furthermore, both models use the same predictor variables to explain

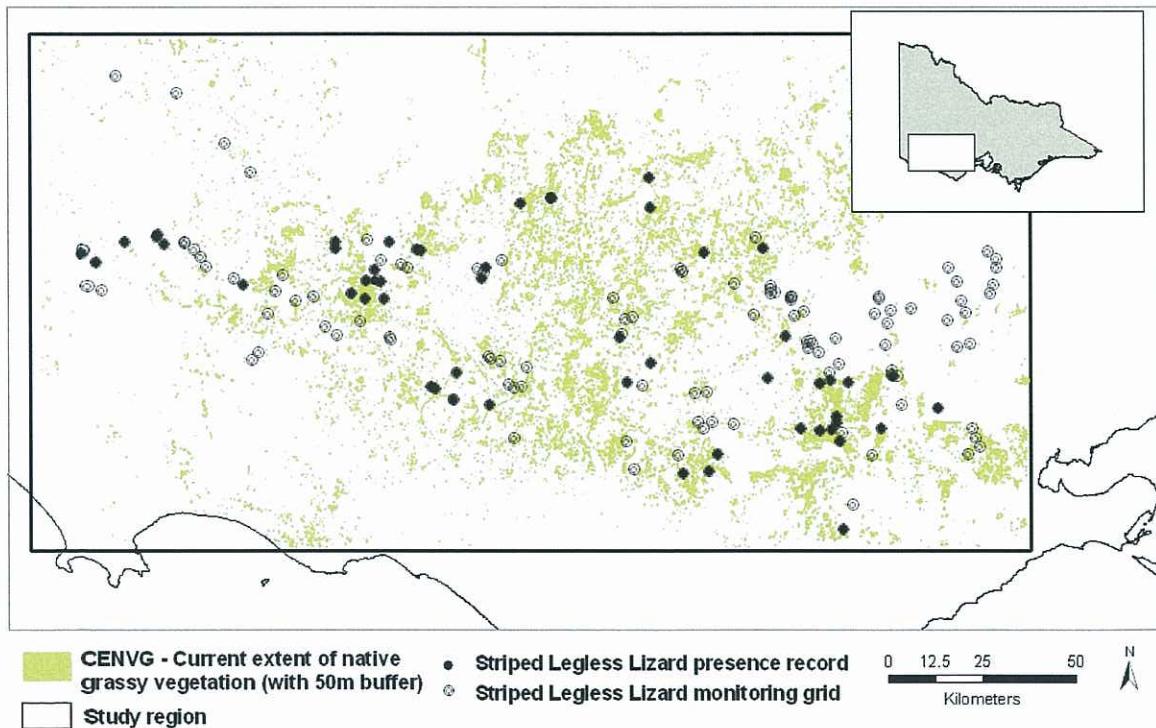
presence/absence, but model 1 is based on a sample size twice that of model 2, and therefore likely to be the more statistically robust model of the two.

The statistical model (model 1) used to predict the spatial distribution of *D. impar* over the study region in south western Victoria, was applied using the probability values between 0 and 1 generated from the final model equation:

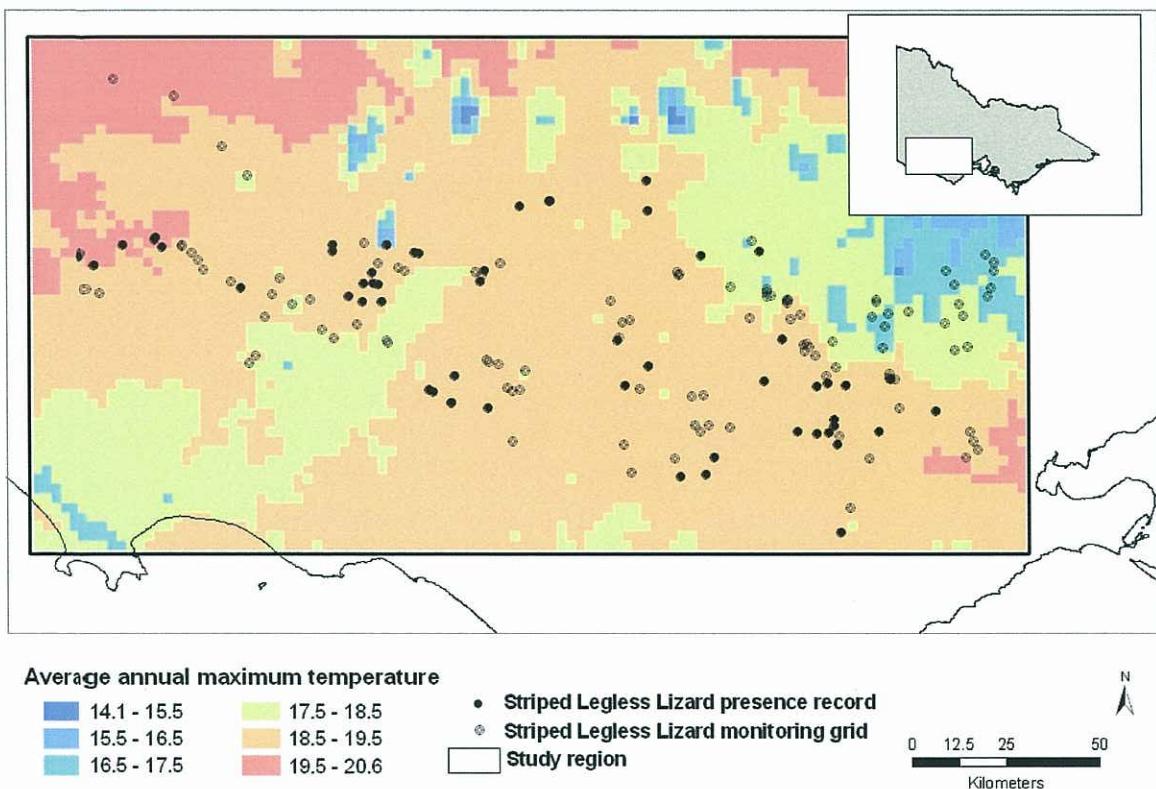
$$\text{Logit}(p) = -32.113 + (0 * \text{CENVG (0)} \text{ OR } 1.218 * \text{CENVG (1)}) + 1.618 * \text{TEMPMAX} + 0 * \text{GEOL (sedimentary non-marine)} \text{ OR } 0.966 * \text{GEOL (basalt)} \text{ OR } -0.427 * \text{GEOL (sedimentary marine)}$$

The spatial distribution of predictor variables and sample sites used in the final prediction model are shown separately (Figure 4.6 a, b, c), and together with predicted probabilities of *D. impar* presence (Figure 4.7) over the study region.

(a)



(b)



(c)

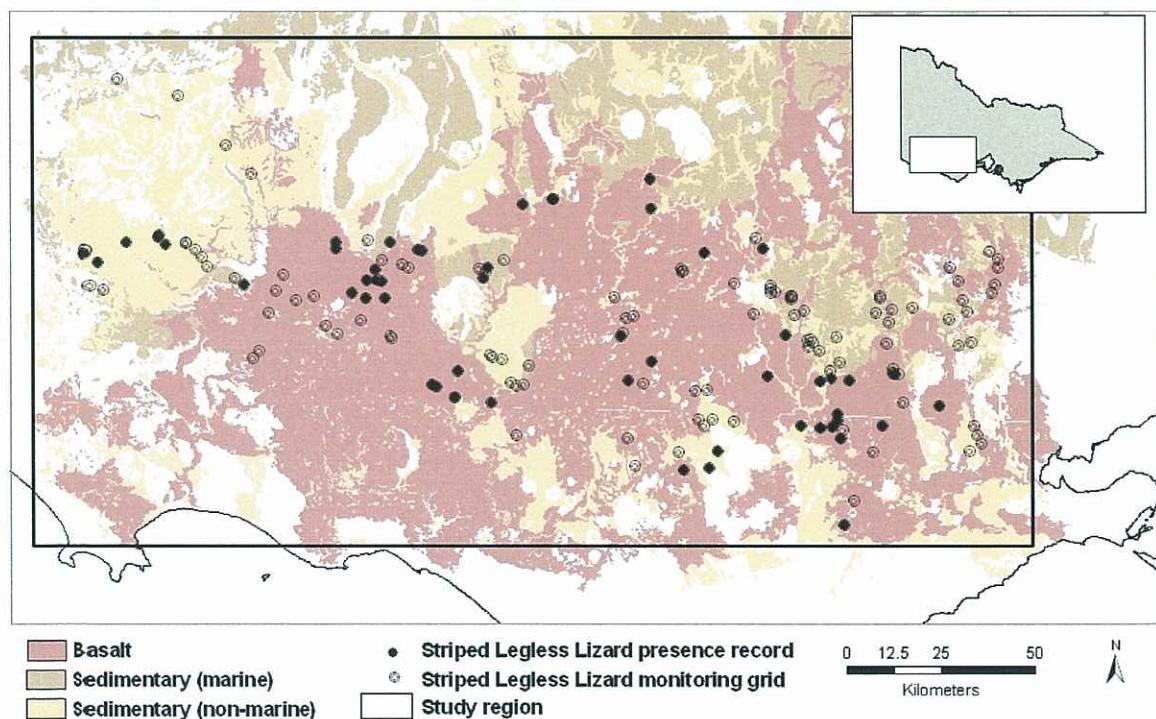


Figure 4.6 The predictor variables used to explain the variance in the observed *Delma impar* presence/absence data. Shown separately over the study region (a) native grassy vegetation (current extent with 50m buffer), (b) average annual maximum temperature, and (c) geology.

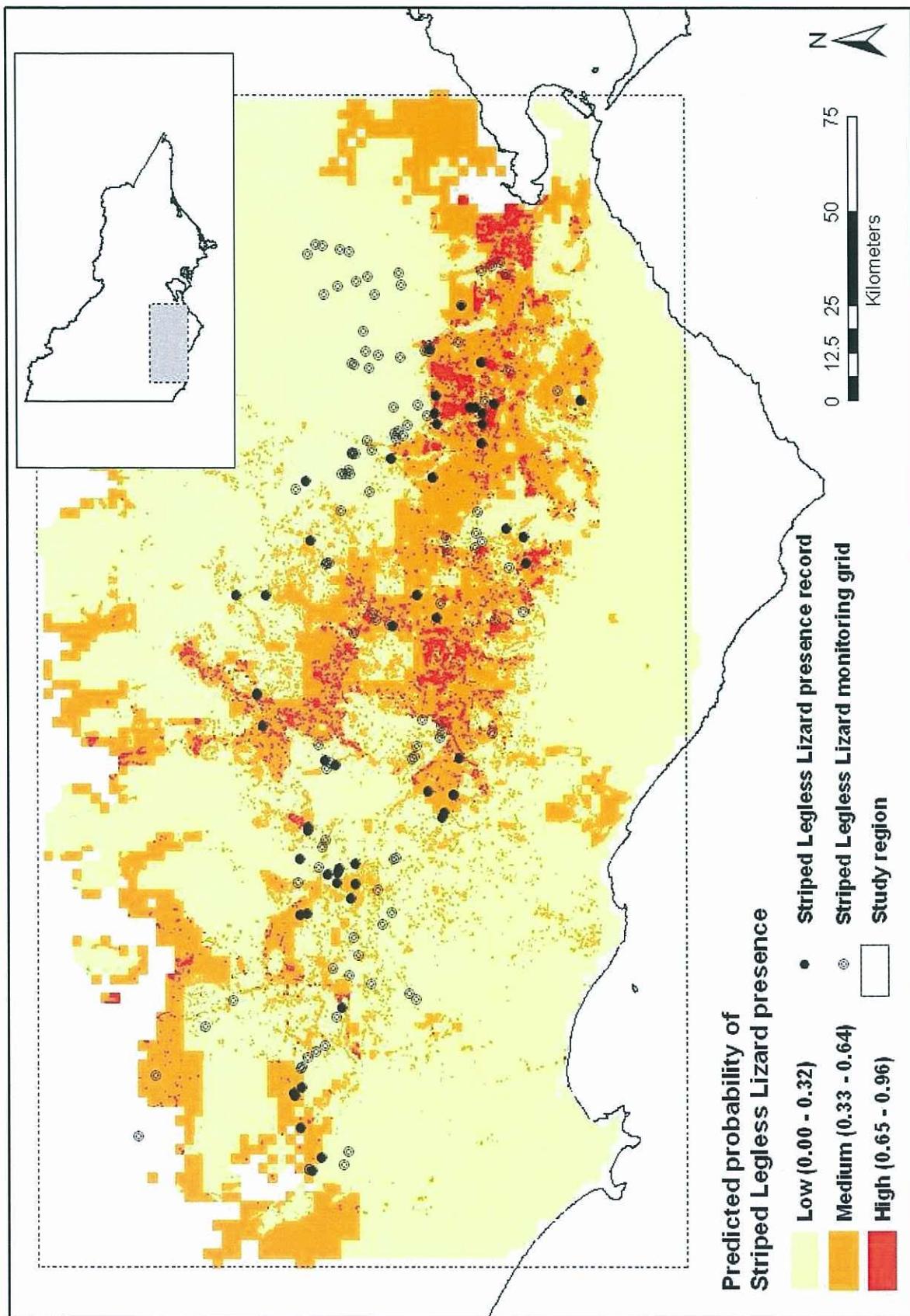


Figure 4.7 The probability of *Delma impar* presence as predicted by model 1 based on the observed presence/absence monitoring data.

DISCUSSION

Available habitat, land use and management

Patch size

At sampled locations in south western Victoria, *D. impar* was found most often at sites within habitat patches estimated to be \leq 5 hectares in size (Table 4.1). Most of these small patches occurred on roadsides or active rail reserves (72%), which are generally recognised as sharing a similar history of management, with burning the most likely disturbance (Kirkpatrick *et al.* 1995). Grid site within habitat patches between 6 and 50 hectares recorded *D. impar* less often than expected, and inspection of these cases found the majority to be within the conservation/reserve land use category (includes cemeteries and non-active railway reserves). Sites within this land use category are generally characterised by a lack of regular disturbance (i.e. burning, grazing).

If patch size was directly influencing *D. impar* occurrence then the smallest patches would be expected to have the lowest frequency of species presence. This idea follows research on patch size which indicates that localised species extinctions are more likely to occur as patch size decreases (Soulé 1985; Ewers & Didham 2005). It is therefore suggested that due to the significant relationship between patch size and land use (Table 4.4), that patch size (at the scale considered here) is not directly influencing observed *D. impar* presence and absence, but instead is acting as an indicator of disturbance or management type (represented by land use). Another possible explanation could be that the patch sizes estimated in this study do not adequately reflect the true size of available habitat for *D. impar* at survey site, or *D. impar* might not be responding to the effects of patch size at the scale considered here.

If estimates of patch size in this study are representative of the true area available to *D. impar* populations at survey sites, it raises questions about the future viability of these populations. It is generally accepted that when species are restricted to small habitat areas they consequently have small populations, and are therefore at

increased risk of reduced genetic diversity and natural catastrophe leading to localised extinctions (Ewers & Didham 2005). Considering that 50% of survey sites where *D. impar* was found were within small habitat patches ($\leq 5\text{ha}$), we might expect that these populations are at highest risk of extinction.

Hadden (1995) postulated that only remnants $>10\text{ha}$ might support viable populations of *D. impar* in the long term. Whereas Koehler (2004) concluded that the detection of *D. impar* on small roadside areas near historic records implicates that these patches can support viable populations in the long term. Nevertheless, the scarcity of information on a species traits, life history parameters and interactions with other species limits assessments of long-term viability (Armstrong 2005; Lindenmayer & Fischer 2006). Information on life history parameters was recognised as a research priority to improve population and habitat viability modelling for *D. impar* (ARAZPA 1996) and remains a priority if we are to assess the longer term prospects of *D. impar* survival in small habitat patches.

Site management

D. impar occurrence was found to increase with the frequency of fire at monitoring sites in this investigation, supporting similar findings from Koehler (2004) and O'Shea (2005). Frequent controlled burning, primarily for the purpose of property protection against wildfire, is a site management activity often undertaken on roadsides and rail reserves in the south west, and other parts of Victoria (Kirkpatrick et al. 1995; Lunt 1995). However a decline in the use of fire on roadsides and on rail reserves is now being reported (Kirkpatrick et al. 1995; Williams 2007). Due to the observed positive relationship between *D. impar* occurrence and fire frequency, a move away from fire as a regular management tool may have a negative impact on these populations.

Previous studies on *D. impar* have suggested reasons as to why burning may be beneficial to the species, for example burning can maintain floral diversity which might be considered representative of high quality grassland/habitat (Koehler 2004). Further possible explanations are that an open structure creates inter-tussock spaces which provide warming of the substrate (through direct irradiance) and

basking opportunities for thermoregulation (Hadden 1998), and the increased soil cracking, that may result from burning, is a habitat component that is exploited by *D. impar* when available (Walton 1995; Koehler 2004). However it has been suggested that there may be an increased reliance on tiles as refuge sites in recently burnt areas, thereby increasing species detection by this method (O'Shea 2005). While this is a recognised possibility, the presence/absence data used in this study was the product of a relatively high number of repeat site visits (average of 12 per site), which should reduce the rate of false-negatives (Tyre *et al.* 2003).

Interestingly, analysis of land use in relation to relative frequencies of *D. impar* presence showed that the species was found more often at sites with a combined management regime of grazing and conservation than at sites dominated by grazing or managed with very little to no grazing (conservation/reserve) (Figure 4.2). This was not found to be statistically significant ($P = 0.052$), but with the p-value so close to the alpha level of 0.05 and some categories not well represented, this is considered inconclusive (Table 4.2). The trend observed in the data (Figure 4.2) indicates that some intermediate level of grazing might be beneficial to *D. impar*. Research on grazing impacts suggests that an intermediate level of grazing can reduce biomass, effectively opening the structure of grassy vegetation and maintaining plant diversity (Lunt *et al.* 2007). Therefore some grazing may be considered beneficial to *D. impar* for the same reasons as burning. If, as proposed here, *D. impar* does respond positively to an open vegetation structure resulting from biomass reduction, then the occurrence of this species in moderately grazed areas is to be expected. This theory, and the implications that may flow from it, require further investigation if we are to gain a better understanding of grazing impacts on *D. impar* habitat.

It is important to recognise that the land use categories used in this study might not reflect past management, and while there is a general understanding of the management history of road and rail reserves, the history of land use at many other survey sites (particularly freehold land) can be difficult to trace and was not investigated here. Furthermore, Dorrough (1995) found when investigating the past and present habitat of this species in the ACT, that to explain the current distribution of *D. impar*, an understanding of past land use was valuable. Therefore an attempt to

trace the history of land use at as many of the grid survey sites as possible in south western Victoria may contribute to a better understanding of the relative influence of past land use on the current distribution of *D. impar* in this landscape.

Modelling outcomes

This study found that, of the variables used in logistic regression analysis and at the scale investigated, the best predictors of *D. impar* occurrence in south western Victoria were the presence of CENVG (referred to as *native grassy vegetation* from here on), the annual maximum temperature and geology (Table 4.5; Table 4.7). These variables have each been linked to *D. impar* habitat in previous studies, but they have not been used together to calculate and display the predicted probability of *D. impar* occurrence at a landscape scale. The distribution of *D. impar* has previously been predicted based on climatic variables (bioclimatic modelling with BIOCLIM), which resulted in coarse grain mapping of the species past range in south eastern Australia (Coulson 1990; Hadden 1995). The predictive map produced here is relevant to south western Victoria - a large area of the species range - and has the potential to identify precise locations with the highest likelihood of *D. impar* occurrence (Figure 4.7). This prediction map will be valuable for locating currently unrecorded extant populations of this endangered species on both private and public land. The predictor variables that best explained the observed *D. impar* presence/absence data and used to map predicted probability values are now discussed, as well as soil texture as a potential habitat predictor.

Native grassy vegetation

A significant finding from this habitat analysis is the association between the distribution of native grassy vegetation and observed *D. impar* presence in south western Victoria (Table 4.6; Table 4.8). This variable was adapted from recently updated modelling of the current extent of native vegetation in Victoria created by the Arthur Rylah Institute (ARI – the biodiversity research base for DSE) using a time-series of remotely sensed images between 1989 and 2005, ground-truthing points,

spatial data and expert validation (DSE 2008) (Figure 4.6a). The updated modelling recognises an extra two million hectares of native vegetation across Victoria, previously not spatially documented and predominantly grassland (perennial cover > 50% native) (A. Oates, pers. comm. 2008). When native grassy vegetation was identified within 50m of survey sites using this modelled current extent vegetation data, it was classified as present at that site.

Two of three logistic regression models found the spatial distribution of native grassy vegetation (CENVG) to be the best single predictor of *D. impar* presence and absence (Table 4.5; Table 4.7). Model 1 ($n = 166$) found that when only using the presence and absence of native grassy vegetation to predict presence and absence of *D. impar*, predictions of presence were correct 50% of the time and predictions of absence were correct in 83.9% of cases. Similarly for the roadside and rail reserve sites (model 2, $n = 79$) *D. impar* presence predictions based on the native grassy vegetation variable were accurate 54.5% of the time and predictions of *D. impar* absence 91.3% of the time. These results demonstrate the predictive strength of native grassy vegetation alone, although predictions of presence were improved further by the additional significant predictors - temperature and geology.

The significance of finding native grassy vegetation as the best predictor of *D. impar* presence/absence in the modelling is that the spatial distribution of this vegetation data might be considered an indicator of areas and small patches in the landscape that have undergone minimal disturbance (excluding burning). This is because cultivation, application of fertiliser, and intensive grazing (land uses considered detrimental to *D. impar*, Dorrough(1995)) generally change vegetation from native perennial tussock grass species to exotic annual and exotic perennial grasses (Kirkpatrick *et al.* 1995; Wong *et al.* 2007). It has also been found that *D. impar* is increasingly likely to be found as the number of years since these types of land use occurred at a site increase (Coulson 1990; Dorrough 1995). The distribution of native grassy vegetation can therefore not only assist efforts to locate *D. impar* populations, but may also highlight potential hotspots for other native grassland flora and fauna that benefit from fewer disturbances.

One implication of finding that the spatial vegetation data is significantly associated with *D. impar* presence and absence is a reiteration of the importance of native grassy vegetation to this species, amidst speculation as to the value of exotic dominated vegetation (Smith & Robertson 1999). There is no documented evidence of exotic dominated vegetation supporting *D. impar* in isolation from areas of native dominated grassland. If structure is the important habitat component of grassy vegetation to *D. impar*, as suggested by Dorrough & Ash (1999), the potential value of exotic tussock-forming vegetation to this species cannot be dismissed. However, the results of this study highlight the current and sustained importance of native dominated grassy vegetation to the species persistence in south west Victoria. This finding suggests that the unremitting losses of native grassy vegetation in south western Victoria (Williams 2007) will be detrimental to the remaining populations of *D. impar* currently persisting in an extensively modified agricultural landscape.

Temperature and geology

Maximum temperature was found to improve predictions of *D. impar* distribution in south western Victoria by increasing the accuracy of positive predictions in model 1 (Table 4.6) and model 2 (Table 4.8). The odds of *D. impar* occurrence were shown to increase as maximum temperature increased (Table 4.5; Table 4.7), with the exception that *D. impar* was not found at the site recording the highest temperature (20.4°C). Future sampling at the higher end of the temperature range sampled here could indicate an upper-limit to the positive relationship between increasing maximum temperature and *D. impar* presence.

At the scale modelled it is perhaps more likely that annual average maximum temperature is acting as a proxy for the former distribution of native grassland rather than reflecting a direct physiological relationship between *D. impar* and temperature. Climatic variables are linked to the distribution of native grasslands in western Victoria (Jones 1999), and mapping of the average maximum temperature over the study area clearly shows similarities in the distribution of native grassy vegetation and warmer annual temperatures (Figure 4.6a & b).

Logistic regression modelling indicated that there was a strong association between basalt and the presence of *D. impar*, supporting previous findings by Coulson (1990)

and Hadden (1995). It is likely that geology acts as an indirect indicator of potential *D. impar* habitat, through its influence on soil characteristics and vegetation types (Gibbons & Rowan 1993) which will have more of a direct influence on *D. impar* habitat, as tussock grasses, soil cracks and burrows are utilised directly by the species (Kutt 1992; Smith & Robertson 1999; Dorrough & Ash 1999). Depending on the age, position and weathering history, basalt may produce a variety of different soils on the western plains of Victoria (Jones 1999), hence soil properties may be better indicators of *D. impar* habitat, such as clay content as an indicator of a soils potential to form cracks (Dorrough & Ash 1999).

Soil texture

Model 3 was fit with only the sites in the GHCMA region ($n = 86$) because compatible soil texture data was not available for the CCMA region. The soil texture variable that represented the clay content of both the A and B horizons (A/BCLAY) outperformed separate horizon A (ACLAY) and horizon B (BCLAY) soil texture variables and all other environmental variables in logistic regression model 3 (Table 4.9; Table 4.10). The finding that the variable A/BCLAY was the best predictor variable to explain the observed presence and absence of *D. impar* supports previous study findings that associate soil texture with *D. impar* habitat (Hadden 1995; Koehler 2004). But more notably it highlights the relative importance of considering the subsoil texture (B horizon) as well as surface soil texture, because the variable A/BCLAY represents both (see Appendix 2).

Previous studies on *D. impar* habitat in south western Victoria used soil hand texture testing to measure the clay content of soils at survey sites (Hadden 1995; Koehler 2004), but the authors do not provide information on the extent to which the soil profile was sampled, and it is possible that the B horizon of soils was not tested in these studies. Stratman (2007) used soil mapping rather than field texture testing to describe soil characteristics at *D. impar* survey sites in the Mosquito Creek catchment, (spans border between Victoria and South Australia) only measuring clay content of the A horizon. Considering that the dominant soil types in south west Victoria generally display a high texture contrast between A and B horizons (Gibbons & Rowan 1993; Baxter & Robinson 2001) it is logical to suppose that measuring

properties of the B horizon might be just as important as the surface soil. This can be considered particularly relevant to *D. impar* habitat if we are measuring clay content as an indicator of a soil's potential to crack, because it is the physical properties of the B horizon that can be directly influencing this soil characteristic (Gibbons & Rowan 1993).

Limitations of modelling

A common source of error in biological surveys, which may then be propagated in habitat analyses which utilise this data, is the failure to record a species in a location where it is in fact present (false-negative error) (Tyre *et al.* 2003). The presence/absence data for *D. impar* used in this habitat analysis should have a reasonably low false-negative error rate considering the number of repeat site visits. Comparatively, previous studies on this species have used presence/absence data obtained from fewer site visits and/or a much shorter sampling period (Koehler 2004; Thompson 2006) potentially increasing the rate of false-negative errors in the data of these studies (Tyre *et al.* 2003).

The number of site visits alone should not be seen as a reliable measure of relative false-negative errors without consideration of other influential factors including species traits, the survey technique, the weather and observer experience (Tyre *et al.* 2003). For example, if we consider the survey technique relied upon to provide species occurrence data for analysis in this study, it might be reasonable to assume that at some locations roof tiles will be used more often than at other locations, increasing the detection rate (O'Shea 2005). Perhaps in locations where the quality of habitat is low, and important habitat components are not available (either temporarily or permanently), *D. impar* may be increasingly likely to use the tiles to meet biological requirements (shelter, food, and thermoregulation). While the effectiveness of roof tile grids to survey *D. impar* may require further investigation, at this stage it is the preferred technique over pit-fall trapping for this species (Koehler 2004; O'Shea 2005; Thompson 2006). With time, the continued monitoring of the SWSLLP sites should further reduce the chance of false-negative observations.

When modelling species habitat, a number of other potential sources of error are recognised, and these can manifest in the modelling process to produce uncertainty in predictions (Elith *et al.* 2002; Wintle *et al.* 2005). As recognised by Elith *et al.* (2002) there is margin for error where predictor variables undergo a process of classification, modelling and interpolation. These processes would have already occurred in the base data, before these data were further aggregated and summarised for the purposes of this study (for examples see Appendix 2 & 3).

Sites occurring close to the interface between two different categories of an environmental variable could potentially have been attributed the wrong information depending on measurement error within mapped data, or extrapolation errors between survey point data (e.g. soil mapping). Ground-truthing remotely mapped attributes might have reduced these types of possible errors, but was not feasible due to the number of sites and constraints of the project timeline. Attempts were made to identify and minimise potential errors, by investigating metadata files relating to GIS layers, reading accompanying reports (where available) and contacting authors and organisations responsible for the spatial data to verify limitations.

There is also uncertainty about model predictions arising from natural biological variation and processes that might be influencing site occupancy but could not be included in the model (Guisan & Zimmermann 2000). For example, only broad scale variables were considered, yet differences at finer scales are likely to be influencing the distribution of *D. impar*, such as historic site disturbance events (Dorrough 1995), microhabitat characteristics, interactions with other species (Lindenmayer & Fischer 2006), stochastic events and limited dispersal ability (Tyre *et al.* 2001)

The factors influencing a species will alter over a range of temporal and spatial scales (Lindenmayer & Burgman 2005), and therefore the predicted distribution of *D. impar* produced from this study is relevant only to the scale considered and will inevitably change over time. However the available data mapped at this scale produced models which identified biologically relevant variables which appear to be significantly associated with the distribution of *D. impar* across south western

Victoria. Furthermore, the model has the capacity to be updated as new data become available.

Management implications, recommendations and future research

Due to the continual loss of remnant native grassy vegetation in south western Victoria (Williams 2007) and local trends to intensify agricultural land use (Institute of Land and Food Resources 2000; Lang 2000), *D. impar* populations continue to be threatened by impending habitat loss. An important outcome of this study is that the prediction map generated from modelling could result in *D. impar* populations being found before they disappear by directing search efforts to locations more likely to support populations. Furthermore, the modelling does not discriminate between land tenure, potentially highlighting areas on private property that might otherwise not have been recognised – particularly as *D. impar* is a small, cryptic species that landowners may not be aware of. In circumstances where high probability areas occur on private property it is suggested that land owners could be approached regarding the establishment of monitoring grids, and if *D. impar* is subsequently detected, attempts could be made to negotiate some form of protection agreement.

Meaningful and practical evaluation of the model ultimately requires the collection of new field data at locations not previously sampled within the prediction region, in order to validate model predictions. Furthermore, future data collection will contribute to refinement of the model, and attempts should be made to fill gaps in the current data set where combinations of environmental characteristics are underrepresented (Wintle *et al.* 2005). The predictive performance of soil texture found in this study indicates that when soil mapping becomes available at the right scale covering both CMA regions it should be incorporated into the model to see if it improves prediction accuracy.

Field texture testing of soil from both the A and B horizons of the soil profile at current and future survey sites is recommended due to the results of model 3 which found soil texture of the A and B horizons to be more strongly associated with *D. impar* presence and absence than any other variable for sites in the GHCMA region. Soil testing at the site level should provide more information on the relative importance of the clay content of each soil horizon as an indicator of *D. impar* habitat.

For the purpose of broad scale habitat prediction, only the factors relevant to the scale of interest were considered for distribution modelling. It is acknowledged that other environmental attributes and population processes are likely to be influencing the presence or absence of the species at a local or site level (Lindenmayer & Fischer 2006). It is therefore recommended that locations identified by the prediction map be assessed with regard to the findings of previous site scale habitat studies before survey sites are established.

Findings indicate that some degree of biomass control (in the form of controlled burning or intermediate grazing pressure) might be beneficial to the species. However, as it is also recognised that grasslands with little to no active management to reduce biomass do still support populations in some locations, it is recommended that monitoring be maintained at these sites (and possibly increased) to gauge whether these populations are increasing, stable or in decline. In addition, further research is advised to investigate and evaluate the impacts of grazing intensity and duration at sites where *D. impar* is persisting in south western Victoria.

Conclusions

Logistic regression modelling was effective at highlighting which broadly mapped variables can be used as habitat indicators for the species. The current extent of native grassy vegetation in conjunction with temperature and geology were found to be the best predictors of *D. impar* presence and absence. This finding was the same for both the model testing all sites and the model testing only sites occurring on roadside and rail reserves.

The third model found soil texture to be the best predictor of *D. impar* presence and absence, but was only considered for sites in the GHCMa region, and therefore could not be applied to predictive mapping for the region. This variable should be analysed for all sites when compatible soil spatial data becomes available for the whole study area.

This study has made a valuable contribution to the future management of the threatened *Delma impar* by focussing search efforts to locations where the species is most likely to occur. Validation of the predicted probability distribution map will require future survey results to be undertaken at presently unsampled locations within the study region in south western Victoria. The statistical model can be refit as new data become available, and modelled parameter estimates adjusted to reflect changes. This will keep predictive mapping up to date and should improve prediction accuracy.

This study has demonstrated the value of using rapidly advancing GIS technology with multivariate statistical modelling to predict the distribution of a species. This approach has the potential to assist conservation managers dealing with endangered species, especially in cases where little is known of the species ecological traits.

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APPENDICES

Appendix A - Patch size class: guidelines followed to determine patch boundaries

Creating patches around SWSLLP monitoring grid sites

Boundary delineation involved interpretation of aerial photography followed rules/guidelines consistent with current understanding of the species habitat associations and likely barriers to movement. The objective was to include surrounding structurally similar land cover (e.g. tussock grass) except where physical barriers or land use was perceived to be inconsistent with *D. impar* movement or survival. The following set of guidelines/rules explains what was deemed a barrier to *D. impar* movement:

- Road, railway line, obvious permanent track, permanent/maintained fire break or other linear feature which results in cleared/ploughed/unvegetated ground.
- Obvious rivers/ creeks/ drainage lines which appeared eroded, steep or prominent in the landscape.
- Significant tree lines or a change in the dominant vegetation structure (i.e. immature trees, shrubs, large trees dominating projective ground cover).
- Significant water bodies
- Urban infrastructure
- Ploughed/cropped paddocks

Obviously some of these things were difficult to determine from the aerial photography, and land use/ management may have altered (site photos were used where available to improve accuracy of land feature interpretation).

Some very large patches have rough boundaries, because when size classes are used the exact size past a particular point became arbitrary.

Appendix B - Defining soil texture variables – ACLAY, BCLAY and A/BCLAY

The soil mapping that was used in this project covers the Glenelg Hopkins Catchment Region at a scale of 1:100 000, and is correct as at 2001 when the Glenelg Hopkins Land Resource Assessment (GHLRA) was published. The GHLRA project aimed to investigate and assess the suitability of the region for future primary production development, and therefore provides consistent soil mapping of the Glenelg Hopkins CMA region (Baxter & Robinson 2001).

Texture is a soil property which can indicate the amount of clay present at a site. Soil texture grades have been identified by the GHLRA (and are given separately for both the A and B horizons), but we are referred to the Australian Soil and Land Survey Field Handbook (McDonald *et al.* 1990) to understand how soil texture is determined. The following tables show how classes have been assigned to texture grades in an attempt to minimise the number of discrete groups representing soil texture (ACLAY & BCLAY), and how the resulting classes have then been used to assign A horizon and B horizon combinations into classes which represent different texture class combinations of AB soil profile (A/BCLAY).

ACLAY, BCLAY

Grade*	% Approx. clay content*	Class created
HC, MHC, MC, LMC	>40	4
LC, ZCL, CLS, CL	30-40	3
SCL, ZL, L	20-30	2
SL, CS, LS, S	<20	1

*using texture grade descriptions in McDonald *et al.* (1990)

A/BCLAY

A/B class combination (as defined in table A)	A/B % clay represented	Codes created to describe different amounts of clay (A/B)	Single codes created for A/B clay combined classes*
3/4	30-40/>40	H/H	H
4/4	>40/>40	(high over high)	
1/4	<20/>40	L/H	C
1/3	<20/30-40	(low over high)	
2/4	20-30/>40		
1/2	<20/20-30	L/L	L/M
2/2	20-30/20-30	(low over low)	
2/3	20-30/30-40	M/M	
3/3	30-40/30-40	(medium over medium)	

*H – heavy, C – contrast, L – light, M – medium.

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Appendix C - Defining Pre-1750 structural vegetation categories for the variable HVS

HVS categories were determined by aggregating Ecological Vegetation Classes. Reducing the number of vegetation type categories from raw EVCs to 5 (then 4) aggregated groups, was based on structurally dominant components (measured by estimated % cover) as described in the EVC benchmarks. Vegetation has been grouped according to structure predominantly, because it has been indicated by previous investigations that *D. impar* is more reliant on tussock structure as a habitat component, than particular plant species. Grid sites were characterised by their EVC and bioregion, which was necessary because the same EVCs can occur in different bioregions and can have different benchmark attributes accordingly.

Group no.	Group description	EVCs included	Defining structural components for inclusion
1	Grassy	132, 897	40-45% MTG Trees where woodland- 10% TCC (only 5/ha)
2	High grass woodland	175, 56, 55	40-45% MTG 10-15% TCC (8-15/ha)
3	Low grass woodland	68, 164, 203, 641, 3, 649	20-25% MTG 15-20% TCC (15/ha)
4	Forest /shrubby	20, 22, 47	20-30 % MTG 20-30% TCC (20/ha)
	Wetland	125, 647	30% sedges and grasses

MTG – medium to small tufted graminoid (Note: *Poa labillardierei* was classified as MTG and LTG (large tufted graminoid) depending on the EVC, but is consistently included here as MTG), TCC – tree canopy cover

EVC Descriptive name

- 132 Plains grassland
- 897 Plains Grassland/Plains Grassy Woodland Mosaic
- 175 Grassy Woodland
- 56 Floodplain Riparian Woodland
- 55 Plains Grassy Woodland
- 68 Creekline Grassy Woodland
- 164 Creekline Herb-rich Woodland
- 203 Stony Rises Woodland
- 641 Riparian Woodland
- 3 Damp Sands Herb-rich Woodland
- 649 Stony Knoll Shrubland
- 20 Heathy Dry Forest
- 22 Grassy Dry Forest
- 47 Valley Grassy Forest
- 125 Plains Grassy Wetland
- 647 Plains Sedgy Wetland