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Using artificial neural networks to assess the impacts of future climate change on ecoregions and major vegetation groups in Australia

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Executive summary

Extensive research has demonstrated that Earth's biodiversity has been affected by climate change in the previous decades, and various modelling techniques have been used to assess ecological changes that are likely in the future as climate change continues. But there have been few climate change impact assessments at large scales (national or continental). This report describes and illustrates a method for assessing broad ecological impacts of future climate change for the vegetation of all of Australia. The report focuses on a methodology but also presents preliminary results that can inform conservation policy, planning and management for very large areas.

For all of Australia, we classified ecological environments using artificial neural networks (ANN) at two broad scales: seven terrestrial ecoregions (global biomes) and 23 major vegetation groups (MVGs). These classifications were then used to analyse likely climate change impacts in a variety of ways. The environmental variables included many bioclimatic indices, three soil variables and nine topographic variables. Two climate change scenarios were considered for 2070 using CSIRO's Mk3.5 GCM (a medium impact scenario, using the A1B emissions scenario; and a high impact scenario, using the A1FI emissions scenario).

Outputs of the ANN classification consist of a suitability of each location for each of the ecological classes based on the environmental inputs. The training process seeks to calibrate the functions linking the environmental inputs and the suitability scores for the ecological classes to get the best match between the predicted ecological class and the mapped ecological class.

The ANN classifiers can assess possible climate change impacts using a variety of techniques. The simplest approach is to apply the ANNs to an altered set of input patterns that represent a future climate, then map the reclassified new environments. By comparing these new classified maps with the original unclassified map we calculate the transition matrixes that show the areas that become more favourable to some other class or remain favourable to the class that is mapped now.

Classification of the seven ecoregions is highly accurate: 96.8% producer accuracy with a Kappa value of 0.95. Classification of the 23 MVGs is less accurate: 64.2% producer accuracy with a Kappa value of 0.61. While the accuracy is not high, the expected accuracy of a random model is only 2.3%.

The ANN classifiers provide much more information than is apparent in a classification per se, where the output node with the largest value is chosen as a pattern's (location's) classification. By using the values of all the output nodes we calculated the dissimilarity of this vector to the 'ideal' vector with the value of 1.0 for the class that is mapped at that location and all other values of 0.0.

We also calculated a measure of environmental change that uses the Bray–Curtis dissimilarity measure at all map locations. This is a pairwise distance measure between the ANN classification output in the baseline climate and the classification output in the A1B and A1FI climate scenarios, using all 23 outputs from the model that represent environmental suitability for each of the 23 vegetation types.

The results are complex in detail, but broadly:

1. The method appears to be useful for broad, continental analyses
2. Climate change will alter the spatial distribution and extent of the environments of Australia's biomes to some degree and have major impacts on the extent and distribution of environments suitable to the major vegetation groups with a trend toward less wooded and more open vegetation. Much of the continent's vegetation as it exists now will be in large disequilibrium with climate in the future with many locations having climates unlike what occurs now anywhere in Australia. This implies that climate change will stress existing ecosystems considerably and result in rapid change in the condition and character of vegetation throughout Australia.

1 Introduction

This report describes and illustrates a method for assessing broadscale ecological impacts of future climate change for all of Australia. The discussion focuses on the method and does not draw conclusions concerning the ecological or policy implications of the results.

Extensive global research has demonstrated that Earth's biodiversity has been affected by climate change in the previous decades (Parry et al. 2007), and various modelling techniques have been used to assess ecological changes that are likely in the future as climate change continues. Most of the projections of climate change impacts on biodiversity in the future are based on and extrapolated from habitat models of individual species (e.g. Thomas et al. 2004). While this approach may be able to answer questions about the risk of species extinction when good distribution data are available, it is inevitably limited by the paucity of distribution data for most species and cannot be used to infer changes in broader biodiversity patterns such as biomes and ecosystem structure. While conservation policy, planning and management are frequently concerned with preservation of individual iconic species, their goals are often much broader and more at landscape and ecosystem scales. Policy is often at national or continental scales. There have been few climate change impact assessments at these larger scales (regional, national or continental). Here we present an approach and preliminary results that can inform conservation policy, planning and management for very large areas such as Australia as a whole.

At large scales vegetation is thought to be in dynamic equilibrium with climate (Prentice 1986; Webb 1986), and the distribution of biomes is controlled by ecophysiological constraints related mainly to temperature and water availability (Schulze 1982; Woodward 1987). So our approach uses maps of vegetation classes at various scales along with detailed spatial estimates of climate, topographic and edaphic variables to objectively classify environments that are characteristic of these vegetation classes. The goal is to transform a high dimensional, physical environment space (many climate variables and, in the case of the major vegetation groups, a number of terrain and soil variables as well) into a lower dimension, ecologically meaningful, biotically scaled space. This is accomplished through supervised classification using artificial neural networks (ANNs; Rumelhart and McClelland 1986). Then, given any spatial scenario of change in the climate we can map these *ecological* environments in geographic space. Most importantly, we can compare this new spatial map of environments with what it looks like today and also with the spatial distribution and extent of the actual ecological classes. In this way, we can quantify how climate may stress existing ecosystems, predict how the extent and distribution of ecologically meaningful environmental classes may change in the future and infer how climate change may affect vegetation classes and, consequently, biodiversity and ecosystem function.

Like the modelling of species habitat (e.g. Elith and Graham 2006) our approach classifies environments in relation to their suitability for biological classes, and we can map potential 'habitat' for these classes given any future or past climatic scenario. But unlike habitat modelling of species, our classes are more conceptual and often display much more inertia in response to climate change. Consequently, we developed quantitative indexes, based on the classification of environments, that spatially identify the degree of stress that existing classes may experience and where significant ecological change is most or least likely to occur. We also identify areas that will have novel environments in the future.

This methodology builds on the successes of a similar approach that was used in the Wet Tropics Ecoregion of north-east Queensland where an ANN was used to classify 15 structural/physiognomic forest environments based on a range of climatic, edaphic and topographic variables. This research demonstrated that the environments of mapped vegetation classes can be classified very well using ANNs (Hilbert and Van Den Muyzenburg 1999), that further analyses of the model can provide useful ecological insights (Hilbert and Ostendorf 2001; Ostendorf et al. 2001) and that the impacts of past (Hilbert et al. 2007) and future climate change (Hilbert et al. 2001) can be assessed in ways that are useful for informing policy and planning as well as providing ecological and biogeographic insights.

2 Methods

We used ANNs for the supervised classification of environments based on mapped vegetation classes. ANNs are well known to be very good at a wide variety of classification problems. In our application ANN modelling was used to transform multiple environmental parameters into relative suitability for multiple ecological classes; these parameters were then used to predict an environmental class for each point and various change metrics. Among their advantages, ANNs make no assumptions as statistical approaches must do. Historically, it was difficult to understand them analytically – that is, what variables are most important in a classification? – but recent advancements allow more insight, and some software includes ranking of variables' importance.

For all of Australia, we classified environments at two broad scales: seven terrestrial ecoregions (global biomes) and 23 major vegetation groups (MVGs). These classifications were then used to analyse likely climate change impacts in a variety of ways for all of the continent and for the four biomes as defined in this project: 1) northern savannah grasslands – wet and dry tropics, includes grassy savannah woodlands; 2) south-eastern Australian sclerophyll forests – wet and dry sclerophyll forests; 3) hummock grasslands of central Australia – acacia and eucalypt hummock grasslands; and 4) temperate lowland grassy ecosystems – tussock grasslands, grassy woodlands. Here, we present the full continental maps and data.

2.1 Vegetation data

2.1.1 TERRESTRIAL ECOREGIONS

The ecoregions are derived from Thackway and Cresswell's (1995) biogeographic regionalisation for Australia. These were incorporated into a global map of terrestrial ecoregions (Olson et al. 2001) from which the spatial data were obtained. The spatial resolution of these data is 1 km^2 over the entire continent. The classes include seven ecoregions that are mapped in Figure 1 and listed in Table 1. We have retained the numbering system used in the global map.

2.1.2 MAJOR VEGETATION GROUPS

The data consist of a digital map of the pre-clearing distributions of 23 MVGs at a one hectare resolution for the entire continent (Thackway et al. 2007). The MVGs are displayed in Figure 2 and listed in Table 2. Their correspondence with biomes, as defined in this project, is presented in Table 3.

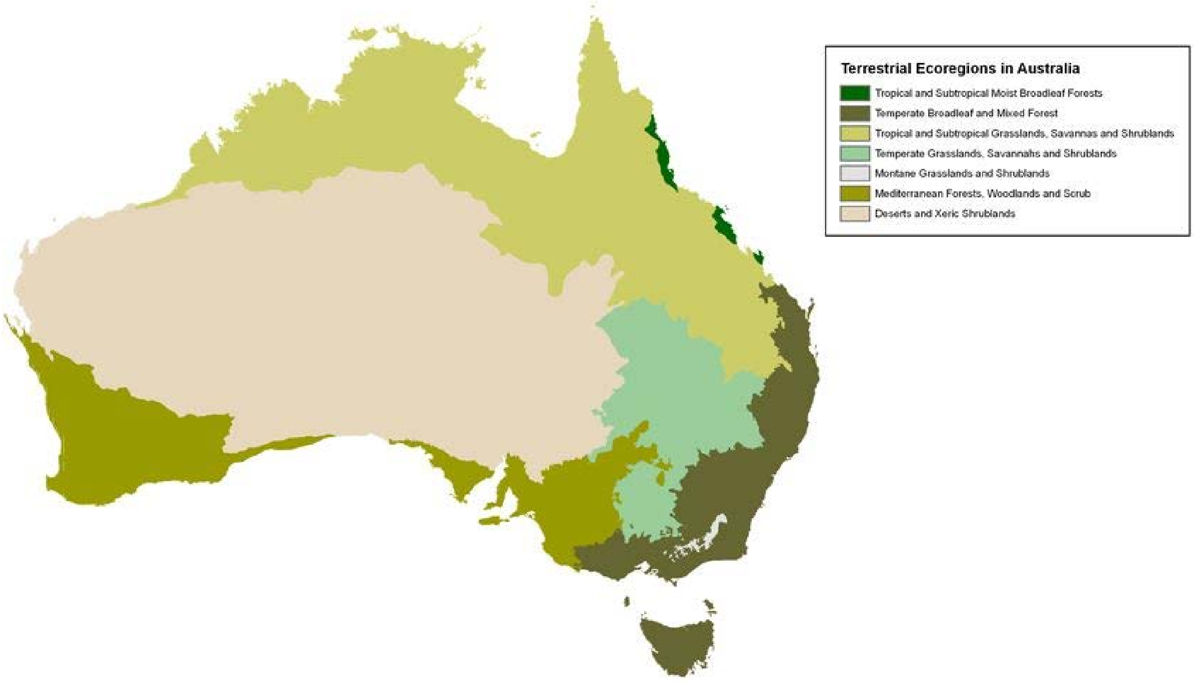

Figure 1 Map of Australian ecoregions (remapped using data from NVIS)

Table 1 List of Australian ecoregions and their area (km^2) as mapped

	ECOREGION	AREA
1	Tropical and Subtropical Moist Broad Leaf Forests	27 672
4	Temperate Broadleaf and Mixed Forest	548 744
7	Tropical and Subtropical Grasslands, Savannas and Shrublands	1 810 712
8	Temperate Grasslands, Savannas and Shrublands	539 788
10	Montane Grasslands and Shrublands	11 800
12	Mediterranean Forests, Woodlands and Scrub	761 072
13	Deserts and Xeric Shrublands	3 158 488

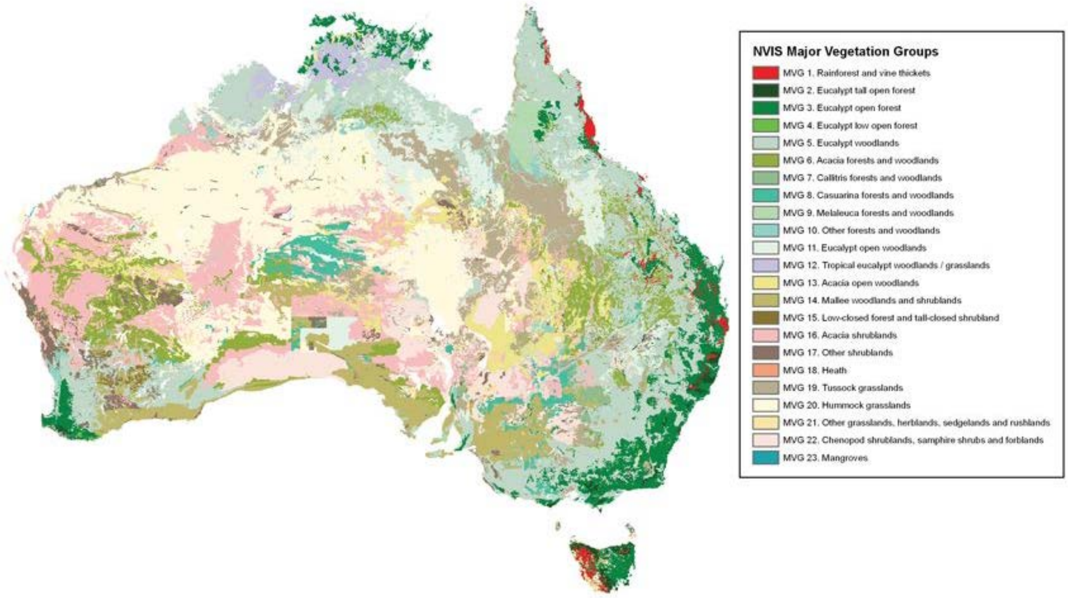

Figure 2 Map of Australian major vegetation groups (remapped using data supplied by NVIS)

Table 2 The major vegetation groups of Australia used in this analysis

NUMBER	MAJOR VEGETATION GROUP
1	Rainforests and vine thickets
2	Eucalypt tall open forests
3	Eucalypt open forests
4	Eucalypt low open forests
5	Eucalypt woodlands
6	Acacia forests and woodlands
7	Callitris forests and woodlands
8	Casuarina forests and woodlands
9	Melaleuca forests and woodlands
10	Other forests and woodlands
11	Eucalypt open woodlands
12	Tropical eucalypt woodlands/grasslands
13	Acacia open woodlands
14	Mallee woodlands and shrublands
15	Low closed forests and tall closed shrublands
16	Acacia shrublands
17	Other shrublands
18	Heathlands
19	Tussock grasslands
20	Hummock grasslands
21	Other grasslands, herblands, sedgelands and rushlands
22	Chenopod shrublands, samphire shrublands and forblands
23	Mangroves

Table 3 Correspondence between the four biomes, as defined in this project, and the major vegetation groups

BIOME	MAJOR COMPONENTS	MINOR COMPONENTS
Northern savannah grasslands	MVG 5 Eucalypt woodlands	MVG 19 Tussock grasslands
	MVG 12 Tropical eucalypt/woodlands/grasslands	MVG 9 Melaleuca forests and woodlands
	MVG 11 Eucalypt open woodlands	MVG 1 Rainforests and vine thickets
	MVG 3 Eucalypt open forest	MVG 6 Acacia forests and woodlands
	MVG 6 Other forests and woodlands	
Hummock grasslands of central Australia	MVG 20 Hummock grasslands	MVG 5 Eucalyptus woodlands
	MVG 16 Acacia shrublands	MVG 6 Acacia forests and woodlands
	MVG 13 Acacia open woodlands	MVG 17 Other shrublands
	MVG 8 Casuarina forests and woodlands	
	MVG 14 Mallee woodlands and shrubs	
Temperate lowland grassy ecosystems	MVG 19 Tussock grasslands	MVG 11 Eucalypt open woodlands
	Subgroup 'eucalypt woodlands with a grassy understorey' of MVG 5	MVG 21 Other grasslands
Sout-eastern Australian sclerophyll forests	MVG 1 Rainforest and vine thicket	MVG 5
	MVG 2 Eucalypt tall open forests	excluding the subgroup 'eucalypt woodlands with a grassy understorey''
	MVG 3 Eucalypt open forests	
	MVG 4 Eucalypt low open forests	

Note that it is difficult to precisely delineate the 'ecoregions' with the MVGs. For example, Eucalyptus woodlands (MVG 5) appear to be particularly problematic since all 'biomes' contain at least some of this class. And, as will be described later, Eucalyptus woodland environments are not well distinguished from other MVGs.

2.2 Environmental data

2.2.1 CURRENT ENVIRONMENTS

All the environmental variables used in the analyses are listed in Table 4, including 23 bioclimatic variables (Houlder et al. 2000), three soil variables and nine topographic variables. Thirty-five bioclimatic variables were available but we found that some of these display serious artefacts at continental scales, especially in the climate change scenarios, so they were not used in the multi-output classification. All the data consisted of grids at a 1 km^2 resolution for the entire continent.

Table 4 List of the environmental variables used in the multi-output classifications

CODE	NAME	DESCRIPTION
		BIOCLIMATIC VARIABLES
BioClim1	Annual Mean Temperature	mean of all the weekly mean temperatures where each weekly mean temperature is the mean of that week's maximum and minimum temperature
BioClim2	Mean Diurnal Range	mean of all the weekly diurnal temperature ranges where each weekly diurnal range is the difference between that week's maximum and minimum temperature
BioClim3	Isothermality	mean diurnal range (BioClim2) divided by the Annual Temperature Range (BioClim7)
BioClim4	Temperature Seasonality	the temperature coefficient of variation, the standard deviation of the weekly mean temperatures expressed as a percentage of the mean of those temperatures (i.e. the annual mean). For this calculation, the mean in degrees Kelvin is used to avoid the possibility of division by zero
BioClim5	Max Temperature of Warmest Period	the highest temperature of any weekly maximum temperature
BioClim6	Min Temperature of Coldest Period	the lowest temperature of any weekly minimum temperature
BioClim7	Temperature Annual Range	the difference between the Max Temperature of Warmest Period and the Min Temperature of Coldest Period
BioClim10	Mean Temperature of Warmest Quarter	The warmest quarter of the year is determined (to the nearest week), and the mean temperature of this period is calculated
BioClim11	Mean Temperature of Driest Quarter	The driest quarter of the year is determined (to the nearest week), and the mean temperature of this period is calculated
BioClim12	Annual Precipitation	The sum of all the monthly precipitation estimates
BioClim13	Precipitation of Wettest Period	The precipitation of the wettest week
BioClim14	Precipitation of Driest Period	The precipitation of the driest week
BioClim16	Precipitation of Wettest Quarter	The wettest quarter of the year is determined (to the nearest week), and the total precipitation over this period is calculated
BioClim20	Annual Mean Radiation	The mean of all the weekly radiation estimates
BioClim22	Lowest Period Radiation	The lowest radiation estimate for all weeks
BioClim23	Radiation Seasonality	The Coefficient of Variation (C of V) is the standard deviation of the weekly radiation estimates expressed as a percentage of the mean of those estimates (i.e. the annual mean)
BioClim28	Annual Mean Moisture Index	The mean of all the weekly moisture index values
BioClim29	Highest Period Moisture Index	The maximum moisture index value for all weeks
BioClim30	Lowest Period Moisture Index	The minimum moisture index value for all weeks
BioClim31	Moisture Index Seasonality	The Coefficient of Variation (Cv) is the standard deviation of the weekly moisture index values expressed as a percentage of the mean of those values (i.e. the annual mean)
BioClim32	Mean Moisture Index of Highest Quarter MI	The quarter of the year having the highest moisture index value is determined (to the nearest week), and the average moisture index value is calculated
BioClim33	Mean Moisture Index of Lowest Quarter MI	The quarter of the year having the lowest moisture index value is determined (to the nearest week), and the average moisture index value is calculated
BioClim35	Mean Moisture Index of Coldest Quarter	The coldest quarter of the year is determined (to the nearest week), and the average moisture index value is calculated
		TERRAIN VARIABLES
	SLOPE	Mean of the 9 second slope values in each 36 second grid cell (%)
	RELIEF	Range of the 9 second DEM elevation values in each 36 second grid cell (m)
	ROUGHNESS	Cv of the 9 second DEM elevation values in each 36 second grid cell (m) Computed mean elevation values greater than -1 and less than +1 were set to a value of 1 to calculate the Cv (%)
	TWI	Maximum of the Topographic Wetness Index (TWI) values in each 36 second grid cell. TWI was calculated as ln(a/tan ß) where a is the upslope area per unit contour length and tan ß is the local slope (dimensionless)
	MRVBF	Median value of the multi-resolution Valley Bottom Flatness index values (mrVBF) in each 36 second grid cell (dimensionless)
	MRRTF	Median value of the multi-resolution Ridgetop Flatness index values (mrRTF) in each 36 second grid cell (dimensionless)
	VALLEYBOTTOM	Proportion of the 9 second grid cells classed as valley bottoms according to the values of mrVBF and mrRTF (i.e. mrRF – mrRTF >2) (%)
	RIDGETOPFLAT	Proportion of the 9 second grid cells classed as ridgetop flats according to the values of mrVBF and mrRTF (i.e. mrRTF – mrVBF >2) (%)
	EROSIONAL	Proportion of the 9 second grid cells classed as valley bottoms according to the values of mrVBF and mrRTF (i.e. mrVBF & mrRTF both < 2.5) (%)
		SOIL ATTRIBUTES
	SOILDEPTH	The weighted average of the solum depth values (m)
	SOLPAWHC	The weighted average of the solum plant available water holding capacity (PAWHC) (mm)
	A_KSAT	The weighted average of median A horizon saturated hydraulic conductivity (mm/h)

2.2.2 FUTURE ENVIRONMENTS

Two scenarios were considered for 2070 using the CSIRO Mk3.5 GCM (Gordon et al. 2002): a medium impact scenario, using the A1B emissions scenario; and a high impact scenario using the A1FI emissions scenario (IPCC 2000).

Monthly climate grids from the GCM at 0.25° resolution for maximum temperature, minimum temperature, rainfall and evaporation were downscaled using the ANUCLIM software (Houlder et al. 2000), that produces grids of 35 bioclimatic parameters (BioClim variables; Busby 1986). The beta release of ANUCLIM version 6.0 was used, which allows climate change grids to be applied over the historical 1990-centred climate surfaces. New software (Harwood and Williams 2009) was written to interpolate the raw 0.25° CSIRO grids to cover the whole Australian land mass, and relate evaporation change to the date range used in ANUCLIM 6.0. Following this interpolation, monthly maximum temperature, minimum temperature, rainfall, and evaporation change grids were input to ANUCLIM 6.0 with a 0.01° digital elevation model, resulting in the 1 km^2 resolution future climate surfaces of 35 BioClim variables for each scenario (see Harwood et al. 2012 for more detail).

2.3 Classification

2.3.1 GENERAL ISSUES

In any supervised classification problem there are a number of possible sources of confusion that collectively contribute to classification 'error' or the inability of a method to distinguish classes (Hilbert and Van Den Muyzenberg 1999). By 'confusion' we mean the inability to perfectly distinguish classes with the available data. These include 'intrinsic confusion' when the classes are not well-defined for the problem or are in boundary areas where there is real overlap in environments for adjacent classes, measurement errors in class identification and/or the associated independent variables, and estimation errors due to limitations in the classification method. To our knowledge there are no quantitative methods that can distinguish these sources of confusion, but it is worthwhile to consider these issues when interpreting the environmental classifications that we present here.

In the context of this research, intrinsic confusion occurs to the degree that mapped vegetation classes (ecoregions or MVGs) are not well correlated with environmental variables or, in the case of transition zones, between classes. The latter is expected and inevitable, since vegetation responds more continuously to environmental gradients than its categorical representation in maps. Measurement errors are certainly present in the class maps (e.g. obvious artefacts in the NVIS MVG map) and are no doubt present in maps of the baseline climate and other environmental variables. Unfortunately, these errors are typically not quantified by the data providers or reported. Estimation errors, that is, classification errors due to limitations of the method are, unfortunately, impossible to separate from the other sources of confusion, since these have not been quantified.

2.3.2 RE-SAMPLING THE SPATIAL DATA TO A COMMON SCALE

The available data over the entire continent differed in resolution from one hectare (MVGs) to 1 km^2 for all the other data. The fine-grained mapping of the MVGs could not possibly be classified at this resolution from 1 km^2 resolution environmental data. Also, the accuracy of the pre-settlement MVG map is unknown. Consequently, we considered a range of re-sampling of the data that was equal to or larger than the 1 km^2 resolution of the environmental data, recognising that the spatial accuracy of the latter is not known and probably much less than 1 km^2. In an *ad hoc* fashion, we determined that a 4 km^2 re-sampling of the MVG data preserved a reasonable amount of detail that we believed could be classified using our methods. Consequently, we re-sampled *all* the spatial data at a 4 km^2 resolution in ArcMap (Esri Australia n.d.) using a majority rule for the ecoregion and MVG data and the mean for the environmental data. This produced slightly more generalised data for use in the classifications.

2.3.3 CLASSIFICATION OF ENVIRONMENTS

We used FANN (Fast Artificial Neural Network Library) to classify environments of both the ecoregions and the MVGs. This software is a free, open source neural network library (available from http://leenissen.dk/fann/) that implements multilayer ANNs in C with support for both fully connected and sparsely connected networks. It provides a number of options, including the network structure, the training algorithm, and the ability to choose training parameters for the specified algorithm. We experimented with a wide range of structures, training algorithms and parameters to find a combination of these choices that provided the best classification accuracy. For both ecoregions and the MVGs we chose a neural network structure with a single hidden layer with 150 nodes trained with the standard, classic training method. In both cases the learning rate was set at 0.05 and momentum at 0.0. Both networks use the standard logistic transformation for the hidden and output nodes, with the steepness parameter set at 0.5.

In machine learning parlance a vector (list) of inputs and an associated output vector is called a pattern. In our case a pattern corresponds to a 4 km^2 geographic location where the environmental variables are known as the vegetation class. These patterns are used to either train the neural network or to validate (test) the generality of the classification. The validation or test set of patterns is used to determine the best classification that is not overtrained, that is, is as accurate as possible in classifying patterns that were not used in the training.

Outputs of the ANN classification consist of a suitability of each location for each of the ecological classes based on the environmental inputs. The predicted environmental class was defined as the class with the highest suitability score. The training process seeks to calibrate the functions linking the environmental inputs and the suitability scores for the ecological classes to get the best match between the predicted ecological class and the mapped ecological class.

2.3.4 TRAINING AND VALIDATION DATA

Training and validation data were sampled in an *ad hoc* way from the re-sampled (4 km^2) ecoregions or MVGs and the environmental data in order to achieve a reasonable classification of both rare and abundant vegetation types and to balance producer and consumer accuracies. Since total class areas vary by from two to three orders of magnitude, we included a large proportion of the rare classes and a very small proportion of the most common classes. The sample sizes are provided in Appendix A, Table 1 (ecoregions) and Appendix A, Table 2 (MVGs). The samples were then split randomly into independent training (80%) and test sets (20%).

2.4 Ranking the importance of variables in the classification of vegetation's environments

Here, we trained *individual* models for each of the ecoregions and each of the NVIS MVGs using the Tiberius software (Brierley unpublished), which ranks variable importance using the Gini Coefficient (Breiman et al. 1984). The Gini coefficient is directly related to the area under the receiver operator characteristic curve (Hand and Till 2001) that is the standard for assessing the success of classification algorithms.

Classification of the seven ecoregions used the 35 BioClim variables (35 input nodes) in the baseline climate presented in Table 5. Classification of the 23 MVGs used all the variables in Table 5 and all the terrain and soil variables in Table 4 (47 input nodes). For both the ecoregions and the MVGs, the number of hidden nodes was ten, the training rate was 0.07 and training stopped automatically when the overall Gini coefficient was minimised.

Training data were sampled from (4 km^2) vegetation and environmental data. In all cases, approximately half of the training data consisted of presences for the target vegetation class with the remainder (absences) equally divided among the remaining classes. Twenty percent of the sample was then used as test data. Appendix A, Table 3 provides the sample sizes for the ecoregions and Appendix A, Table 4 provides the sample sizes for the MVGs.

Table 5 List of the environmental variables used in the classifications to rank the importance of the variables

BIOCLIMATIC VARIABLES	
CODE	NAME
BioClim1	Annual Mean Temperature
BioClim2	Mean Diurnal Range
BioClim3	Isothermality
BioClim4	Temperature Seasonality
BioClim5	Max Temperature of Warmest Period
BioClim6	Min Temperature of Coldest Period
BioClim7	Temperature Annual Range
BioClim8	Mean Temperature of Wettest Quarter
BioClim9	Mean Temperature of Driest Quarter
BioClim10	Mean Temperature of Warmest Quarter
BioClim11	Mean Temperature of Driest Quarter
BioClim12	Annual Precipitation
BioClim13	Precipitation of Wettest Period
BioClim14	Precipitation of Driest Period
BioClim15	Precipitation Seasonality (Coefficient of Variation)
BioClim16	Precipitation of Wettest Quarter
BioClim17	Precipitation of Driest Quarter
BioClim18	Precipitation of Warmest Quarter
BioClim19	Precipitation of Coldest Quarter
BioClim20	Annual Mean Radiation
BioClim21	Highest Period Radiation
BioClim22	Lowest Period Radiation
BioClim23	Radiation Seasonality
BioClim24	Radiation of Wettest Quarter
BioClim25	Radiation of Driest Quarter
BioClim26	Radiation of Warmest Quarter
BioClim27	Radiation of Coldest Quarter
BioClim28	Annual Mean Moisture Index
BioClim29	Highest Period Moisture Index
BioClim30	Lowest Period Moisture Index
BioClim31	Moisture Index Seasonality
BioClim32	Mean Moisture Index of Highest Quarter MI
BioClim33	Mean Moisture Index of Lowest Quarter MI
BioClim34	Mean Moisture Index of Warmest Quarter
BioClim35	Mean Moisture Index of Coldest Quarter

See Houlder et al. (2000) for a full description of the BioClim variables

2.5 Analysis methods

2.5.1 CLASSIFICATION ACCURACY AND UNCERTAINTY

To calculate accuracy, the confusion matrices and Kappa, we applied the best models we obtained to classify all the 4 km^2 patterns across the entire continent. Overall producer accuracy was calculated as the percentage correspondence between the predicted classes and the mapped classes. The accuracy by class was calculated in the same way. The confusion matrices show in detail how errors (confusion) in each class are distributed among the other classes. Kappa is a classification statistic (Hudson and Ramm 1987) that uses the confusion matrix to provide an overall estimate of the classification's ability to discriminate classes. These statistics provide an overview of how well the ANN classifiers can separate environments that are characteristic of the vegetation mapping classes. As mentioned previously, the inability to do so perfectly, that is, confusion, has many possible sources.

2.5.2 POSSIBLE CLIMATE CHANGE IMPACTS

The ANN classifiers can assess possible climate change impacts using a variety of techniques. The simplest approach is to apply the ANNs to an altered set of input patterns that represent a future climate and map the reclassified new environments. By comparing these new classified maps with the original unclassified map we calculate the transition matrixes that show the areas that become more favourable to some other class or remains favourable to the class that is mapped.

Vector angle dissimilarity or stress

The ANNs provide much more information than is apparent in a classification, where the output node with the largest value is chosen as a pattern's (location's) classification. By using the values of all the output nodes we calculated the dissimilarity of this vector to the 'ideal' vector with the value of 1.0 for the class that is mapped at that location and all other values of 0.0. Hilbert and Van Den Muyzenberg (1999) defined dissimilarity (D) by the angle (γ) between the 'ideal' vector for the mapped forest type and the vector produced by the model for the environment at that location. The angle (radians) between two vectors can be found from

$$\cos\gamma = \frac{e \cdot m}{\sqrt{e \cdot e}\sqrt{m \cdot m}} \tag{1}$$

where (e) is the neural net output vector and (m) is the 'ideal' vector consisting of 1.0 for the mapped vegetation type and 0.0 otherwise. D is defined as γ divided by $\pi/2$, which normalises the index to the range [0,1]. A location that is mapped as Rainforest and vine thickets with a dissimilarity of 0.1, for example, has an environment that is more typical of this class than another location, also mapped as this class, with a dissimilarity of 0.4. Hilbert and colleagues (Hilbert et al. 2001; Hilbert and Ostendorf 2001) have interpreted this vector angle dissimilarity as an index of relative environmental stress. It could also be thought of as a propensity to change. Dissimilarity greater than 0.5 indicates an environment that is more like some other class than the one that is mapped.

Vector angle dissimilarity is illustrated in Figure 3 for the case where two environmental classes (EC_1 and EC_2) are distinguished. Our higher dimensional cases are analogous. Assuming that EC_1 corresponds with the mapped vegetation class, the ideal or reference vector is V_0, coinciding with the EC_1 axis, and has a dissimilarity of 0.0. V_1 (0.82, 0.13) illustrates the vector from the classification in the baseline climate with the angle with respect to V_0 of θ_1 so the dissimilarity (D_1) is approximately 0.15. V_2, with a dissimilarity of approximately 0.3, is an example of a possible result under a moderate climate change scenario, for the same geographic location. The environment is now less like EC_1 than it was and is now proportionately much more like EC_2. However, V_1 is still in the space (yellow) where the environment is more like EC_1 than EC_2. We interpret the increased dissimilarity of this location from 0.15 to 0.3 as an indication that the local biodiversity, corresponding to the classified environment EC_1, will be stressed in this climate change scenario because its environment has become less like the 'ideal' environment for this vegetation class as a result of climate change. V_3, with a dissimilarity of approximately 0.6, is an example of a possible result under a more extreme climate change scenario. We interpret this as greater environmental change, resulting in greater propensity for change in biodiversity than in the moderate climate change scenario. Now, the vector component for EC_2 is greater than for EC_1. In terms of the continuous measure of stress (D), this is immaterial. However, when the ANN is used to classify and map environments, this means that this location will be mapped as having an EC_2 environment. This result does not predict that this location will have vegetation class 2 in the future date corresponding to this climate change scenario. It does say that the environment at this location will become more like the environment typical of the second vegetation class so ecological processes are likely to change the character of the vegetation in this place in the direction of the new class.

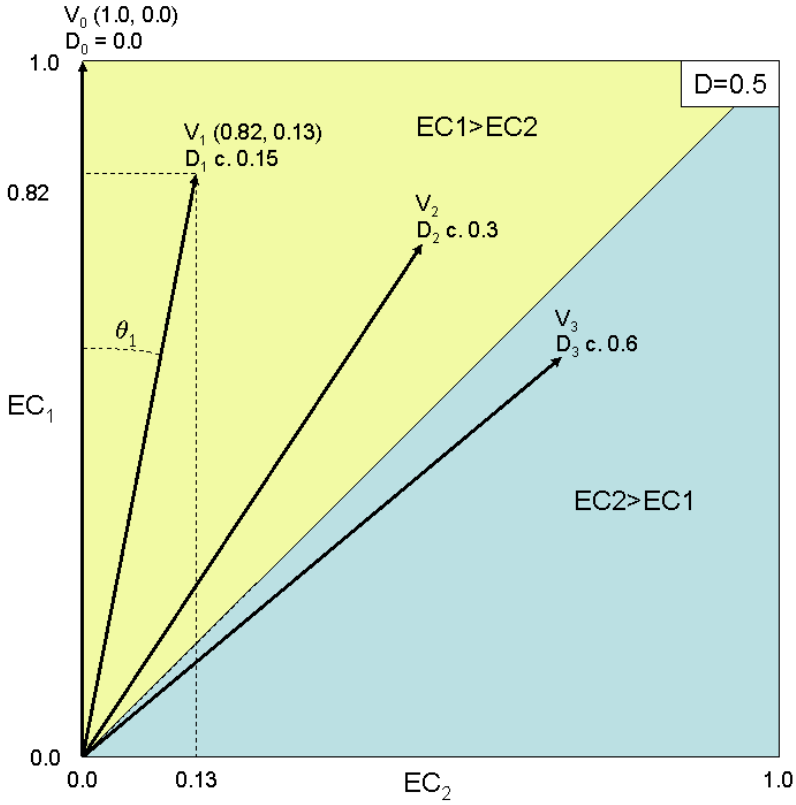

Figure 3 An illustration of how vector angle dissimilarity is calculated

Inevitably, dissimilarity includes aspects of classification confusion, but this confusion is unchanged when the model is applied to a new scenario. So, when considering climate change scenarios, the change in dissimilarity is due mostly to the change in climate. Here we calculated the mean and standard error of the dissimilarities from the mapped classes for the baseline climate and the two climate change scenarios. We also calculated and mapped the difference between the dissimilarity for the baseline climate classification and the dissimilarity for each of the two climate change scenarios. This shows the areas where climate change improves the local environment for the current vegetation and those areas where the climate becomes less suitable, while lessening the confusion inherent in the classifications.

Biotically scaled environmental stress

Dissimilarities as defined above were used in the project's four biome reports. For the synthesis report, we also calculated a measure of environmental change that uses the Bray–Curtis dissimilarity measure at all map locations. This is a pairwise distance measure between the ANN classification output in the baseline climate and the classification output in the A1B and A1FI climate scenarios, using all 23 outputs from the model that represent environmental suitability for each of the 23 vegetation types. Unlike the dissimilarity discussed above based on ideal vectors, it is not in reference to the mapped vegetation and considers changes in vector length as well as angle. This metric of environmental change is entirely independent of any confusion in the original classification.

Novel or non-analogue environments

The vector angle dissimilarity metric uses only the angle of the vector with respect to the ideal vector representing the mapped vegetation class, but vectors have both a direction and magnitude. In climate change scenarios where there are major changes in climatic patterns, the magnitude (length) of the vector may also change and possibly become quite small. In other words, the ANN classifier may produce an output vector for some locations where the suitability for all of the classified environment types is low. When this happens it is an indication that a new kind of environment exists that does not correspond to any of the classified environments based on the vegetation–environment patterns that exist today. We applied a very simple method to assess this by mapping the value of the largest ANN output value, in each of the climates, for each location across the continent. Roughly, values below 0.5 indicate environments that cannot be well separated and very low values indicate novel environments. There is little we can infer about the ecology of these very novel environments from this measure other than that they are not well-suited to any of the vegetation classes that we observe now in Australia.

3 RESULTS

3.1 Classification accuracy

3.1.1 ECOREGIONS

Classification of the seven ecoregions is highly accurate: 96.8% producer accuracy with a Kappa value of 0.95. The classification map is given in Figure 4 and the confusion matrix is presented in Table 6. It is apparent that the 23 climate variables are sufficient to distinguish these broad ecoregion classes.

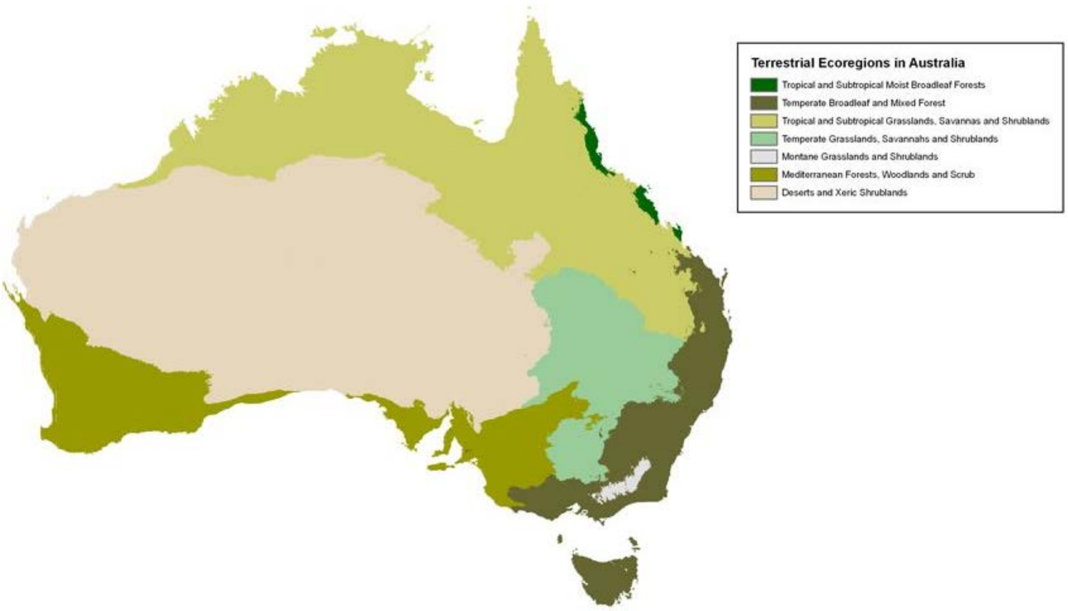

Figure 4 Map of ecoregion environments produced by the classification in the current climate

Table 6 Confusion matrix for the ecoregion classification (4 km^2 patterns)

		MAPPED						
		1	4	7	8	10	12	13
PREDICTED	1	6 907	0	2 155	0	0	0	0
	4	0	131 892	2 775	2 825	13	1 182	0
	7	11	383	443 679	759	0	0	16 502
	8	0	1 510	2 837	128 662	0	2 195	4 968
	10	0	3 178	0	0	2 937	0	0
	12	0	223	0	2 580	0	186 107	8 637
	13	0	0	1 232	121	0	784	759 515

3.1.2 MAJOR VEGETATION GROUPS

Classification of the 23 MVGs is less accurate than for the ecoregions: 64.2% producer accuracy with a Kappa value of 0.61. While the accuracy is not high, the expected accuracy of a random model is only 2.3%. The map produced by the classification is presented in Figure 5. The producer accuracies and Kappa values are presented by class in Table 7 and the confusion matrix is presented in Table 8.

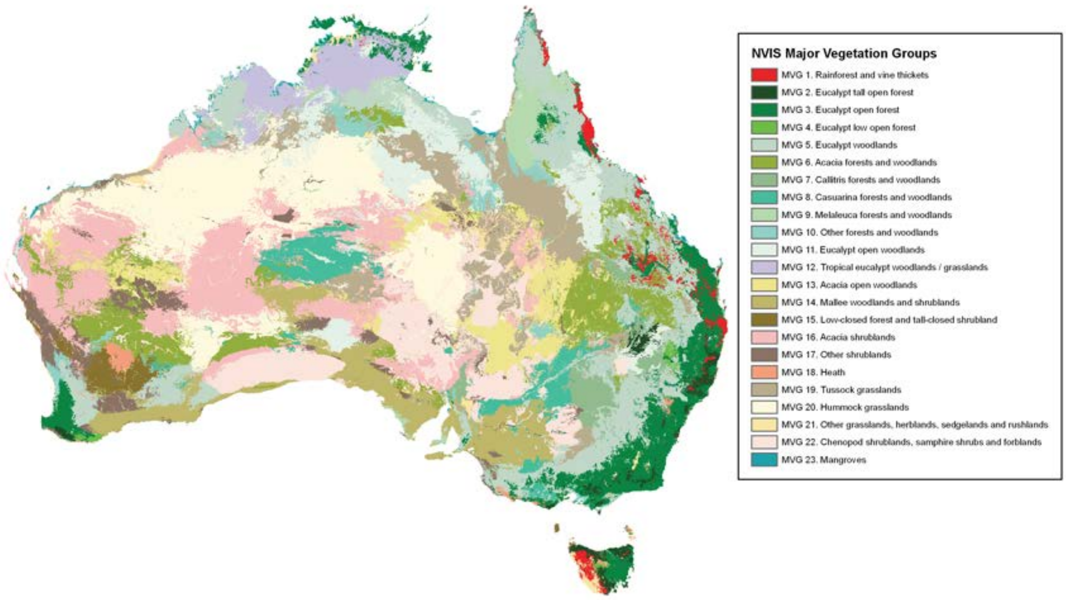

Figure 5 Map of the MVG environments as classified under the baseline climate

Table 7 Accuracies (percent) and Kappa values by MVG

MAJOR VEGETATION GROUP	ACCURACY	KAPPA
Rainforest and vine thickets	66.6	0.663
Eucalypt tall open forest	75.2	0.750
Eucalypt open forest	72.2	0.703
Eucalypt low open forest	85.3	0.853
Eucalypt woodlands	50.6	0.440
Acacia forests and woodlands	54.1	0.509
Callitris forests and woodlands	85.5	0.852
Casuarina forests and woodlands	73.1	0.722
Melaleuca forests and woodlands	73.7	0.733
Other forests and woodlands	60.1	0.593
Eucalypt open woodlands	57.1	0.546
Tropical eucalypt woodlands/grasslands	93.1	0.929
Acacia open woodlands	54.7	0.528
Mallee woodlands and shrublands	74.6	0.731
Low closed forest and tall closed shrubland	83.0	0.828
Acacia shrublands	62.7	0.576
Other shrublands	60.6	0.594
Heath	81.1	0.810
Tussock grasslands	66.5	0.638
Hummock grasslands	72.4	0.679
Other grasslands, herblands, sedgelands and rushlands	60.5	0.600
Chenopod shrublands, samphire shrubs and forblands	75.7	0.739
Mangroves	81.7	0.816

Table 8 Confusion matrix for the MVG classification (4 km^2 patterns)

PREDICTED	MAPPED																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	7 533	611	3 146	27	3 446	929	35	46	122	139	410	20	0	1	138	2	92	17	84	6	338	0	22
2	621	7 518	5 064	13	2 051	132	22	18	60	14	1 350	0	0	5	117	3	278	47	401	0	114	32	0
3	1 110	1 271	70 466	36	27 025	201	98	144	611	316	945	705	0	93	28	55	219	80	1 148	22	322	43	90
4	52	60	1 115	1 046	1 132	3	12	6	23	26	79	0	0	218	5	3	18	27	199	2	56	2	2
5	799	37	8 248	12	160 460	7 453	442	1 114	1 354	893	8 287	210	211	2 112	41	1 375	916	39	5 476	1 415	115	1 487	38
6	321	1	269	0	16 504	61 265	245	894	52	723	2 932	1	6 057	1 347	19	11 768	1 094	2	2 054	4 796	167	1 155	0
7	45	1	441	1	11 641	1 803	7 752	874	1	77	2 391	0	322	2 337	13	2 144	201	4	1 258	121	53	554	0
8	32	1	60	0	5 332	2 547	149	27 749	187	75	1 000	0	1 452	2 246	4	6 332	116	1	2 657	4 556	93	2 823	2
9	30	7	823	0	8 315	126	1	86	14 778	410	948	83	66	733	1	79	207	8	915	430	79	103	12
10	8	4	275	0	6 084	2 173	3	49	175	10 207	3 310	43	734	488	14	1 876	606	3	1 688	2 893	372	243	1
11	40	130	129	13	13 209	1 753	52	188	144	695	61 534	99	1 321	668	0	3 133	325	0	3 497	4 970	64	388	0
12	61	0	3 969	0	16 820	39	0	1	1 259	222	3 862	22 459	1	0	0	16	11	0	1 248	2 223	152	0	26
13	0	0	0	0	1 335	6 480	48	151	4	189	2 836	0	40 634	155	0	9 094	745	0	2 498	4 746	379	1 782	0
14	0	1	216	8	9 033	2 046	67	2 851	174	492	805	0	790	70 266	33	3 673	1 331	1	2 109	2 173	63	2 471	4
15	26	85	67	3	6 899	254	19	116	0	62	137	0	27	3 167	4 654	1 901	1 539	13	1	54	52	178	0
16	0	0	0	0	1 977	13 291	14	1 154	43	333	4 113	25	10 187	2 623	44	123 162	1 770	0	4 184	37 273	290	4 821	6
17	17	3	168	0	4 431	4 059	17	376	168	235	515	5	1 458	4 473	218	6042	20 859	34	1 036	1 609	97	1 776	7
18	22	59	957	47	3 025	168	9	29	71	84	52	0	12	384	128	813	184	1 299	30	0	75	3	2
19	6	0	142	0	8 180	3 532	20	349	35	1 155	5 904	69	5 195	135	0	4 871	627	0	83 627	6 837	1 077	4 537	7
20	0	0	0	0	2 062	1 963	0	422	241	196	4 307	200	1 365	797	0	8 880	836	0	2 485	217 187	124	781	1
21	445	178	691	18	1 425	716	23	92	337	263	1 004	69	1 231	370	129	575	430	16	2 605	1 337	7 480	1 840	48
22	0	0	448	0	4 747	2 117	41	1 145	7	60	922	0	3 188	1 471	2	10 468	1 947	0	6 286	7 019	603	78 402	1
23	60	0	745	0	1 436	92	0	26	142	58	102	115	1	10	0	111	47	2	293	231	161	147	1 143

3.2 Projected areas in future climates and transition matrices

3.2.1 ECOREGIONS

Figures 6 and 7 map the ecoregions' environments in 2070 under the medium and high warming scenarios. Table 9 compares the total areas of these environments with the modelled (classified) area of these in the current climate. Tables 10 and 11 show how areas that are now classified as most appropriate to each of the ecoregions change to other classes under the two climate scenarios.

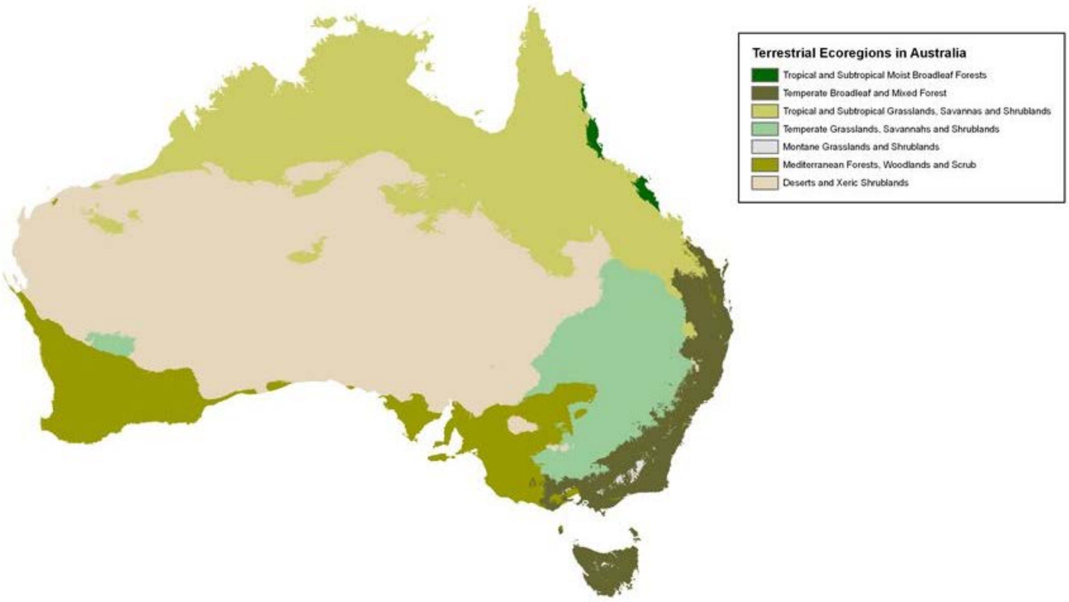

Figure 6 Distribution of ecoregion environments in the medium warming scenario

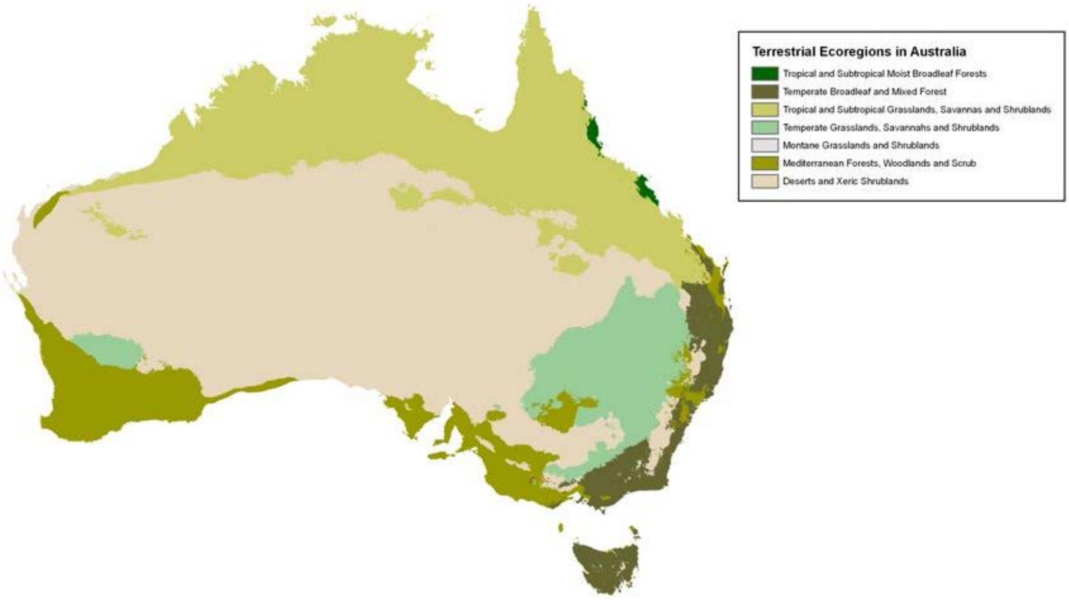

Figure 7 Distribution of ecoregion environments in the high warming scenario

Table 9 Areas of ecological and environmental ecoregional classes as predicted now and in the two climate change scenarios

ECOREGION	AREA OF MAPPED ECOREGIONS (KM^2)	AREAS OF PREDICTED ENVIRONMENTAL CLASS (KM^2)		
		NOW PREDICTED AREA (KM^2)	MED 2070 AREA (KM^2)	HIGH 2070 AREA (KM^2)
1) Tropical and subtropical moist broadleaf forests	27 672	36 248	25 416	19 092
4) Temperate broadleaf and mixed forest	548 744	554 748	444 832	314 108
7) Tropical and subtropical grasslands, savannas and shrublands	1 810 712	1 845 336	1 927 684	1 814 324
8) Temperate grasslands, savannas and shrublands	539 788	560 688	656 376	576 164
10) Montane grasslands and shrublands	11 800	24 460	6 732	696
12) Mediterranean forests, woodlands and scrub	761 072	790 188	702 836	647 716
13) Deserts and xeric shrublands	3 158 488	3 046 608	3 094 400	3 486 176
Total	6 858 276	6 858 276	6 858 276	6 858 276

Table 10 Transition matrix for the medium scenario, compared to the predicted map (1 km^2)

		MAPPED						
		1	4	7	8	10	12	13
PREDICTED	1	24 188	0	1 228	0	0	0	0
	4	0	401 388	21 468	3 368	18 608	0	0
	7	11 852	15 428	1 665 460	12 676	0	0	222 268
	8	0	102 524	77 504	427 076	0	40 120	9 152
	10	0	880	0	0	5 852	0	0
	12	208	32 764	44	24 860	0	640 128	4 832
	13	0	1 764	79 632	92 708	0	109 940	2 810 356

Table 11 Transition matrix for the high scenario, compared to the predicted map (1 km^2)

		MAPPED						
		1	4	7	8	10	12	13
PREDICTED	1	19 004	0	88	0	0	0	0
	4	0	281 176	8 324	1 172	23 436	0	0
	7	17 212	18 148	1 591 656	14 868	0	0	172 440
	8	0	98 064	44 060	336 392	0	88 404	9 244
	10	0	104	0	0	592	0	0
	12	32	87 196	160	19 324	0	529 140	11 864
	13	0	70 060	201 048	188 932	432	172 644	2 853 060

3.2.2 MAJOR VEGETATION GROUPS

Figures 8 and 9 map the MVGs' environments in 2070 under the medium and high warming scenarios. Table 12 compares the total areas of these environments with the modelled (classified) area of these in the current climate. Table 13 lists the area of each MVG environment in the current climate, the two scenarios and the percent changes in the scenarios. Tables 14 and 15 show how areas that are now classified as most appropriate to each of the ecoregions change to other classes under the two climate scenarios.

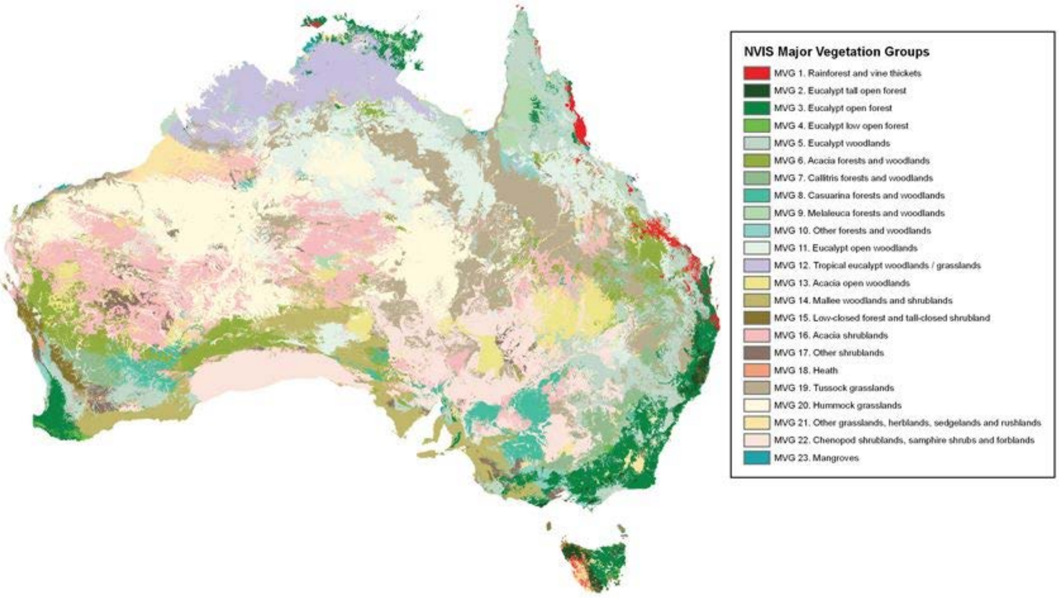

Figure 8 Distribution of MVG environments in the medium warming scenario

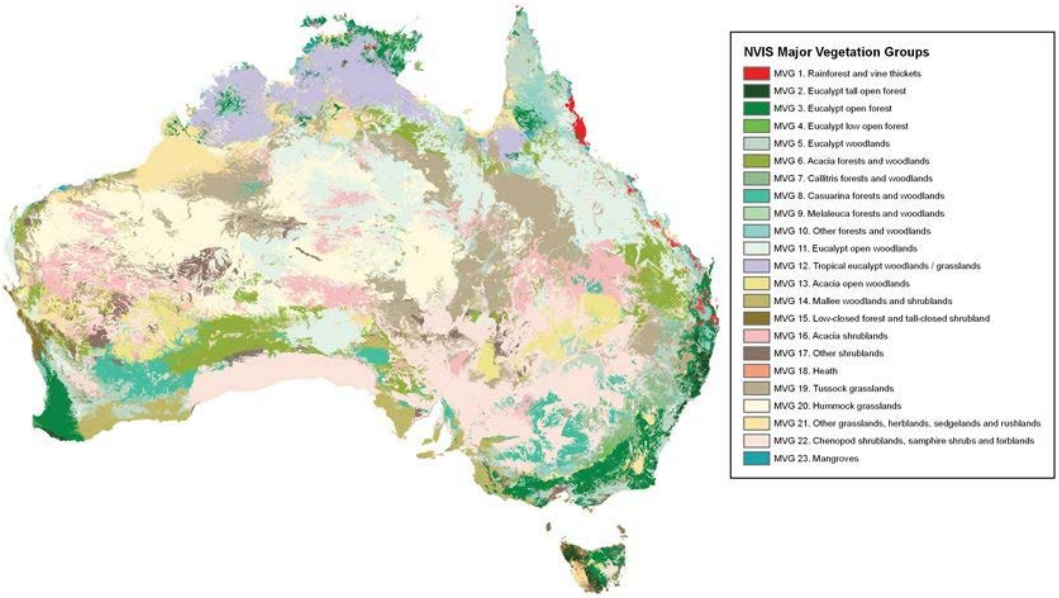

Figure 9 Distribution of MVG environments in the high warming scenario

Table 12 MVG areas as predicted now and areas of environmental classes in the two climate change scenarios

MAJOR VEGETATION GROUP	MAP AREA (KM^2)	NOW PREDICTED AREA (KM^2)	MED 2070 AREA (KM^2)	HIGH 2070 AREA (KM^2)
Rainforest and vine thickets	44 912	68 656	52 904	29 876
Eucalypt tall open forest	39 868	71 440	36 656	42 080
Eucalypt open forest	389 756	420 112	341 584	320 088
Eucalypt low open forest	4 896	16 344	12 524	10 644
Eucalypt woodlands	1 266 276	810 136	574 824	361 380
Acacia forests and woodlands	452 568	446 664	348 232	387 164
Callitris forests and woodlands	36 276	128 136	162 904	92 532
Casuarina forests and woodlands	151 520	229 656	163 508	207 388
Melaleuca forests and woodlands	79 952	112 960	73 412	28 924
Other forests and woodlands	67 696	124 996	82 488	140 900
Eucalypt open woodlands	430 980	369 408	631 860	898 284
Tropical eucalypt woodlands/grasslands	96 412	209 476	355 944	362 152
Acacia open woodlands	297 008	284 304	242 080	223 236
Mallee woodlands and shrublands	376 396	394 428	318 468	171 244
Low closed forest and tall closed shrubland	22 352	77 016	42 292	23 032
Acacia shrublands	785 504	821 240	746 396	418 180
Other shrublands	137 592	190 412	93 724	148 836
Heath	6 372	29 812	6 200	3 020
Tussock grasslands	503 116	505 220	750 964	751 068
Hummock grasslands	1 199 600	967 388	976 604	920 940
Other grasslands, herblands, sedgelands and rushlands	49 304	85 288	132 316	278 296
Chenopod shrublands, samphire shrubs and forblands	414 272	475 496	702 720	1 023 004
Mangroves	5 648	19 688	9 672	16 008

Table 13 Areas of predicted MVG environmental classes in the current and two future climates (km^2) and percent changes in area in the two climate change scenarios

ENVIRONMENTAL CLASS BASED ON MAJOR VEGETATION GROUPS	NOW PREDICTED AREA (KM^2)	MED 2070 AREA (KM^2)	HIGH 2070 AREA (KM^2)	PERCENT CHANGE MED 2070 CF. NOW	PERCENT CHANGE HIGH 2070 CF. NOW
Rainforest and vine thickets	68 656	52 904	29 876	-22.94	-56.48
Eucalypt tall open forest	71 440	36 656	42 080	-48.69	-41.10
Eucalypt open forest	420 112	341 584	320 088	-18.69	-23.81
Eucalypt low open forest	16 344	12 524	10 644	-23.37	-34.88
Eucalypt woodlands	810 136	574 824	361 380	-29.05	-55.39
Acacia forests and woodlands	446 664	348 232	387 164	-22.04	-13.32
Callitris forests and woodlands	128 136	162 904	92 532	27.13	-27.79
Casuarina forests and woodlands	229 656	163 508	207 388	-28.80	-9.70
Melaleuca forests and woodlands	112 960	73 412	28 924	-35.01	-74.39
Other forests and woodlands	124 996	82 488	140 900	-34.01	12.72
Eucalypt open woodlands	369 408	631 860	898 284	71.05	143.17
Tropical eucalypt woodlands/grasslands	209 476	355 944	362 152	69.92	72.88
Acacia open woodlands	284 304	242 080	223 236	-14.85	-21.48
Mallee woodlands and shrublands	394 428	318 468	171 244	-19.26	-56.58
Low closed forest and tall closed shrubland	77 016	42 292	23 032	-45.09	-70.09
Acacia shrublands	821 240	746 396	418 180	-9.11	-49.08
Other shrublands	190 412	93 724	148 836	-50.78	-21.83
Heath	29 812	6 200	3 020	-79.20	-89.87
Tussock grasslands	505 220	750 964	751 068	48.64	48.66
Hummock grasslands	967 388	976 604	920 940	0.95	-4.80
Other grasslands, herblands, sedgelands and rushlands	85 288	132 316	278 296	55.14	226.30
Chenopod shrublands, samphire shrubs and forblands	475 496	702 720	1 023 004	47.79	115.14
Mangroves	19 688	9 672	16 008	-50.87	-18.69

Table 14 Transition matrix for the medium scenario 2070, compared to the predicted map (km^2)

		MAPPED																						
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
PREDICTED	1	23 352	572	13 056	124	9 964	1 236	40	20	312	4	656	32	0	16	88	0	44	140	16	4	2 260	0	968
	2	6 252	20 372	6 768	388	304	0	0	4	24	8	0	0	0	0	128	0	84	388	16	0	1 912	0	8
	3	7 812	31 060	243 960	3 132	27 924	172	12	1 728	2 780	2 280	40	10 164	0	68	224	4	2 076	4 240	28	0	1 284	0	2 596
	4	332	492	5 384	2 684	1 900	4	164	8	56	124	0	0	0	664	24	0	356	172	0	0	112	0	48
	5	8 372	908	79 256	5 668	311 660	15 100	27 948	8 924	20 644	10 940	11 016	1 612	2 328	18 224	10 348	2 056	12 628	4 716	5 296	240	5 324	7 868	3 748
	6	7 436	204	1 956	196	35 592	120 920	9 644	3 516	184	4 992	1 564	40	11 560	9 296	6 764	72 704	10 672	7 256	4 640	31 844	2 512	4 248	492
	7	1 044	344	9 612	532	70 068	7 168	24 096	932	68	308	2 732	0	0	1 712	27 776	876	7 024	3 336	3 008	1 772	236	248	12
	8	204	0	348	20	15 368	11 516	1 464	31 192	188	1 044	20	168	1 976	61 648	11 264	3 932	1 272	4 712	276	5 480	360	10 992	64
	9	20	12	2 720	4	4 324	52	0	7 356	48 580	1 340	1 180	4 228	8	4	4	536	28	8	504	1 192	924	84	304
	10	648	460	8 900	28	17 688	5 220	1 184	3 540	6 220	20 744	1 388	284	2 100	3 452	828	604	4 808	424	628	2 640	576	64	60
	11	2 592	2 876	6 120	72	75 260	24 736	4 028	7 976	5 732	41 996	253 624	3 228	17 384	5 432	108	44 924	8 944	344	20 940	100 504	1 884	2 472	684
	12	284	0	7 148	0	83 920	180	0	24	11 656	11 692	22 216	186 228	72	0	0	10 588	896	0	4 404	11 476	1 768	0	3 392
	13	0	4	0	0	3 444	79 756	752	8 388	0	3 268	2 456	0	71 444	388	476	37 868	8 892	40	5 460	16 644	756	2 044	0
	14	28	8	4 388	1 304	30 356	2 812	176	9 868	8 700	420	11 300	0	1 644	176 040	1 532	27 828	26 072	1 072	1 308	11 340	180	2 000	92
	15	216	2 268	44	4	7 156	4	0	12	0	2 512	632	0	0	496	9 096	3 692	15 396	340	0	0	400	24	0
	16	336	8	220	0	9 284	92 004	10 644	75 716	608	928	17 364	24	68 756	17 664	1 396	286 456	23 416	164	31 488	93 996	6 724	9 164	36
	17	60	348	3 732	52	8 216	8 444	144	3 392	628	1 012	432	0	10 020	7 212	3 036	7 164	30 448	640	1 264	4 632	1 556	1 192	100
	18	644	604	332	600	68	0	0	80	240	256	0	0	0	4	116	0	2 172	788	0	0	240	0	56
	19	5 164	8 608	15 296	688	35 208	38 680	13 732	6 772	2 120	11 208	27 776	1 636	15 732	308	204	35 504	8 716	360	373 080	35 852	20 984	92 760	576
	20	0	0	12	0	2 248	15 220	0	26 908	2 256	1 600	7 312	1 144	35 156	28 484	4	220 204	10 660	0	13 136	591 232	3 068	17 872	88
	21	3 668	1 596	7 040	824	10 848	1 540	212	1 940	1 428	312	5 228	632	320	248	232	14 600	1 388	556	7 748	51 868	18 148	56	1 884
	22	4	696	2 180	0	48 960	21 864	33 896	31 344	160	7 736	2 452	0	45 804	62 796	3 364	51 700	14 384	116	30 984	6 628	12 684	324 348	620
	23	188	0	1 640	24	376	36	0	16	376	272	20	56	0	272	4	0	36	0	996	44	1 396	60	3 860

Table 15 Transition matrix for the high scenario 2070, compared to the predicted map (km^2)

		MAPPED																						
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
	1	15 672	252	8 432	64	3 220	112	24	8	156	108	56	512	0	0	28	0	24	20	4	24	464	0	696
	2	8 564	17 036	11 416	512	212	0	4	12	128	0	0	0	0	0	236	0	796	776	0	0	2 380	0	8
	3	5 340	26 408	187 080	3 732	38 184	984	0	5 868	11 112	7 504	3 172	18 108	0	112	364	372	4 004	2 640	252	84	2 264	0	2 504
	4	120	184	4 940	56	4 428	0	12	56	20	84	0	0	0	304	16	0	140	96	0	0	152	0	36
	5	5 988	3 708	61 812	5 388	154 476	2 428	10 520	6 308	20 308	8 528	8 060	1 956	924	22 768	10 256	888	14 620	1 324	4 164	640	4 268	9 868	2 180
	6	11 572	268	5 756	12	55 032	84 880	5 852	3 648	544	2 388	14 556	972	5 024	20 588	3 272	63 204	11 812	176	19 844	58 512	756	17 696	800
	7	104	608	21 952	1 544	51 588	84	6 948	28	128	216	4	0	0	76	4 044	408	1 976	2 216	332	8	184	76	8
	8	4	0	164	116	44 696	17 508	5 148	16 276	40	260	328	364	1 528	41 532	26 548	7 864	5 028	7 652	12 568	4 432	396	14 876	60
	9	88	540	3 152	0	1 108	4	0	4	4 464	2 964	1 332	5 064	0	0	96	0	64	12	1 668	7 664	520	0	180
	10	5 584	1 104	26 700	112	43 940	10 028	368	4 348	15 468	10 840	1 060	3 688	1 204	1 176	1 124	1 600	3 144	816	1 808	5 584	576	84	544
PREDICTED	11	6 600	1 184	16 696	100	135 920	42 484	1 256	35 020	5 044	29 528	248 948	536	37 736	20 164	548	128 032	25 316	112	22 608	123 340	4 548	10 880	1 684
	12	452	0	6 428	0	81 956	584	0	64	27 864	9 284	36 760	168 084	0	0	0	1 680	696	0	12 336	12 424	888	64	2 588
	13	0	0	0	0	7940	69 628	1 264	7 224	16	1 044	2 624	0	43 064	304	3 596	41 400	15 936	4 632	1 580	16 704	660	5 620	0
	14	316	312	6 380	2 092	22 736	2 152	1 500	452	8 200	560	260	0	840	92 992	1 024	3 264	17 384	3 268	32	2 992	476	3 964	48
	15	256	1 960	12	4	744	0	0	0	0	600	0	0	0	80	3 316	1 836	12 848	364	0	0	988	24	0
	16	1 724	236	2 696	100	11 008	71 660	16 400	15 224	20	2 988	5 304	12	50 484	19 192	1 608	123 828	12 692	68	32 680	29 308	14 548	6 400	0
	17	440	1 780	6 548	120	6 376	14 136	236	1 292	704	4 484	376	4	11 316	3 676	2 228	48 868	13 808	4 180	2 368	8 624	1 564	15 652	56
	18	560	1 028	660	128	64	0	0	64	12	116	0	40	0	0	48	0	8	80	0	0	212	0	0
	19	784	7 352	16 584	1 020	20 540	21 320	5 572	3 000	1 436	5 948	18 604	1 104	23 076	676	920	54 588	8 392	372	321 984	127 472	15 556	94 576	192
	20	0	0	88	0	744	24 216	0	64 696	2 408	1 148	8 500	1 720	45 548	25 900	28	242 368	13 496	116	24 472	454 048	2244	9 000	200
	21	3 904	1 440	19 056	832	26 596	3 808	344	844	13 092	24 572	5 260	6 776	444	68	520	34 052	3 416	780	15 576	97 608	16 376	88	2 844
	22	92	6 040	9 548	376	97 360	80 604	72 688	65 176	596	11 420	13 848	0	63 116	144 804	17 192	66 892	24 656	92	29 668	17 792	13 548	286 576	920
	23	492	0	4 012	36	1268	44	0	44	1 200	412	356	536	0	16	4	96	156	20	1 276	128	1 720	52	4 140

3.3 Dissimilarity and changes in dissimilarity

3.3.1 ECOREGIONS

Figure 10 displays ecoregion dissimilarity, inferred by the classification, in the current climate. For the most part, dissimilarity is concentrated at the edges where ecoregions are adjacent. This is expected since the precise boundaries of ecoregions are hard to delineate. This map further illustrates the high certainty of the environmental classification by showing that the uncertainty is concentrated on the edges rather than in a biased or random way. Dissimilarity maps for the ecoregions in the two climate change scenarios are presented in Figures 11 and 12.

Figures 13 and 14 are maps of changes in dissimilarity relative to the current climate. This is calculated as the dissimilarity in the climate change scenario minus the dissimilarity in the baseline climate. In a sense, these maps remove uncertainty in the classification and emphasise changes due to climate change.

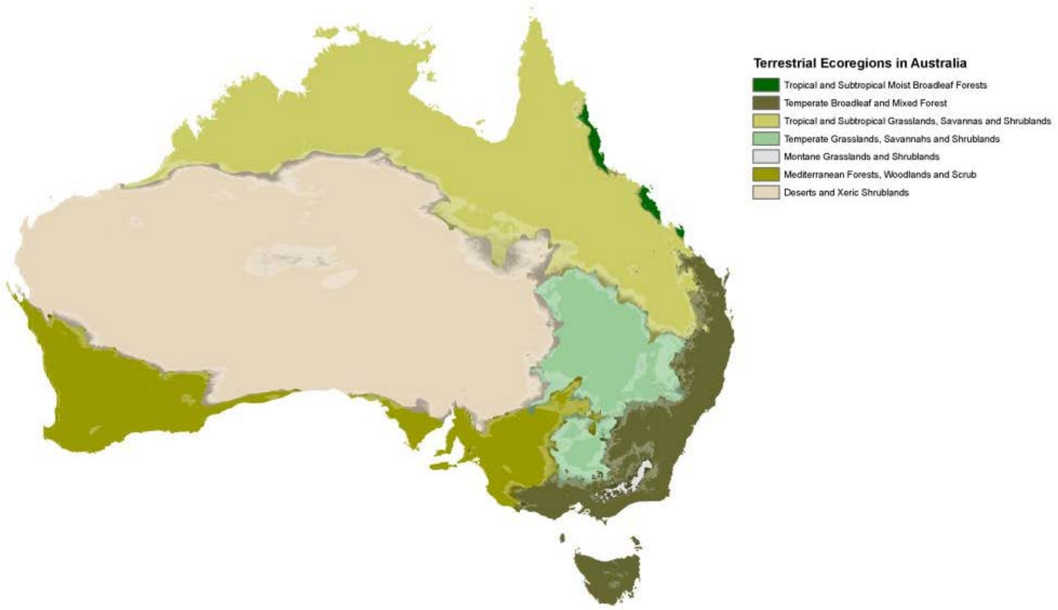

Figure 10 Dissimilarity map for the predicted environmental classification in the current climate; darker shading indicates greater dissimilarity, with lighter shading indicating little change from the mapped ecoregions (shown in colours)

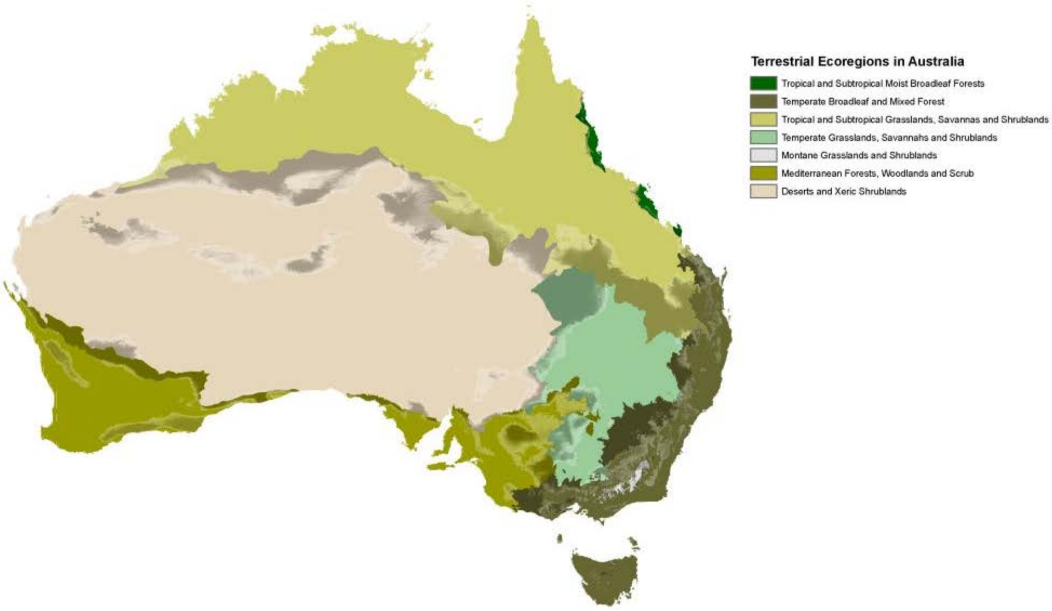

Figure 11 Dissimilarity map for the classification in the medium climate change scenario 2070; darker shading indicates greater dissimilarity, lighter indicates less dissimilarity, colours indicate the environmental class

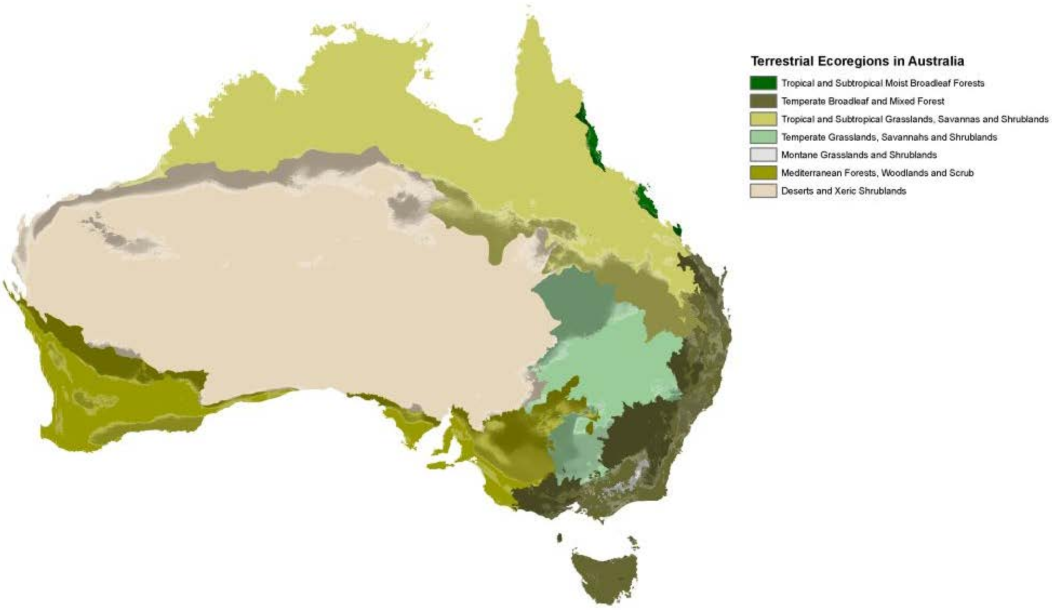

Figure 12 Dissimilarity map for the classification in the high climate change scenario 2070; darker shading indicates greater dissimilarity, lighter indicates less dissimilarity, colours indicate the environmental class

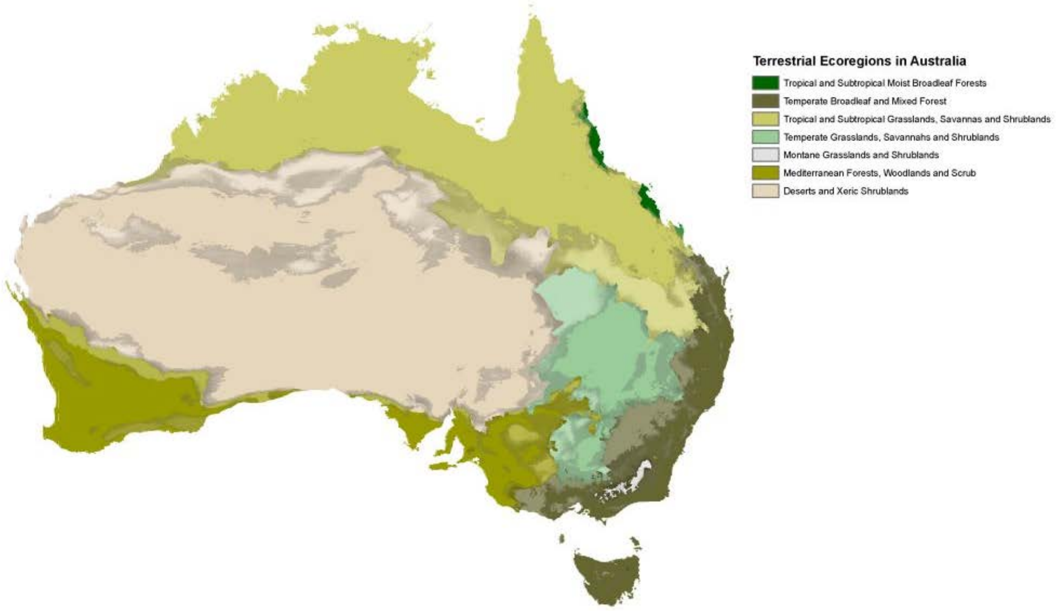

Figure 13 Difference between the dissimilarity for the baseline climate environmental classification and that of the medium climate change scenario 2070 environmental classification; darker shading indicates a reduction in dissimilarity, while lighter shading indicates an increase, superimposed on the mapped ecoregions in colour

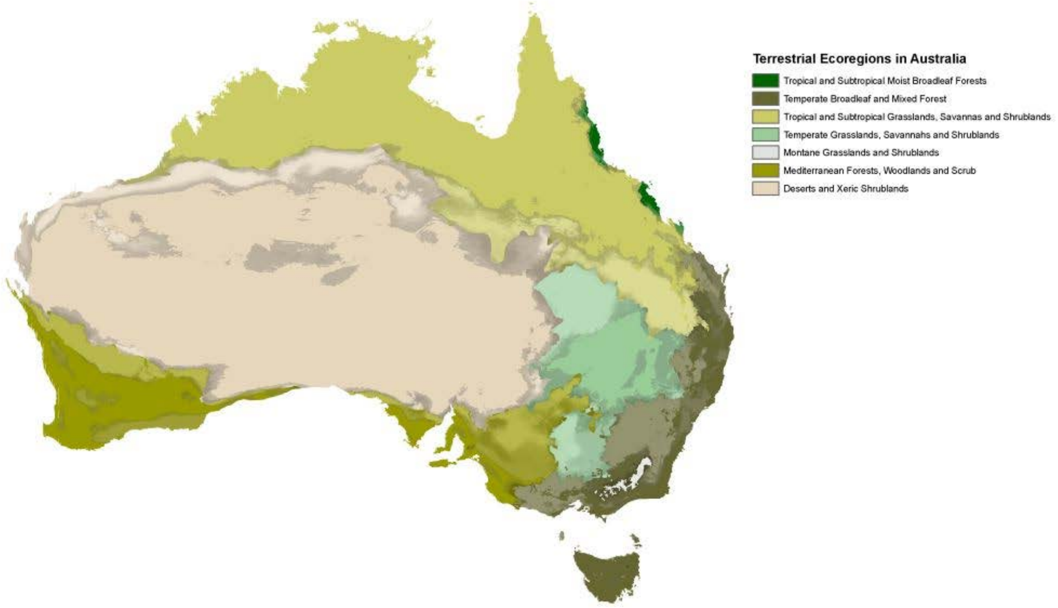

Figure 14 Dissimilarity change map for the high climate change scenario 2070; darker shading indicates a reduction in dissimilarity, while lighter shading indicates an increase or no change, superimposed on the mapped ecoregions in colour

3.3.2 MAJOR VEGETATION GROUPS

Figure 15 displays MVG dissimilarity, inferred by the classification, in the current climate. Dissimilarity maps for the predicted MVG environments in the two climate change scenarios are presented in Figures 16 and 17. The spatial pattern of dissimilarity is more complex than it is for the ecoregions and is difficult to see at this map scale. But in general, dissimilarity is greater throughout the MVGs and not solely concentrated at the edges. The mean dissimilarity for each MVG (averaged across all the 4 km^2 mapped locations) in each of the climates is graphed in Figure 18. MVGs 5, 6, 11 and 13 have mean dissimilarities greater than 0.5. This indicates the classification's relatively poor ability to distinguish these environments from those of some other class or classes. Mean dissimilarity equals or exceeds 0.5 in the two climate change scenarios for all classes with the exception of Tropical eucalypt woodlands/grasslands (MVG 12), which is a component of the Northern savannah and grassland biome.

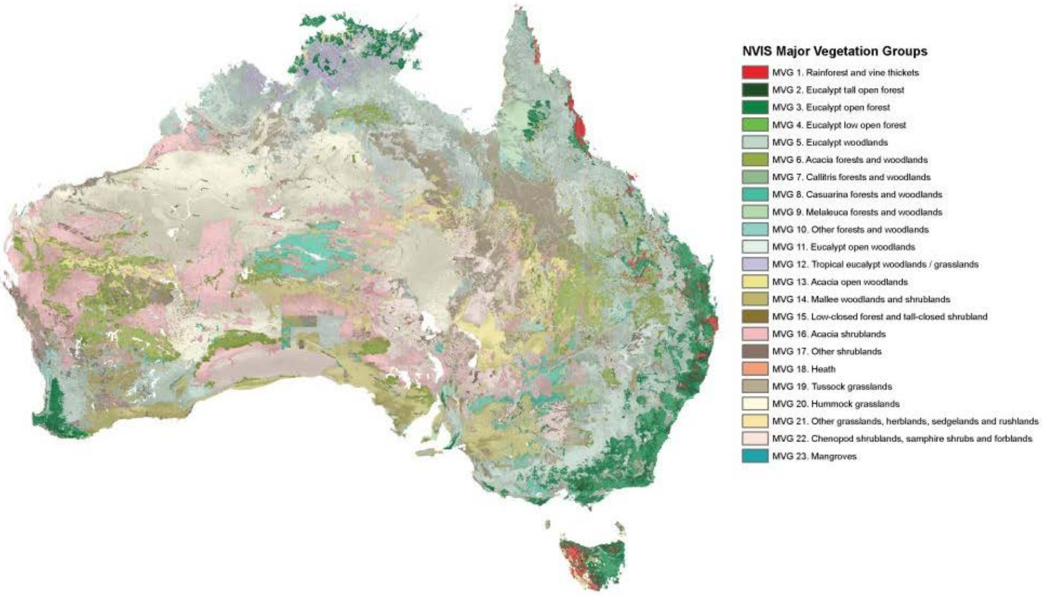

Figure 15 Dissimilarity map for the classification of MVG environments in the current climate; darker shading indicates greater dissimilarity, superimposed on the mapped MVGs

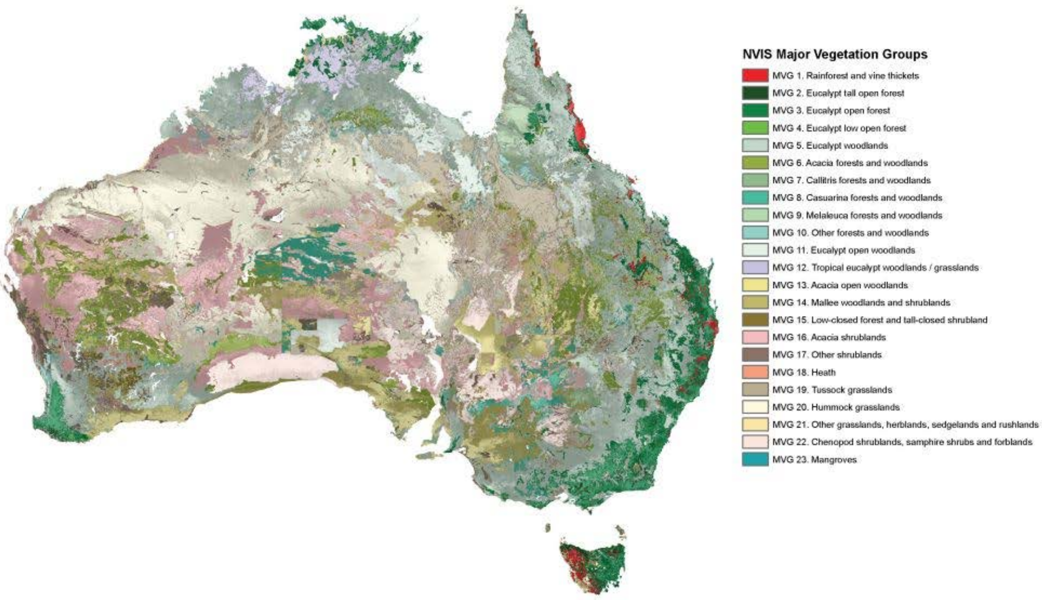

Figure 16 Dissimilarity map for the classification of MVG environments in the medium climate change scenario; darker shading indicates greater dissimilarity, superimposed on the mapped MVGs

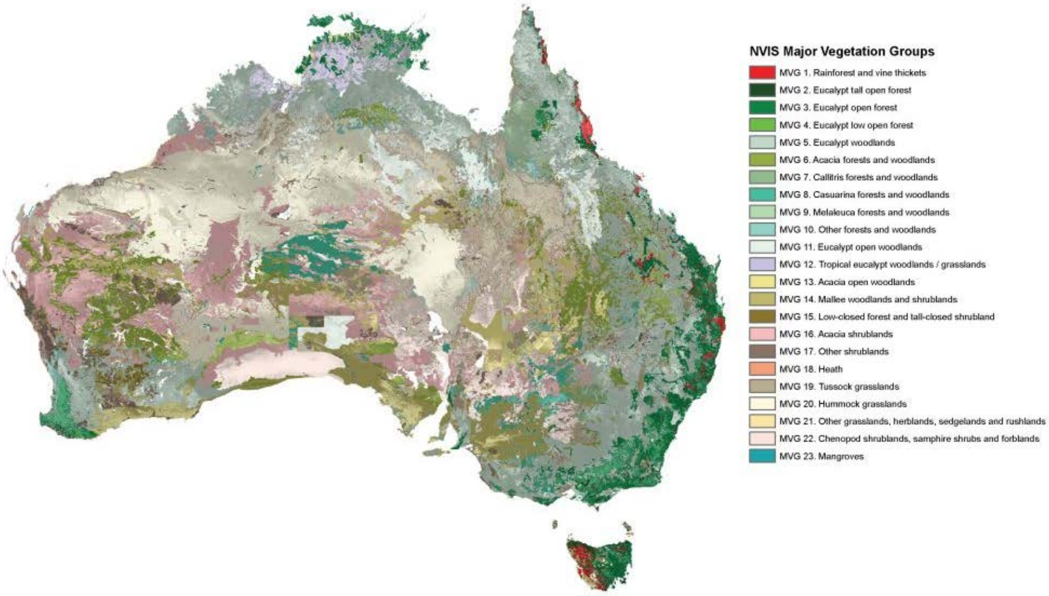

Figure 17 Dissimilarity map for the classification of MVG environments in the high climate change scenario; darker shading indicates greater dissimilarity, superimposed on the mapped MVGs

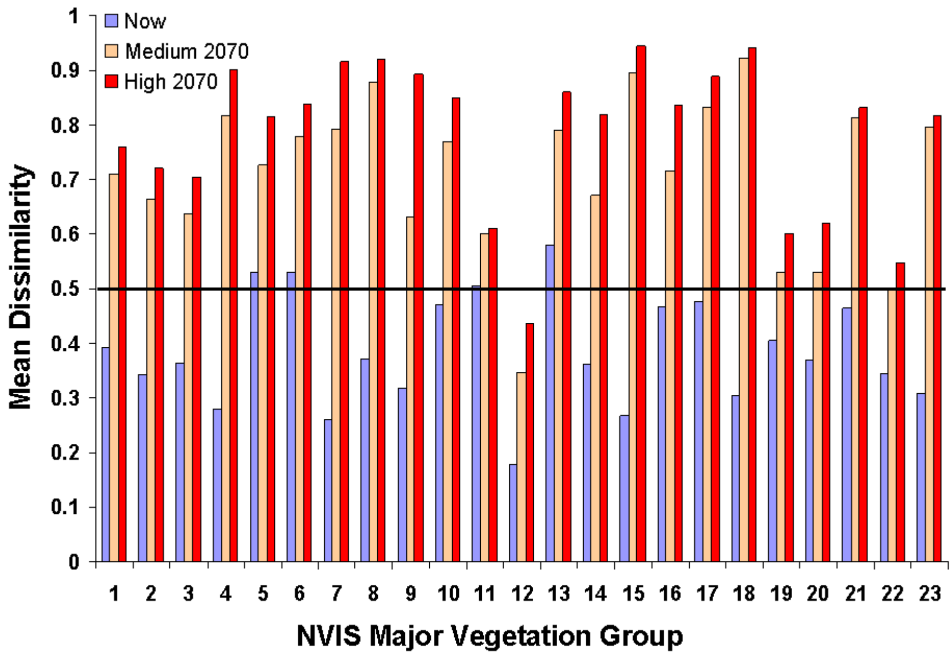

Figure 18 Mean dissimilarity now and in two climate change scenarios based on the NVIS mapping

Figures 19 and 20 map change in dissimilarity relative to the current climate. This is calculated as the dissimilarity in the climate change scenario minus the dissimilarity in the baseline climate. In a sense, these maps remove uncertainty in the classification and emphasise changes due to climate change. Like the dissimilarity maps, these maps are difficult to interpret visually at this scale.

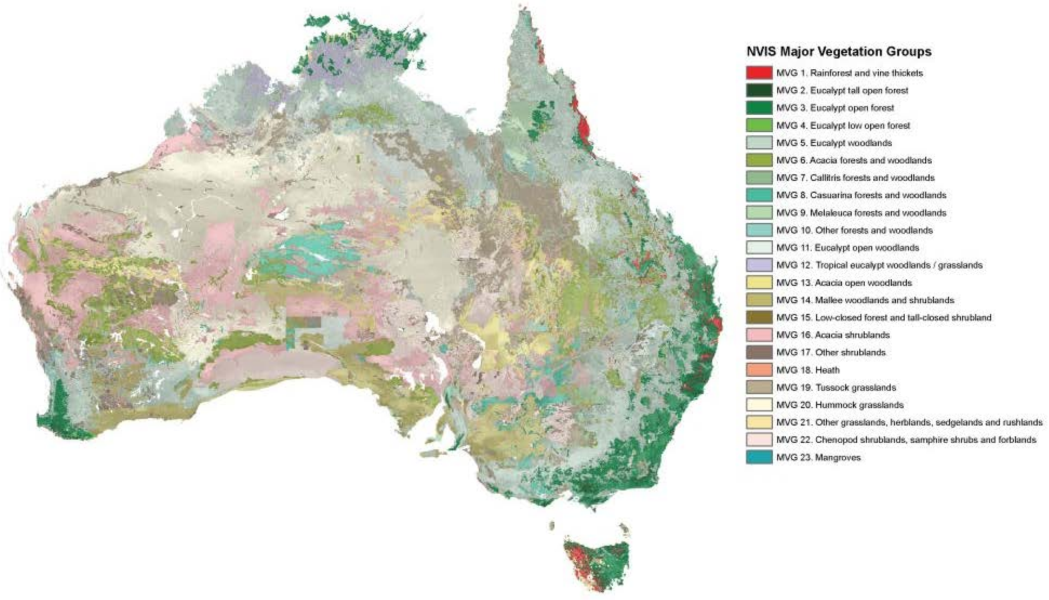

Figure 19 Dissimilarity change map for the medium climate change scenario; darker shading indicates a reduction in dissimilarity, while lighter shading indicates an increase

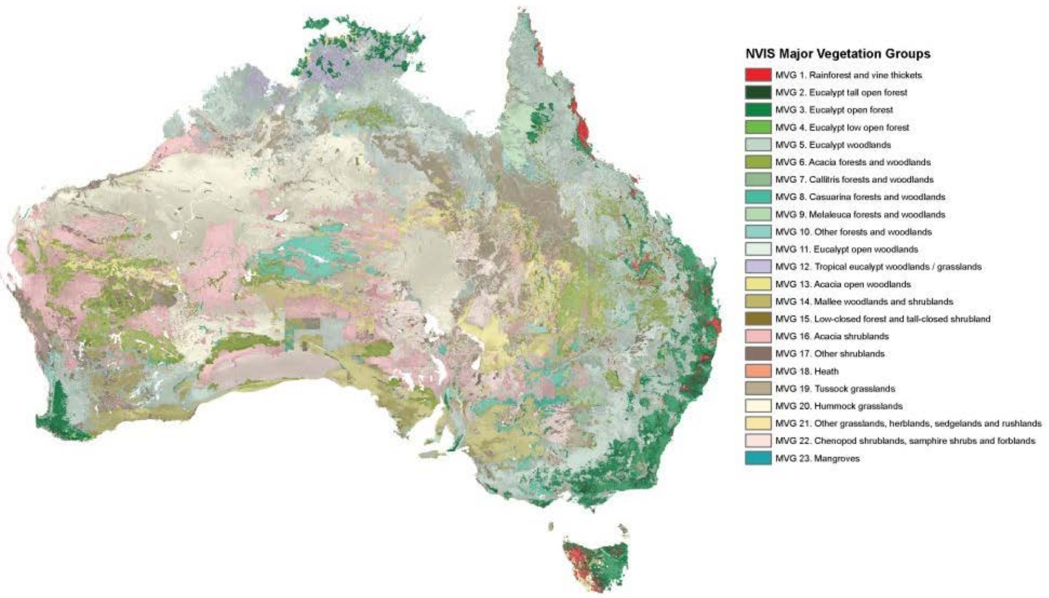

Figure 20 Difference between the dissimilarity for the baseline climate environmental classification change map and that of the medium climate change scenario 2070 environmental classification; darker shading indicates a reduction in dissimilarity, while lighter shading indicates an increase, superimposed on the mapped MVGs in colour

3.4 Biotically scaled environmental stress

Using this measure produces a more continuous picture of environmental change than the change in dissimilarity because the vegetation categories are not used explicitly. The results are presented in Figure 21. The map highlights the regions where environmental change resulting from global climate change may be more ecologically significant.

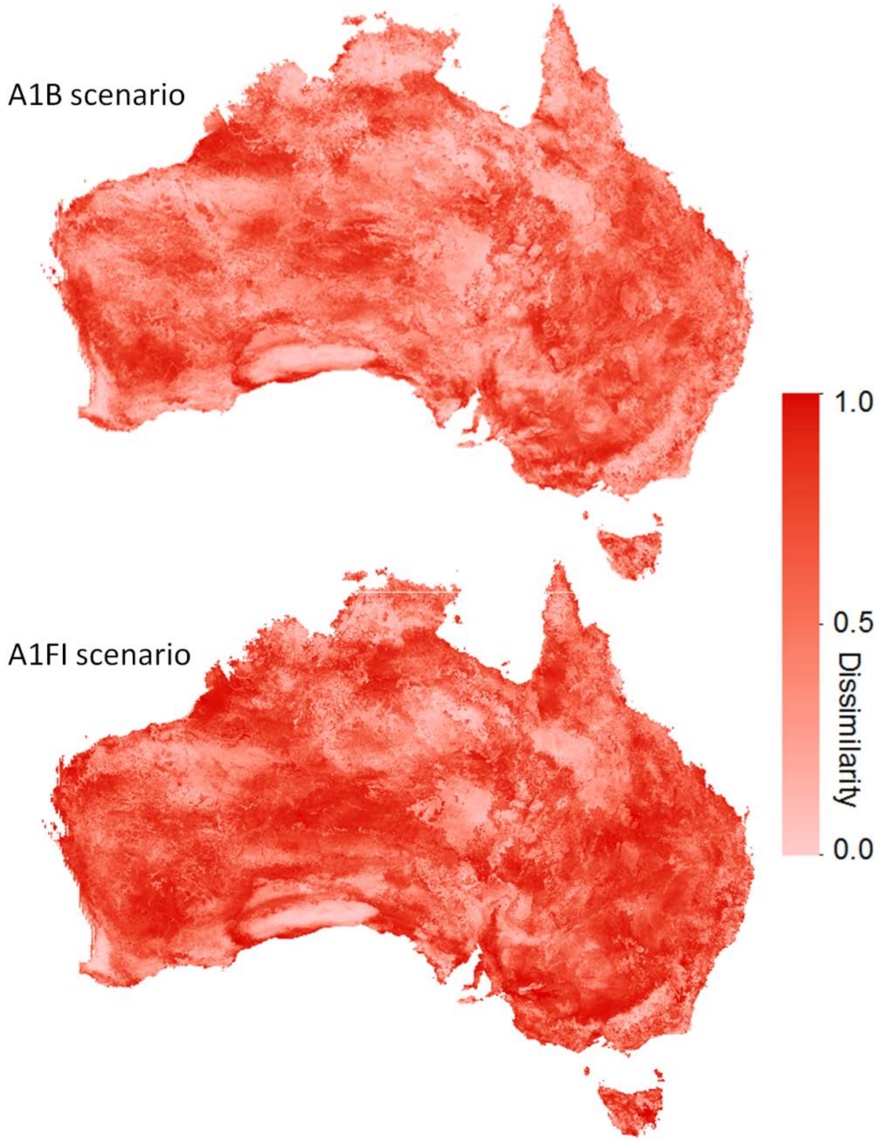

Figure 21 Dissimilarity change map for the high climate change scenario; darker shading indicates a reduction in dissimilarity, while lighter shading indicates an increase

Figure 22 displays the mean change in dissimilarity for the MVG classes using this method.

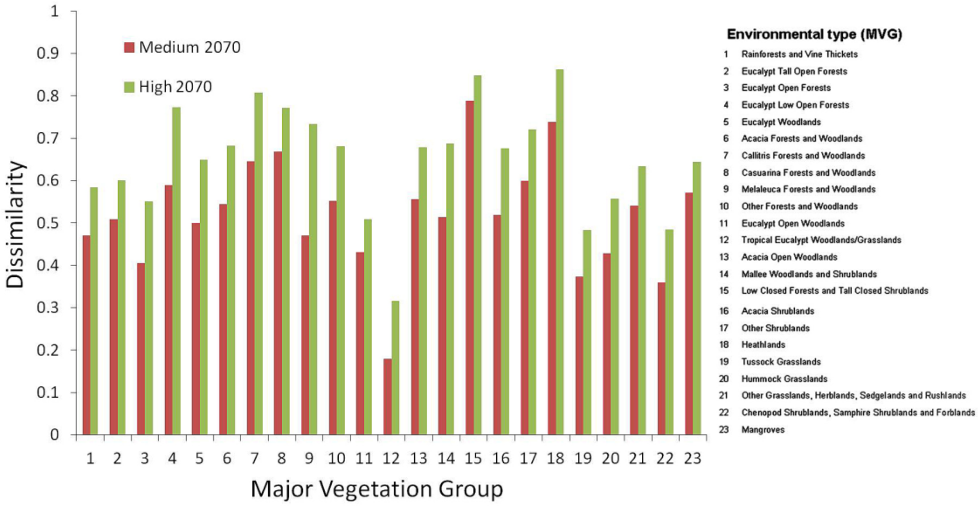

Figure 22 Mean biotically scaled dissimilarity for each of the environmental classes in both climate change scenarios

3.5 Ranking the importance of variables in the classification of vegetation environments

All the individual classifications of the vegetation classes were highly accurate, based on the Gini coefficient of the models. The resulting top 20 variable rankings are listed in Table 16 (MVGs) and Table 17 (ecoregions). Analyses of these results are beyond the scope of this report, but they generally conform to ecological expectations. For example, the highly ranked BioClim variables tend to be those that distinguish summer from winter rainfall–dominated areas.

Table 16 Ranking of the top 20 variables in the classification of environments for each major vegetation group

RAINFORESTS AND VINE THICKETS	EUCALYPT TALL OPEN FORESTS	EUCALYPT OPEN FORESTS	EUCALYPT LOW OPEN FORESTS	EUCALYPT WOODLANDS	ACACIA FORESTS AND WOODLANDS	CALLITRIS FORESTS AND WOODLANDS	CASUARINA FORESTS AND WOODLANDS	MELALEUCA FORESTS AND WOODLANDS	OTHER FORESTS AND WOODLANDS	EUCALYPT OPEN WOODLANDS	TROPICAL EUCALYPT WOODLANDS /GRASSLANDS
BioClim34	BioClim08	BioClim28	BioClim34	BioClim35	BioClim32	BioClim04	BioClim15	BioClim32	BioClim31	BioClim35	BioClim32
BioClim31	A_KSAT	BioClim35	BioClim35	BioClim29	BioClim15	BioClim15	BioClim22	BioClim24	BioClim32	BioClim04	BioClim35
BioClim32	BioClim15	BioClim29	BioClim28	BioClim15	BioClim25	BioClim24	BioClim07	BioClim27	BioClim29	BioClim22	BioClim28
BioClim14	BioClim19	BioClim34	BioClim08	BioClim32	BioClim35	BioClim25	BioClim23	BioClim35	BioClim15	BioClim09	BioClim04
BioClim19	BioClim35	BioClim32	BioClim33	BioClim22	BioClim29	BioClim03	BioClim27	BioClim29	BioClim25	BioClim31	BioClim23
BioClim29	BioClim26	BioClim31	BioClim29	BioClim04	BioClim04	BioClim31	BioClim29	BioClim22	BioClim35	BioClim27	BioClim27
BioClim23	BioClim31	BioClim23	EROSIONAL	BioClim31	BioClim24	MRVBF	BioClim32	BioClim06	BioClim09	BioClim34	BioClim34
BioClim30	MRVBF	BioClim15	BioClim01	BioClim34	SOILDEPTH	BioClim28	BioClim25	BioClim31	BioClim04	BioClim15	BioClim21
EROSIONAL	BioClim09	BioClim27	BioClim03	BioClim21	BioClim08	BioClim32	BioClim34	SOILDEPTH	BioClim34	BioClim29	BioClim07
BioClim08	BioClim14	BioClim22	BioClim20	BioClim09	BioClim31	BioClim29	BioClim20	BioClim28	BioClim27	BioClim23	MRVBF
A_KSAT	BioClim34	BioClim04	BioClim26	BioClim27	BioClim09	BioClim21	BioClim28	BioClim25	BioClim10	BioClim28	BioClim03
BioClim35	BioClim05	BioClim13	BioClim30	BioClim26	BioClim02	BioClim35	BioClim04	BioClim15	BioClim22	BioClim25	BioClim15
BioClim26	BioClim04	BioClim19	BioClim11	BioClim23	SOILPAWHC	BioClim09	BioClim03	BioClim20	BioClim08	BioClim32	BioClim06
BioClim07	BioClim30	BioClim30	BioClim10	BioClim25	BioClim26	BioClim22	BioClim24	BioClim02	BioClim20	BioClim24	BioClim11
BioClim04	BioClim07	BioClim24	BioClim32	BioClim24	A_KSAT	BioClim02	BioClim05	BioClim18	BioClim02	BioClim06	BioClim22
BioClim03	BioClim02	SOILPAWHC	BioClim23	BioClim03	BioClim27	EROSIONAL	BioClim35	BioClim26	BioClim23	BioClim26	ROUGHNESS
ROUGHNESS	BioClim10	MRVBF	BioClim19	BioClim07	BioClim03	BioClim08	BioClim08	BioClim34	BioClim24	SOILDEPTH	BioClim13
BioClim06	BioClim27	BioClim09	BioClim02	BioClim28	BioClim28	SOILDEPTH	SOILPAWHC	BioClim07	BioClim01	BioClim21	BioClim29
BioClim24	BioClim24	BioClim07	A_KSAT	BioClim20	BioClim22	BioClim23	BioClim09	MRVBF	BioClim26	EROSIONAL	BioClim31
BioClim02	BioClim17	BioClim25	BioClim05	BioClim06	BioClim34	A_KSAT	A_KSAT	BioClim04	BioClim03	BioClim10	BioClim05

Table 16 continued Ranking of the top 20 variables in the classification of environments for each major vegetation group

ACACIA OPEN WOODLANDS	MALLEE WOODLANDS AND SHRUBLANDS	LOW CLOSED FORESTS AND TALL CLOSED SHRUBLANDS	ACACIA SHRUBLANDS	OTHER SHRUBLANDS	HEATHLANDS	TUSSOCK GRASSLANDS	HUMMOCK GRASSLANDS	OTHER GRASSLANDS, HERBLANDS, SEDGELANDS AND RUSHLANDS	CHENOPOD SHRUBLANDS, SAMPHIRE SHRUBLANDS AND FORBLANDS	MANGROVES
BioClim32	BioClim28	BioClim24	BioClim32	BioClim25	BioClim25	BioClim15	BioClim32	BioClim31	BioClim29	ROUGHNESS
BioClim35	BioClim34	BioClim31	BioClim15	BioClim28	BioClim24	BioClim29	BioClim29	BioClim35	A_KSAT	BioClim02
BioClim04	BioClim08	BioClim08	BioClim35	BioClim15	BioClim31	A_KSAT	BioClim31	BioClim15	BioClim32	BioClim29
BioClim15	BioClim04	BioClim28	BioClim25	BioClim35	BioClim04	BioClim35	BioClim15	BioClim29	BioClim15	EROSIONAL
BioClim21	BioClim35	BioClim25	BioClim31	BioClim04	BioClim08	BioClim24	BioClim35	BioClim27	MRVBF	BioClim03
BioClim22	BioClim15	BioClim32	BioClim24	BioClim29	BioClim09	BioClim28	BioClim25	BioClim04	BioClim26	BioClim28
BioClim31	BioClim31	BioClim26	A_KSAT	BioClim22	BioClim07	BioClim32	BioClim34	BioClim10	BioClim34	BioClim09
BioClim29	BioClim24	BioClim21	BioClim22	A_KSAT	A_KSAT	BioClim25	BioClim27	BioClim22	BioClim23	MRVBF
BioClim34	BioClim10	BioClim20	BioClim29	BioClim32	BioClim03	BioClim22	BioClim02	BioClim09	BioClim21	BioClim07
BioClim25	BioClim26	BioClim23	BioClim28	BioClim21	BioClim35	BioClim27	BioClim22	BioClim08	BioClim25	BioClim25
A_KSAT	A_KSAT	BioClim04	BioClim08	BioClim24	BioClim02	BioClim04	A_KSAT	BioClim25	BioClim31	BioClim35
BioClim02	BioClim20	BioClim09	BioClim09	MRVBF	EROSIONAL	BioClim23	BioClim28	A_KSAT	BioClim24	BioClim31
BioClim08	BioClim27	BioClim22	BioClim21	BioClim27	BioClim15	BioClim34	BioClim20	BioClim01	BioClim28	BioClim23
SOILDEPTH	BioClim22	BioClim35	BioClim04	BioClim31	BioClim32	BioClim05	BioClim26	BioClim23	BioClim04	BioClim12
SOILPAWHC	BioClim29	BioClim05	BioClim23	BioClim20	BioClim28	BioClim31	BioClim24	BioClim06	BioClim08	BioClim15
BioClim09	SOILDEPTH	BioClim15	BioClim05	BioClim34	BioClim29	BioClim09	BioClim04	BioClim32	BioClim27	A_KSAT
BioClim23	BioClim32	BioClim29	BioClim34	BioClim02	BioClim14	BioClim26	BioClim07	BioClim11	BioClim07	BioClim04
BioClim27	MRVBF	BioClim14	BioClim06	BioClim26	BioClim30	BioClim07	SOILPAWHC	BioClim21	BioClim22	BioClim06
BioClim24	SOILPAWHC	BioClim27	SOILDEPTH	BioClim03	BioClim33	BioClim21	BioClim10	BioClim26	BioClim35	SOILPAWHC
BioClim28	BioClim07	BioClim34	BioClim10	SOILDEPTH	BioClim21	BioClim06	BioClim03	BioClim24	BioClim09	VALLEYBOTTOM

Table 17 Ranking of the top 20 variables in the classification of environments for each ecoregion

TROPICAL AND SUBTROPICAL MOIST BROADLEAF FORESTS	TEMPERATE BROADLEAF AND MIXED FOREST	TROPICAL AND SUBTROPICAL GRASSLANDS, SAVANNAS AND SHRUBLANDS	TEMPERATE GRASSLANDS, SAVANNAS AND SHRUBLANDS	MONTANE GRASSLANDS AND SHRUBLANDS	MEDITERRANEAN FORESTS, WOODLANDS AND SCRUB	DESERTS AND XERIC SHRUBLANDS
BioClim34	BioClim34	BioClim35	BioClim04	BioClim08	BioClim34	BioClim32
BioClim18	BioClim15	BioClim29	BioClim28	BioClim28	BioClim31	BioClim29
BioClim30	BioClim21	BioClim31	BioClim34	BioClim34	BioClim28	BioClim24
BioClim35	BioClim14	BioClim28	BioClim08	BioClim24	BioClim35	BioClim20
BioClim33	BioClim08	BioClim02	BioClim31	BioClim21	BioClim22	BioClim08
BioClim15	BioClim29	BioClim32	BioClim10	BioClim14	BioClim33	BioClim26
BioClim03	BioClim28	BioClim34	BioClim26	BioClim01	BioClim29	BioClim34
BioClim04	BioClim23	BioClim27	BioClim22	BioClim10	BioClim08	BioClim31
BioClim23	BioClim31	BioClim23	BioClim29	BioClim11	BioClim27	BioClim09
BioClim13	BioClim24	BioClim20	BioClim09	BioClim23	BioClim02	BioClim35
BioClim16	BioClim35	BioClim08	BioClim20	BioClim30	BioClim20	BioClim10
BioClim11	BioClim30	BioClim22	BioClim27	BioClim03	BioClim26	BioClim22
BioClim09	BioClim13	BioClim13	BioClim32	BioClim26	BioClim15	BioClim01
BioClim31	BioClim09	BioClim15	BioClim15	BioClim07	BioClim32	BioClim15
BioClim27	BioClim06	BioClim06	BioClim07	BioClim06	BioClim09	BioClim28
BioClim05	BioClim10	BioClim09	BioClim23	BioClim27	BioClim19	BioClim11
BioClim25	BioClim26	BioClim10	BioClim02	BioClim15	BioClim04	BioClim05
BioClim01	BioClim03	BioClim25	BioClim24	BioClim16	BioClim03	BioClim25
BioClim19	BioClim16	BioClim24	BioClim17	BioClim02	BioClim25	BioClim04
BioClim08	BioClim01	BioClim05	BioClim01	BioClim04	BioClim30	BioClim21

3.6 Novel environments

3.6.1 ECOREGION MAPS

The following figures display the value of the largest output value from the ANN classifiers for the ecoregions, irrespective of the mapped class. High values indicate a high correspondence with an ecological environment that is now present in Australia as inferred by the classifications. Moderate values suggest environments that are compatible with existing ecological environments but not well distinguished, as is expected in ecotones. Low values indicate environments that are unlike any of the ecoregions as they exist now in Australia or where several classes overlap.

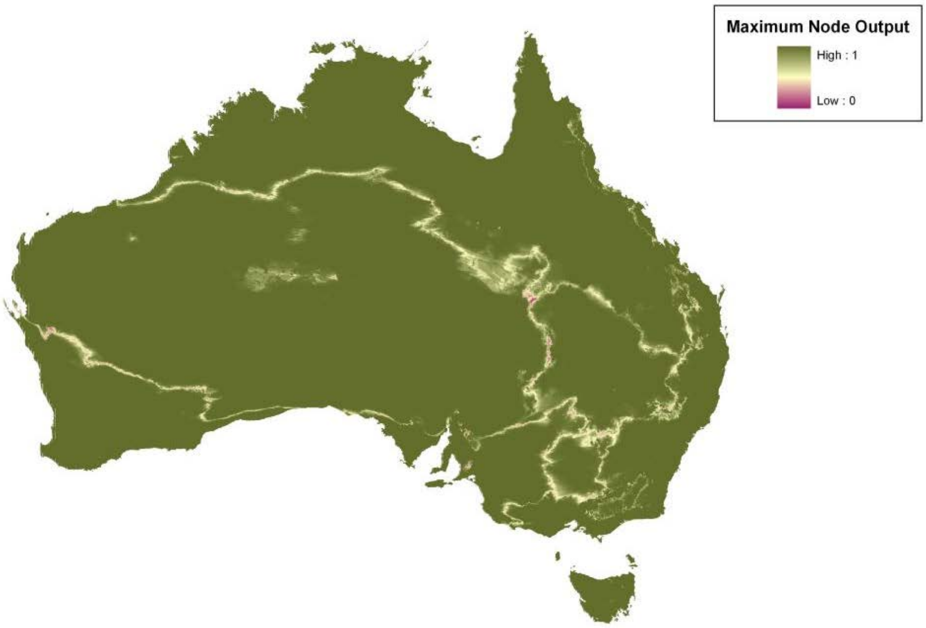

Figure 23 Map of the maximum output value of the ecoregion ANN classifier in the baseline climate

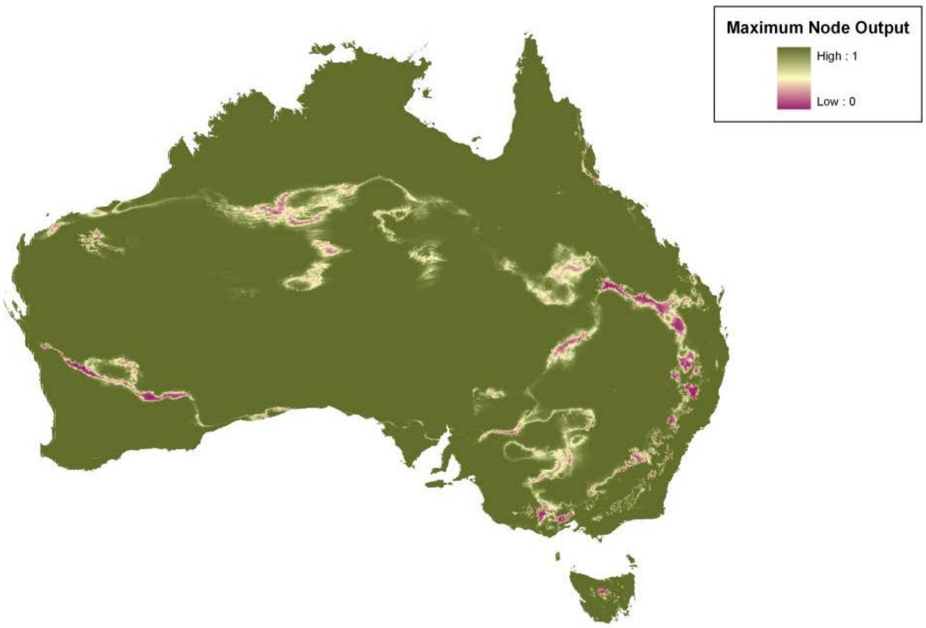

Figure 24 Map of the maximum output value of the ecoregion ANN classifier in the medium scenario 2070 climate

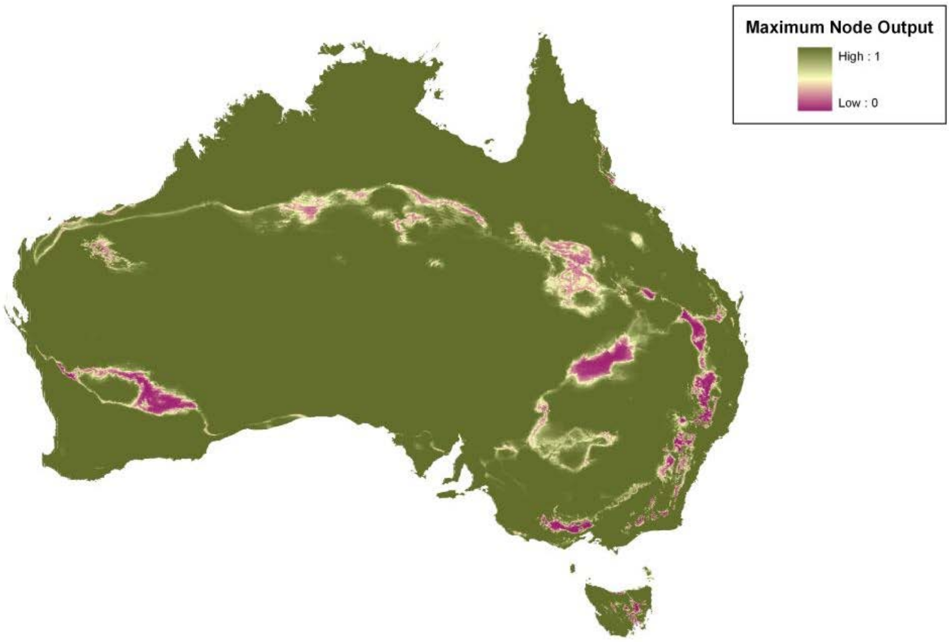

Figure 25 Map of the maximum output value of the ecoregion ANN classifier in the high scenario 2070 climate

3.6.2 MVG MAPS

The following figures (Figures 26, 27 and 28) display the value of the largest output value from the ANN classifiers for the MVGs, irrespective of the mapped class. High values indicate a high correspondence with an ecological environment that is now present in Australia as inferred by the MVG classifications. Moderate values suggest environments that are compatible with existing MVG environments, but two or more classes are not well distinguished, as is expected in ecotones. Low values indicate environments that are unlike any of the MVG environments as they exist now in Australia as defined by the classification, or the classification confusion is high. Substantial areas with low to moderate values in the baseline climate reflect confusion or uncertainty of the classifier rather than novel environments, and this must be considered when interpreting the results for the climate change scenarios.

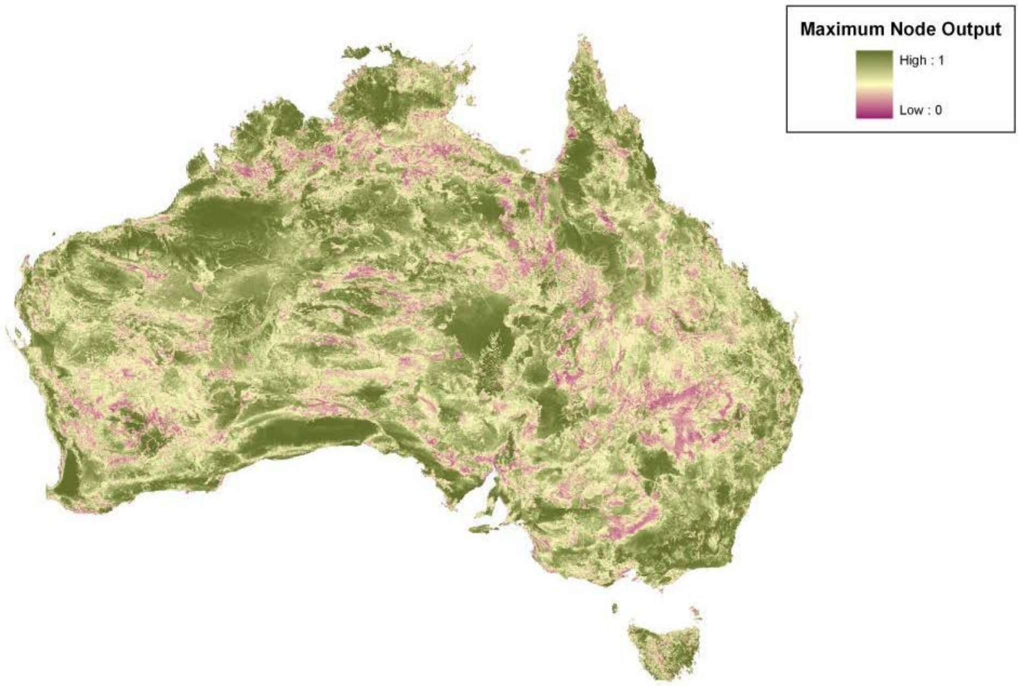

Figure 26 Map of the maximum output value of the MVG ANN classifier in the baseline climate

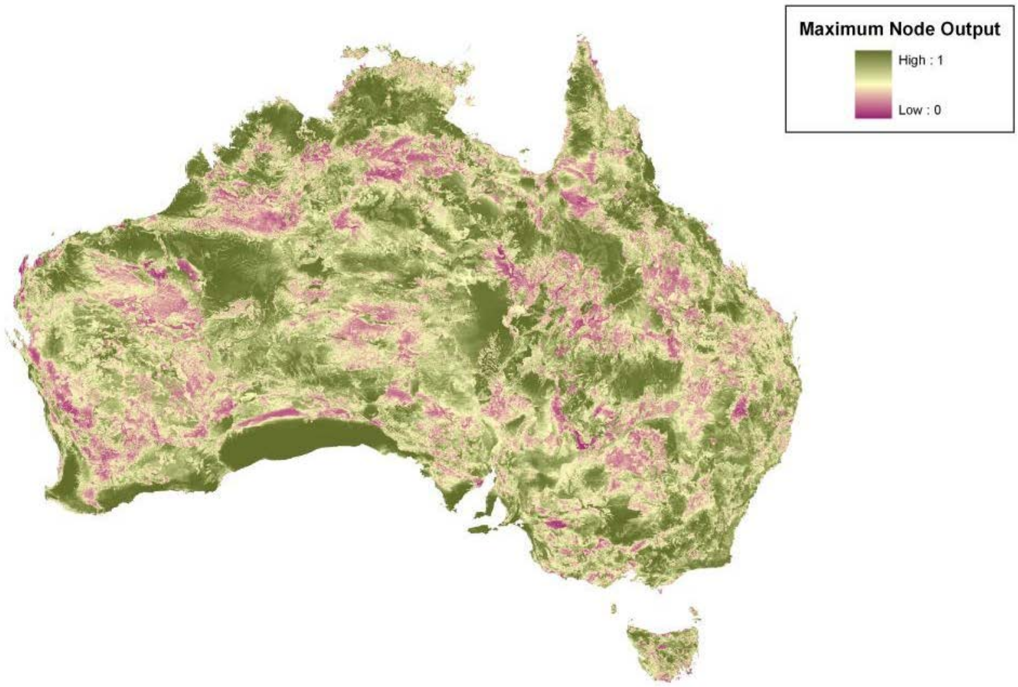

Figure 27 Map of the maximum output value of the MVG ANN classifier in the medium scenario 2070 climate

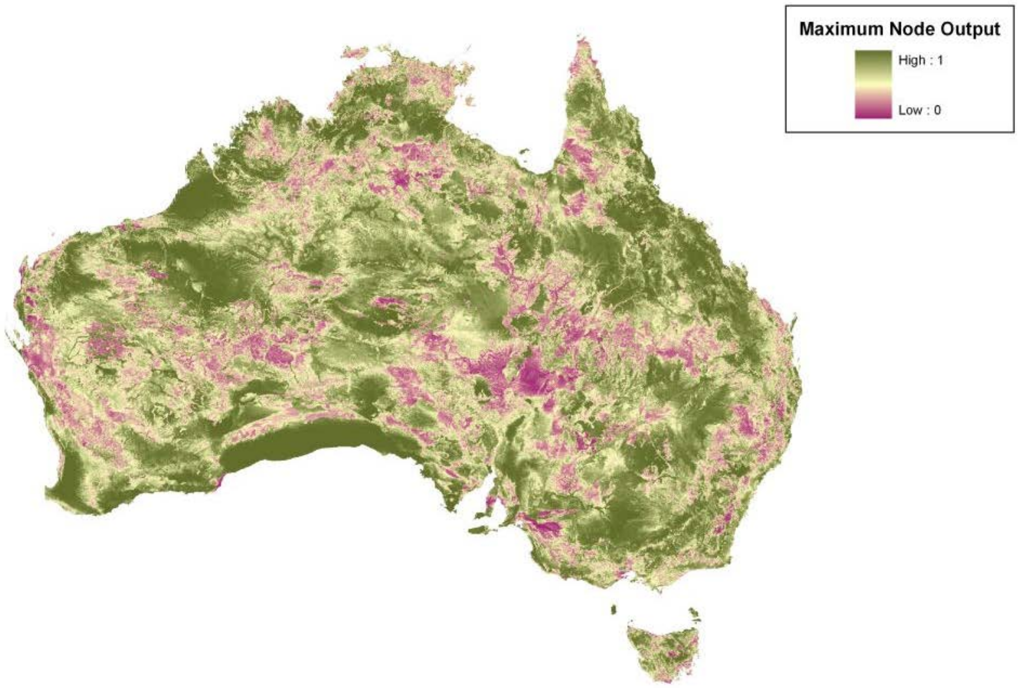

Figure 28 Map of the maximum output value of the MVG ANN classifier in the high scenario 2070 climate

4 Discussion

4.1 The classifiers

The ability of our approach to classify the environments of continent-wide ecoregions or vegetation is partly dependent on the accuracy and spatial resolution of the mapped data, both the ecological classes and the environmental data. But it is especially dependent on the characteristics of the biological classification, especially the degree to which it represents ecological classes that are the result of, and thus correlate with, abiotic conditions. The ecoregions and major vegetation groups differ in this regard, although both provide insights about the impacts of future climate change.

4.1.1 ECOREGIONS

The ecoregions we use were defined as very broad, global biomes. As such they represent vegetation and ecosystem structure and, to some degree, function that is controlled by climate, independent of taxonomic composition. For example, Amazonian rainforest has little taxonomic overlap with Australian or Southeast Asian rainforest, but they have a similar ecological structure and function due to similar climates.

Ranking of climatic variables for the individual ecoregions shows that the BioClim variables that relate to the seasonality of rainfall (e.g. Mean Moisture Index of Warmest Quarter and Mean Moisture Index of Coldest Quarter) are often important. This is not surprising, given the well-known ecological importance of dominant summer rainfall vs. winter rainfall in Australia.

Because this map classification is so broad and primarily dependent on climate, our classification of these environments is very accurate, despite possible spatial errors in mapping the classes and the climates. We have high confidence in the results from the ecoregion classification because it is quite general from an ecological perspective and distinguishes the climatic environments very well.

4.1.2 MAJOR VEGETATION GROUPS

The 23 MVGs are related to climate but are also expected to be correlated with topographic and edaphic variables since the spatial scale (grain) of their distributions is small compared with the much broader ecoregions. Consequently, we included the few additional variables available to us that describe spatial patterns in soils and topography. The variable rankings for the individual classifications suggest that the topographic variables are rarely important in the classifications, the exception being mangroves. In contrast, soil variables are more often important, especially the saturated hydraulic conductivity of the A horizon. This variable is a good quantitative measure of the broad soil types: clay, loam and sand. Soil depth and water-holding capacity are often important as well. All three of these soil variables relate to water availability for plants, implying that the distributions of MVGs, as opposed to climatically controlled ecoregions, is largely controlled by water – though rainfall amount and seasonality – interacting with soil properties.

This classification is much less able to separate the MVG environments than was possible for the ecoregions. There are numerous reasons for this. A fundamental problem is that some of the MVGs are not well-defined for our purposes and occur in more than one climatic zone and ecoregion; Eucalypt woodlands (MVG 5) is a prime example. Since Eucalypt woodlands were mapped by NVIS in such a broad range of environments, their environments overlap with other MVGs and this increases the uncertainty or ‘confusion’ of the classification. This illustrates that the effectiveness of our approach depends on the quality of the mapped vegetation classification as much as on the quality of the mapped environments.

Another cause of reduced classification accuracy for the MVGs is their complex and detailed spatial pattern that results in large areas where MVGs are adjacent. Consequently. the training and test sets include many ecotonal areas where it is difficult or impossible to distinguish environments that are solely representative of one class over another. More accurate and detailed environmental mapping with more topographic and edaphic variables could partially increase classification accuracy. But there will always be unpredictable, contingent factors that limit our capacity to completely classify distinct environments for any classification of vegetation.

Given the inherent difficulties in separating environments that are appropriate to many vegetation classes at a fine scale over an entire continent, we conclude that our classification of MVGs provides a useful *generalisation* of the environments that are characteristic of these mapped vegetation classes.

4.2 Dissimilarity

Dissimilarity is an important result from our method since it indicates the degree of biotically scaled environmental change, interpreted as stress on existing vegetation (ecosystems) in the climate change scenarios. When the classification can separate environmental classes very well, as is the case with the ecoregions, dissimilarity under climate change scenarios is a straightforward measure of stress that implies impact on the existing ecosystems. When there is more uncertainty in the classification, as is the case for the MVGs, it is useful to consider the change in dissimilarity relative to that in the baseline climate.

A disadvantage of our vector-angle dissimilarity metric is that it does not account for the length of the classification vector, which is a better measure of the certainty of the classification. For example, a vector with a value of 0.2 for the mapped class and 0.0 for all other classes has a dissimilarity of 0.0 but the suitability for the mapped class is low. In other words, this location has an environment that is within the range of environments that is classified as this class but it is on the outer bounds of the frequency distribution. It is also affected by confusion in the original classification.

The measure of biotically scaled environmental stress using the Bray–Curtis metric has the advantage of including the vector length as well as the angle. It is also completely independent of any confusion in the original classification, hence it is a direct measure of predicted environmental change.

4.3 Novel environments

This application of the ANN classification outputs is intended to provide a complementary metric to dissimilarity that does consider an aspect of vector length. It appears to be useful when the classification is able to distinguish classes very well, as is the case for the ecoregions. It is probably of less value when the classes are less separable, as is the case for the MVGs at indicating novel environments.

Hilbert and Ostendorf (2001) developed a 'confidence' index (C_f) using all outputs from the model at each location that can be linearly related to the probability of observing a mapped class given any particular environment. This index combines the absolute environmental suitability from the output node corresponding to vegetation class (O_f) with the *relative* suitability given by O_f divided by the sum of all outputs of the vector. Thus, the index is the product of the absolute and relative suitability:

$$C_f = \frac{O_f^2}{\sum_{i=1}^{n} O_i} \quad . \qquad (2)$$

where i is the class index, f is the index of the mapped vegetation class and n is the number of classes. This metric has the range [0,1]. It may be preferable to using the largest output value, as we have done here, to indicate novel environments. Future research should consider a metric that is the product of confidence (C) and dissimilarity (D) that may be a superior measure of climate change–induced stress that includes both vector angle and vector length.

4.4 Ranked variable importance

Ranking the importance of the environmental variables for the classification of each environmental class can provide additional ecological understanding that the multivariate classifications do not provide in our case. ANN classifiers are not analytical. They are known to be superior at identifying patterns in many circumstances than analytical, statistical methods but they generally do not explain the patterns, although some ANN software have implemented algorithms that attempt to do so, such as the Tiberius code we used here. Provisionally, the rankings appear to be consistent with broad ecological expectations but further analysis is necessary before we can draw firm conclusions. It would be particularly useful to compare these rankings with analogous results from a statistical approach such as generalised additive models (Hastie and Tibshirani 1990). Hilbert and Ostendorf (2001) showed that ANNs are superior classifiers to both maximum likelihood and generalised additive models in a similar application, but they did not compare their abilities to rank variable importance.

4.5 Changing environmental variables that are not included in our modelling

The models we use to infer biotically scaled environmental change are empirical and rely on correlations between the spatial distributions of biota and environments in the present landscape. Consequently our models' scenario-based projections of altered, biotically scaled environments are partial – they represent only the impact of temporal and spatial changes in climate, and they do that within the limitations of the biotic, climatic and other environmental variables used to fit the models. In this sense, the modelled environmental stress is one component of the total environmental change that species may experience. Additional environmental change may result from changes in atmospheric CO_2 concentration, climate variables not included in model fitting or available in climate projections, altered disturbance regimes (e.g. fire, flood), soil and landscape hydrological processes (which are non-linear responses to changes in patterns of rainfall, evaporation and vegetation), and biotic environment (an ecosystem feedback resulting from the impact on nutrients, moisture, shading, CO_2, food, habitat, etc. of other species that may be positive or negative). This is the case for all empirical models of potential future climate change impacts, and one of the reasons we avoid making direct inferences about specific, future biodiversity change directly from the model projections.

These additional changes in the environment will vary spatially, and species and ecosystems will respond differentially in unknown ways. In some situations some of these factors may mitigate ecological responses to the factors that are included in the modelling; however, it is more likely that these factors will add to environmental 'stress' and lead to greater ecological change. These factors would also add to the detail of the spatial patterning of ecological change. One of the main conclusions in this study is drawn from the existence of spatial patterning at multiple scales but not the specific locations of areas of high or low levels of environmental change.

One could make estimates about possible ecological responses to some of these other factors and modify the interpretation of our modelling in a post-hoc fashion. But for the most part we have avoided doing so in this report for three reasons. First, it is essential that we present the direct results of our analysis clearly. Secondly, the spatial and temporal pattern and/or impacts of these additional variables on broadscale biodiversity, as we use here, are largely unknown. Finally, our analyses include the primary, direct variables that are well known to influence biodiversity patterns at large scales.

As an example of a variable with poorly known effects, the possible ecological impacts due to increasing atmospheric CO_2 concentration cannot be assessed directly by our modelling methods. But a post-hoc inclusion of CO_2 effects in our analyses is not possible at this time because there is not enough known and no models exist that project broadscale, spatial biodiversity responses to CO_2 at the resolution or extent of our models. Research on how elevated atmospheric CO_2 will affect biodiversity, from the leaf to ecosystem scale, has been ongoing for at least forty years, using a variety of methods, but there has been little work done in Australia compared to the temperate regions of the northern hemisphere. While there are broad generalities at the leaf level – such as increased water use efficiency of photosynthesis – how or whether this translates into plant growth, much less community dynamics or ecosystem structure, is far from known, certainly not for the great diversity of Australian ecological communities, ecosystems or environments.

While change in atmospheric CO_2 is non-spatial, unlike the rest of our variables, it could have varying spatial effects due to differential impacts depending on local species composition, water and nutrient availability, or ecosystem processes that are largely unknown or stochastic. Furthermore, ecological responses – especially at the community and ecosystem level – to elevated CO_2 coupled with the large changes in mean annual temperature and precipitation in the climate scenarios we used have not been studied.

Our analyses represent a major advance by providing continental analyses based on the best available data with this scope, including the major controls on biodiversity patterns such as climate, soil and terrain variables. Future analyses of the sort we provide here, that also include variables such as CO_2 concentration, will only be possible once models of community- or ecosystem-level responses at fine spatial and continental breadth have been developed. From a conservation or policy perspective, it is likely that changes in the environmental variables not included in our analyses will augment or exacerbate the degree of biotically scaled change we predict here.

4.6 General issues and conclusions

All modelling methods have particular strengths and weaknesses and the choice of a particular method is contingent on a number of factors, including the specific objectives of the study, the level of understanding of the particular system, availability of data, and issues related to the spatial and temporal scale. While empirical or correlative vegetation models have been summarily dismissed by a few authors (for example, Woodward and Beerling 1997), they clearly have been and will continue to be very useful in a number of contexts, including global climate change.

Careful application of empirical methods, including ANNs and other techniques, provides the possibility to make very useful contributions to the understanding and conservation of ecosystems at broad scales in relation to climate change. Even where systems are well understood mechanistically and detailed biogeographic data are available, empirical vegetation modelling is a powerful tool for many applications.

The nature of the vegetation classification is very important in our method. Classification based on non-floristic attributes, such as the vegetation's structural and physiognomic characteristics, has the advantage that the categories reflect environmental constraints and are consequently likely to remain as meaningful map units when the model is applied to past or future climates. In other words, the method can transform climatic change into ecologically meaningful (biotically scaled) change to the degree that the mapped vegetation classes reflect climatic and other environmental constraints. The success of this approach in the Wet Tropics of north-east Queensland is due, in part, to the highly developed typology used in the mapping and its foundation on forest structure and environmental types. The differences between our classifications of the ecoregions and MVGs illustrate the importance of the vegetation classification.

The ecoregions are a very broad classification of global biomes where the general structural and functional characteristics of the classes are controlled by climate and are independent of species composition. For example, savannas in South America, Africa and Australia share few species but have similar structures and dynamics due to their shared climates. Consequently, our classification of these environments is quite good and our confidence in projecting change due to climate change is high.

Our classification of the environments of MVGs is less certain. The classifier is less able to distinguish all classes (lower Kappa and accuracy), mean dissimilarities for some classes are high, and the largest output value for many locations is relatively low in the baseline climate. But the classes vary considerably in our ability to separate their environments. One example of a poor classification is Eucalypt woodlands (MVG 5), with an accuracy of 50.6 and Kappa of 0.44. On the other hand, some MVG environments are distinguished well. For example, Tropical eucalypt woodlands/grasslands environments were distinguished with an accuracy of 93.1 and Kappa of 0.93. Despite the low ability of the classification to distinguish some classes, due to limitations in the classification of the vegetation, the results are useful in assessing spatial patterns of climate change impacts. However, inherent uncertainty in the baseline climate must be considered when interpreting the results under climate change.

Overall, it appears that this is a useful approach that can be applied at a continental scale to assess climate change impacts in a general way (shifts in biotically meaningful environments resulting in stress to existing ecosystems). A complete analysis of the large amount of data generated by this modelling is beyond the scope of the current project, and more research should be aimed at maximising use of the richness of the information from this approach.

While the model is not dynamic and cannot represent the spatio-temporal dynamics of vegetation in response to climate change, we have shown that the results can be analysed effectively to identify the vegetation classes and landscape locations that are likely to be most affected in the medium-term (decades) without any major changes in the extent or distribution of vegetation classes. This is the information that is needed most critically now to guide conservationists and land managers who need to monitor change and develop strategies to cope with the ecological change brought about by rapid modification of climate.

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Appendix A Samples sizes for training and testing the artificial neural networks

This appendix provides tables that list the sample sizes of the total continental data that were used to train the artificial neural networks (ANNs) described in the main body of this report. In all cases the numbers in the tables refer to the number of training patterns, each of which represents data for a 4 km^2 location.

Table A.1 Sample sizes of the training and test data for simultaneously classifying ecoregions

BIOME	NUMBER OF TRAINING PATTERNS IN THE FULL DATASET	NUMBER OF TRAINING PATTERNS IN TRAINING DATASET	NUMBER OF TRAINING PATTERNS IN THE TEST DATASET
Tropical and subtropical moist broadleaf forests	6 918	1 476	369
Temperate broadleaf and mixed forest	137 186	2 691	673
Tropical and subtropical grasslands, savannas and shrublands	452 678	2 690	673
Temperate grasslands, savannas and shrublands	134 947	2 628	657
Montane grasslands and shrublands	2 950	2 360	590
Mediterranean forests, woodlands and scrub	190 268	2 638	659
Deserts and xeric shrublands	789 622	2 662	665
Total	1 714 569	17 145	4 286

Table A.2 Training data for simultaneously classifying all 23 major vegetation groups

MAJOR VEGETATION GROUP	NUMBER OF TRAINING PATTERNS IN FULL DATASET	NUMBER OF PATTERNS IN TRAINING DATASET	NUMBER OF PATTERNS IN TEST DATASET
Rainforest and vine thickets	11 228	2 998	750
Eucalypt tall open forest	9 967	2 854	714
Eucalypt open forest	97 439	4 780	1 195
Eucalypt low open forest	1 224	1 002	251
Eucalypt woodlands	316 569	4 789	1 197
Acacia forests and woodlands	113 142	4 743	1 186
Callitris forests and woodlands	9 069	2 733	683
Casuarina forests and woodlands	37 880	4 702	1 176
Melaleuca forests and woodlands	19 988	3 974	994
Other forests and woodlands	16 924	3 685	921
Eucalypt open woodlands	107 745	4 630	1 158
Tropical eucalypt woodlands / grasslands	24 103	4 482	1 121
Acacia open woodlands	74 252	4 671	1 168
Mallee woodlands and shrublands	94 099	4 722	1 181
Low closed forest and tall closed shrubland	5 588	2 166	542
Acacia shrublands	196 376	4 629	1 157
Other shrublands	34 398	4 821	1 205
Heath	1 593	1 154	289
Tussock grasslands	125 779	4 740	1 185
Hummock grasslands	299 900	4 679	1 170
Other grasslands, herblands, sedgelands and rushlands	12 326	3 174	793
Chenopod shrublands, samphire shrubs and forblands	103 568	4 672	1 168
Mangroves	1 412	1 160	290
Total	1 714 569	85 963	21 491

Table A.3 Sample sizes of the training data for ranking environmental influences by ecoregion

NEURAL NETWORK SAMPLE	ECOREGION						
	TROPICAL AND SUBTROPICAL MOIST BROADLEAF FORESTS	TEMPERATE BROADLEAF AND MIXED FOREST	TROPICAL AND SUBTROPICAL GRASSLANDS, SAVANNAS AND SHRUBLANDS	TEMPERATE GRASSLANDS, SAVANNAS AND SHRUBLANDS	MONTANE GRASSLANDS AND SHRUBLANDS	MEDITERRANEAN FORESTS, WOODLANDS AND SCRUB	DESERTS AND XERIC SHRUBLANDS
Ecoregion training set							
Tropical and subtropical moist broadleaf forests	5 905	2 974	2 986	2 949	2 349	2 903	2 980
Temperate broadleaf and mixed forest	951	17 913	3 019	2 996	2 327	3 059	3 036
Tropical and subtropical grasslands, savannas and shrublands	1 035	2 996	17 703	2 949	2 346	3 003	3 056
Temperate grasslands, savannas and shrublands	959	2 983	2 935	17 731	2 237	2 982	2 888
Montane grasslands and shrublands	1 021	2 946	2 946	2 946	2 946	2 946	2 946
Mediterranean forests, woodlands and scrub	1 008	2 989	2 933	2 891	2 231	17 676	2 973
Deserts and xeric shrublands	959	2 923	2 972	2 902	2 298	2 993	17 777
Total	11 838	35 724	35 494	35 364	16 734	35 562	35 656

Table A.4 Training data for ranking environmental influences by MVG

	NEURAL NETWORK MVG																						
TRAINING SAMPLE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Rainforest and vine thickets	11 390	442	1 200	54	1 293	1 284	365	1 255	886	797	1 285	1 085	1 295	1 247	258	1 241	1 261	67	1 174	1 253	556	1 242	93
Eucalypt tall open forest	535	10 042	1 253	45	1 307	1 217	443	1 234	887	820	1 300	1 075	1 245	1 288	276	1 283	1 295	74	1 268	1 289	566	1 226	69
Eucalypt open forest	548	467	27 598	55	1 234	1 243	366	1 263	898	762	1 262	1 057	1 267	1 185	273	1 220	1 200	71	1 232	1 258	565	1 247	81
Eucalypt low open forest	489	440	1 253	1 253	1 253	1 253	429	1 253	915	736	1 253	1 099	1 253	1 253	254	1 253	1 253	94	1 253	1 253	590	1 253	76
Eucalypt woodlands	539	470	1 284	60	27 560	1 254	451	1 236	899	703	1 202	1 120	1 252	1 209	249	1 188	1 268	58	1 227	1 260	576	1 263	67
Acacia forests and woodlands	502	457	1 299	53	1 268	27 323	366	1 165	922	784	1 287	1 138	1 245	1 283	252	1 241	1 241	71	1 209	1 210	599	1 237	76
Callitris forests and woodlands	524	496	1 220	68	1 270	1 236	9 078	1 329	872	766	1 240	1 078	1 239	1 271	262	1 222	1 229	71	1 253	1 276	533	1 294	100
Casuarina forests and woodlands	478	449	1 260	48	1 286	1 227	416	27 523	880	720	1 261	1 068	1 242	1 285	254	1 280	1 239	81	1 326	1 276	607	1 274	71
Melaleuca forests and woodlands	522	457	1 243	68	1 321	1 258	394	1 188	20 097	758	1 245	1 113	1 292	1 254	243	1 229	1 246	61	1 254	1 273	591	1 229	73
Other forests and woodlands	495	460	1 229	59	1 230	1 240	419	1 250	953	17 023	1 215	1 128	1 230	1 284	255	1 238	1 250	82	1 267	1 243	584	1 193	71
Eucalypt open woodlands	521	455	1 247	45	1 200	1 298	447	1 241	899	790	27 506	1 106	1 228	1 232	270	1 342	1 199	57	1 217	1 221	550	1 234	74
Tropical eucalypt woodlands / grasslands	498	455	1 297	58	1 197	1 244	416	1 249	837	763	1 261	24 165	1 272	1 223	261	1 189	1 242	82	1 259	1 277	569	1 258	63
Acacia open woodlands	492	432	1 245	66	1 198	1 204	431	1 243	922	741	1 226	1 102	27 481	1 300	256	1 261	1 181	80	1 209	1 242	593	1 279	71
Mallee woodlands and shrublands	526	467	1 254	63	1 246	1 220	417	1 206	931	758	1 218	1 071	1 270	27 642	240	1 134	1 235	70	1 239	1 268	577	1 243	73
Low closed forest and tall closed shrubland	487	446	1 205	60	1 273	1 237	418	1 203	918	754	1 261	1 129	1 257	1 234	5 673	1 283	1 263	73	1 258	1 264	551	1 262	62
Acacia shrublands	530	466	1 187	45	1 237	1 235	411	1 262	988	716	1 204	1 128	1 250	1 252	278	27 425	1 253	65	1 230	1 228	580	1 270	79
Other shrublands	487	450	1 190	49	1 275	1 152	409	1 294	880	790	1 275	1 072	1 265	1 332	281	1 258	27 582	86	1 305	1 296	624	1 248	82
Heath	493	426	1 256	62	1 234	1 277	409	1 249	916	816	1 245	1 095	1 252	1 249	269	1 222	1 260	1 669	1 238	1 283	521	1 251	77
Tussock grasslands	500	460	1 256	62	1 246	1 230	349	1 299	880	763	1 245	1 193	1 247	1 240	258	1 292	1 227	92	27 532	1 264	573	1 258	69
Hummock grasslands	500	472	1 279	57	1 188	1 228	455	1 269	930	778	1 325	1 031	1 209	1 281	273	1 291	1 279	71	1 181	27 349	566	1 283	68
Other grasslands, herblands, sedgelands and rushlands	512	445	1 274	54	1 255	1 255	423	1 258	927	770	1 251	1 045	1 276	1 238	263	1 270	1 229	72	1 257	1 219	12 491	1 297	71
Chenopod shrublands, samphire shrubs and forblands	502	489	1 228	56	1 255	1 272	422	1 215	882	796	1 331	1 045	1 232	1 259	275	1 333	1 303	71	1 149	1 216	549	27 509	75
Mangroves	493	466	1 273	51	1 243	1 242	422	1 252	904	805	1 315	1 096	1 310	1 227	241	1 265	1 265	77	1 239	1 247	596	1 266	1 650
Total	22 563	20 109	55 030	2 491	55 069	54 629	18 156	54 936	40 023	33 909	55 213	48 239	55 109	55 268	11 414	54 960	55 000	3 295	54 776	54 965	25 107	55 116	3 291

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FOR FURTHER INFORMATION

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