



Mapping Habitat of Threatened Reptiles in Western Downs, Queensland: A Spatial Modelling Approach Using “Presence-Only” Occurrence Data

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Abstract

Biodiversity conservation planning requires spatial data. Information on the spatial distribution of wildlife species, as well as the location and extent of their habitat, is essential in developing conservation strategies. However, traditional ground-based survey and mapping methods cannot always deliver the necessary information in a timely and cost-effective fashion. For habitat mapping, the development of probabilistic modelling approaches offer some merits for the threatened reptiles in the Western Downs, Queensland, Australia. This study was conducted to identify the predictor variables significant in reptile habitat modelling, and to develop a spatially explicit predictive model for a group of reptiles. The predictor variables and ‘presence-only’ reptile occurrence data (representing seven threatened species of lizards and snakes) were examined using the weights-of-evidence (WofE) approach in a GIS platform. Of the 18 initial variables, seven of these were excluded from the modelling process due to their weak spatial association with reptile occurrences. These refer to topography-related variables (*slope*, *aspect*, *topographic wetness index*, and *elevation*) and ‘vegetation amount’ variables (foliage projective cover and NDVI). Conversely, *land use*, *regional ecosystems type*, *evapotranspiration*, *land cover* and *major vegetation group* variables exhibited strong spatial association with the observed reptile data. The results also show that the 4-map combination of ‘*regional ecosystems type*’ (RE), ‘*distance from water*’, ‘*soils*’, and ‘*distance from stream*’ produced the highest prediction accuracy (up to 87%). This study identified the regional ecosystems layer as the most significant variable, and it highlighted the importance of selected vegetation communities in the region. Since only 9% of the total area has high to moderate habitat preference for the reptiles, further vegetation clearing should be avoided to prevent new habitat loss. The weights-of-evidence approach was found highly suitable for predictive habitat mapping of threatened reptiles with ‘presence-only’ occurrence data.

Introduction

Wildlife conservation planning and management is often hampered by lack of scientific information. This need for information may include species behaviour (e.g. Magrath et al. 2009; Taylor and Knight 2003), b) species abundance and distribution (e.g. Bingham 1998), and the c) relationships between wildlife populations and environmental variables (e.g. Fieberg and Jenkins 2005). While empirical studies and intensive ground surveys can be conducted to address the data requirements, key issues related to human labour and time constraints necessitate the development of probabilistic modelling approaches. Predictive spatial modelling techniques that utilise existing expert knowledge about the species and environmental parameters, along with limited occurrence data, can help identify potential suitable habitat where the species may occur (e.g. Smith et al. 2007).

Literature exists about the habitat preference of selected reptiles in the Brigalow Belt (e.g. Wilson 2008; Wilson 2005; Drury 2001). For many species of lizards and snakes, their known habitat includes areas with fallen leaf-litter, branches, hollow logs, rocky outcrops, native trees, old mature trees, soil cracks, and patches of scrub (Wilson 2008). While this habitat information could serve wildlife conservation and recovery planning efforts, there is a need to identify these areas in specific geographical locations. Habitat mapping is an integral component of sound wildlife management.

Because “habitat” is a species-specific concept (Fischer and Lindenmayer 2007), in theory it demands that mapping needs to be conducted at individual species level. Thus, many studies in predictive habitat mapping are focused on a particular species, e.g. the Julia Creek dunnart (*Sminthopsis douglasi*) (Smith et al. 2007), three-toed woodpecker (*Picoides tridactylus*) (Stachura-Skierczynska et al. 2009), and tigers (*Panthera tigris tigris*) (Imam et al. 2009). While this single-species approach to habitat mapping has certain advantages for conservation planning, a focus on multi-species (but in the same taxonomic rank, e.g. order) approach could be more justifiable in some conditions.

The Southern Brigalow Belt, which stretches from Rockhampton in Queensland to the border of New South Wales, is home to many species of reptiles. In this region, over 130 species of reptiles were identified, comprising geckos, skinks, goannas, dragons, blind snakes, pythons, colubrid snakes, elapid snakes and freshwater turtles (Wilson 2008). Of these, 12 species are threatened with extinction (i.e. either “endangered”, “vulnerable” or “near threatened”) under the *Queensland Nature Conservation Act 1992*. The activities that may be detrimental to reptiles in the region include the following: clearing native vegetation, annual burning, continuous grazing, “tidying up” by removing timber and dead trees or rocky outcrops, and fatality and injury from vehicle strikes (Wilson 2008).

Preserving old growth and remnant vegetation areas are vital to the survival of reptiles. In addition, extensive landscape restoration is needed to help arrest the decline of reptile populations. Consequently, these habitat areas need to be identified and mapped for any species recovery program to progress. While other map based information exists, e.g. the regional ecosystem (RE) maps and the Statewide Landcover and Trees Study (SLATS) dataset from the Queensland Department of Environment and Resource Management, there is no existing framework on how these datasets can be best integrated and interpreted for

analysis. Thus, the development of reptile habitat mapping and analysis techniques is called for.

A habitat model is a representation of a species' habitat preferences. It is useful in several ways, such as: a) to make inferences about a species habitat requirements and likely response to environmental change, and b) to predict a species abundance, density, carrying capacity or probability of occupying a location based on its environmental attributes (Wintle et al. 2005). In conservation planning, the main use of habitat modelling is in predicting the spatial distribution of suitable habitat for a particular species. Habitat modelling requires the application of sound knowledge about the species, its habitat, the ecology of the area, and human activities and impacts. Similarly, it needs a good knowledge of the analysis toolbox that will be applied, particularly those related to statistical and mathematical techniques and spatial data processing.

Several modelling techniques or approaches can be applied in predictive habitat mapping (reviewed by Austin 2007). The choice of method is largely determined by the type of available survey data to be used in model development: little or no data, presence-only data, presence-absence data, ordinal categorical data and counts (Winkle et al. 2005). Some of these techniques include ecological-niche factor analysis (Hirzel et al. 2002), Bayesian belief network (e.g. Smith et al. 1997), logistic regression (Gibson et al. 2004), generalised additive models (GAM) (Zaniewski et al. 2002), habitat suitability indices (HSIs) (Reading et al. 1996). Each method has particular strengths and weaknesses that need to be considered prior to model development.

Although some studies pertaining to predictive habitat mapping have been conducted in Australia (e.g. Smith et al. 2007; Wintle et al. 2005; Yamada et al. 2003), no study has been reported on predictive habitat mapping of threatened reptiles in the Brigalow Belt. While coupling GIS and a predictive model for habitat mapping is not new, however, their applications for a group of threatened reptiles have never been conducted. Hence, the objectives of this study were to: a) identify the bio-physical and environmental variables significant in predictive habitat modelling of selected reptiles, and b) develop a GIS-based spatially explicit predictive model for a group of threatened reptile species.

Methods

The study area was located in the Glenmorgan district (approximately 27° 14' 55" S, 149° 40' 37" E), on the Western Downs region of Queensland, Australia (Figure 1). Comprising a total area of about 377,283 hectares, the land use is dominated by grazing and cropping. Based on the Statewide Landcover and Trees Study (SLATS) dataset (Department of Natural Resources and Water 2003), approximately 17% (64,464 ha) of the study area is classified as "woody vegetation". At Glenmorgan, the 15-year mean maximum temperature is highest at 30.3°C for the month of December, while the mean minimum temperature is lowest at 5.4°C for July (Bureau of Meteorology 2008). The mean monthly rainfall ranges from 28.6mm (August) to 141mm (January). Glenmorgan is also home to Myall Park Botanic Gardens, hosting Queensland's oldest collection of Australian semi-arid zone flora.

The study area's vegetation communities are predominantly brigalow (*Acacia harpophylla*), belah (*Casuarina cristata*) and poplar box (*Eucalyptus populnea*). The following regional ecosystems (RE) type prevail in the study area: a) RE 11.4.3 (*Acacia harpophylla* and/or *Casuarina cristata* shrubby open forest on Cainozoic clay plains); b) RE 11.7.2. (*Acacia* spp. woodland on lateritic duricrust; and c) RE 11.7.4 (*Eucalyptus decorticans* and/or *Eucalyptus* spp., *Corymbia* spp., *Acacia* spp., *Lysicarpus angustifolius* on Cainozoic lateritic duricrust). Regional ecosystems were defined as vegetation communities in a bioregion that are consistently associated with a particular combination of geology, landform and soil (Sattler and Williams 1999).

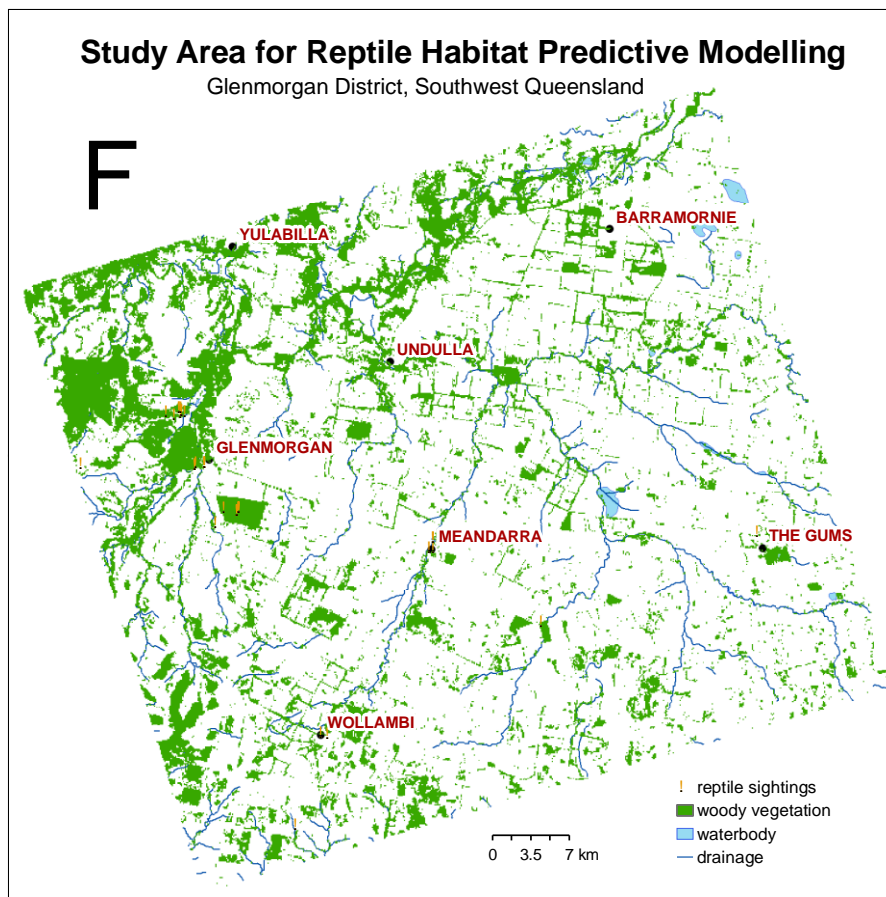


Figure 1. Location map of the study area

The training sites used for predictive modelling were established from the extract of publicly available “WildNet” reptile records for the Brigalow Belt Bioregion (Environmental Protection Agency 2007). Within the study area, only those reptiles that have “vulnerable”, “near threatened” and “endangered” conservation status (based from the *Queensland Nature Conservation Act 1992*) were selected. This process generated a total of 37 records, comprising the following species:

- brigalow scaly-foot (*Paradelma orientalis*)
- common death adder (*Acanthophis antarcticus*)

- Dunmall’s snake (*Furina dunmalli*)
- golden-tailed gecko (*Strophurus taenicauda*)
- grey snake (*Hemiaspis damelii*)
- woma (*Aspidites ramsayi*)
- yakka skink (*Egernia rugosa*)

Out of this, 30 samples were randomly selected and used in model calibration while 7 samples were used as an independent test set for model validation. While a bigger sample size was desired for this study, this was not realised due to limited number of sightings data of these threatened species. Nevertheless, the processing of data and the interpretation of results in this study considered this reality. For instance, in weights-of-evidence modelling, the Studentised value of “contrast” (Cs) was used instead of the simple “contrast” (C) (Bonham-Carter 1994). In a study in the U.S., a weights-of-evidence technique was used to make predictions about bear habitat use, where the study utilised 35 samples to generate logical interpretations (Kindall and Van Manen 2007).

The published literature about reptiles in Queensland (e.g. Wilson 2008; Wilson 2005; Drury 2001) provided the initial knowledge base in selecting the bio-physical and human-related habitat variables for the study. Then, digital maps relevant to the pre-identified variables were acquired from various data custodians, of which a total of 18 map layers were generated (Table 1). Since many datasets were received from disparate sources, in various formats and extent, it became essential to perform various pre-processing techniques. The tasks included projection and coordinate transformation, clipping, vector-to-raster conversion, masking, feature selection, buffering, grid resampling, reclassification, etc. The datasets were processed using ArcGIS 9.1 with Spatial Analyst extension.

Table 1. Spatial data layers tested for the predictive habitat distribution modelling

GIS Map Variable	Primary Data Source
1. Distance from stream (m)	Drainage features (1:100,000 digital topographic map)
2. Distance from water body (dams and lakes) (m)	Water body (1:50,000 digital topographic map)
3. Distance from road (m)	Road map (1:50,000 digital topographic map)
4. Elevation (m)	25m Digital Elevation Model (DEM)
5. Slope (%)	25m Digital Elevation Model (DEM)
6. Aspect (0-360)	25m Digital Elevation Model (DEM)
7. Topographic Wetness Index (index value)	25m Digital Elevation Model (DEM)
8. Geologic type (different classes)	Queensland Geological Digital Data

9. Soils (different classes)	Western Downs Land Management Field Manual
10. Rainfall (mm)	BoM Mean monthly and mean annual rainfall data
11. Incoming solar radiation	CSIRO Mean annual and monthly incoming solar radiation
12. Evapotranspiration	CSIRO Mean annual and monthly potential evaporation
13. Land cover (different classes)	SLATS
14. Land use (Level 1) (different classes)	QLUMP Queensland Landuse
15. Foliage Projective Cover (FPC) (%)	SLATS FPC
16. Major vegetation group (different classes)	NVIS Australia - Present Major Vegetation Groups
17. Normalised Difference Vegetation Index (NDVI)	ALOS-AVNIR2 satellite image
18. Regional ecosystems type (different classes)	EPA Regional Ecosystems Remnant Vegetation of Queensland

The weights-of-evidence (WofE) method for habitat analysis and modelling was implemented for this study. WofE is a discrete multivariate method based on a log-linear form of Bayes' rule (Bonham-Carter 1994; Bonham-Carter et al. 1988, 1989). In a GIS context, it provides measures of spatial association between 'evidence maps' (explanatory variables) and known point data (e.g. wildlife sightings) as 'training sites'. A response theme or map can be derived by the combination of diverse spatial evidential themes.

Aside from its ability to produce accurate results, the WofE approach was chosen for this study due to its capability to handle different data type (e.g. qualitative and quantitative data). Moreover, an interface between the WofE approach and the GIS platform has been developed and distributed free to the public. In this study, the WofE approach was implemented using the Spatial Data Modeller extension for ArcGIS 9.1. (Sawatzky et al., 2004). The key steps involved the following procedures (adapted from Romero-Calcerrada and Luque 2006):

- calculating weights for each evidence map
- generalising the evidential theme
- applying of conditional independence test
- creating a posterior probability theme (generating the habitat map); and
- model evaluation.

The training sample set (i.e. reptile location) was used to calculate the weights for each evidential theme, one weight per class, using the relationships between the points and the different classes on the thematic maps. The weights-of-evidence approach provided several

statistical measures of spatial association between the reptile sighting locations and habitat variables: the weights (W^+ and W^-), contrast (C) and studentised value of C (C_s). If more reptile occurrences occur within a pattern than would be expected by chance, W^+ is positive and W^- is negative. On the contrary, W^+ is negative and W^- is positive when few occurrences occur within a pattern than would be expected by chance. The contrast (C) is the difference between W^+ and W^- . A larger C value indicates stronger spatial association between the evidence map and the training data.

In some cases, however, the Studentised value of C (C_s), the ratio of C to the standard deviation of C, is a useful measure (Bonham-Carter 1994). The C_s is more useful than C for choosing the cut-off when categorising independent variables into evidence maps. Values of C_s greater than 1.96 indicates that the hypothesis that $C = 0$ can be rejected at $\alpha = 0.05$ (Bonham-Carter et al., 1989). Furthermore, selected evidential themes were excluded from the modelling process at the early stage. Themes with low C_s values (i.e. less than 1.96) for any classes were eliminated for further spatial analysis: they have low spatial association with the occurrence data.

Grouping the classes or categories for each evidential theme enhances the statistical robustness of the weights. For this study, a grouping process was adopted from the method applied by Romero-Calcerrada and Luque (2006) and Romero-Calcerrada et al. (2010). For a positive spatial association, C_s will have a positive value, which in turn means high predictive power. C_s values are down to 1.96 for a low spatial association and lower predictive power. The following threshold values of C_s were used to generate different multi-class evidential theme: a) Group W_0 for $C_s < 1.96$; b) Group W_1 for $1.96 \leq C_s < 3$; c) Group W_2 for $3 \leq C_s < 4$; d) Group W_3 for $4 \leq C_s < 5$; and e) Group W_4 for $C_s \geq 5$ (Romero-Calcerrada and Luque, 2006). This rule is repeated for each thematic map.

This study implemented two tests of conditional independence between variables: the Conditional Independence Test and the Agterberg & Cheng Conditional Independence Test (Agterberg and Cheng 2002). For the Conditional Independence Ratio (the ratio of the observed number of training points and the expected number of training points), values below 1.00 may indicate conditional dependence among two or more of the data sets. Bonham-Carter (1994) suggests that values < 0.85 may indicate a problem. For the Agterberg & Cheng Conditional Independence Test, probability values greater than 95% or 99% indicate that the hypothesis of conditional independence should be rejected, but any value greater than 50% indicates that some conditional dependence occurs.

The output predictive map was generated by combining the weighted evidence maps as calculated by the model. It contains posterior probability values for each grid cell of the reptiles' potential distribution. The final predictive habitat map was calculated as the ratio of the posterior probability to prior probability. To make the interpretation more insightful, the output map was categorised into four classes: 'high predictive', 'moderate predictive', 'low predictive' and 'high uncertainty' (Carranza and Hale 2000). These classes were defined by the value of the ratio of the posterior probability to prior probability (e.g. > 5 for 'high predictive' category), and the value of the studentised posterior probability (e.g. > 1.5 for 'high predictive' category). For the 'high uncertainty' category, no prediction was possible

because the studentised posterior probability is less than 1.5, indicating too much uncertainty (Bonham-Carter et al. 1989).

The validation of the model was implemented using a set of independent training samples randomly selected from the original dataset. These points were spatially intersected with the output predictive map to assess the accuracy of prediction. Considering that positional accuracy is an inherent issue in any GIS based modelling, different buffer classes (0m, 100m, and 300m) were also generated to test the accuracy of the predictive habitat map. The buffering process involved growing a certain distance from each point of reptile occurrence. The "0m" buffer corresponded to the class where no buffering was implemented.

Results and Discussion

Of the 18 original variables included in the study, seven variables were excluded from the modelling process due to their low (> 1.96) Studentised value of C (C_s) values. These theme recorded weak spatial association with the reptile occurrences. Most of these variables refer to topography-related variables (slope, aspect, topographic wetness index, and elevation) and 'vegetation amount' variables (foliage projective cover and NDVI). In the literature concerning reptile habitat (Wilson 2008; 2005; Drury 2001), topographic features were not particularly mentioned as significant habitat variables. This present study supports this knowledge reported in the literature. While elevation is relatively close to the C_s threshold value of 1.96, it appeared that the variables slope, topographic wetness index and aspect have no spatial association with reptile occurrences.

The same literature highlighted the importance of habitat pertaining to vegetation types (e.g. dry forests and woodlands) and vegetation understorey attributes (e.g. logs, debris, leaf-litter, etc.). In this study, variables related to vegetation 'amount' (i.e. foliage projective cover and biomass-related NDVI) exhibited no spatial association with reptile occurrences. This result is not totally surprising: the amount (foliage cover and biomass) of vegetation is distinct from vegetation types and understorey characteristics. On the other hand, the result for rainfall is more difficult to interpret. Although rainfall showed no spatial association with the occurrence of reptiles, other 'water-related' variables considered in this study (i.e. distance from stream and distance water body) exhibited high spatial association with reptile occurrence.

Table 2 shows the 11 map variables with high spatial association (C_s values > 1.96) with reptile occurrences. Among those variables that obtained the highest range of C_s values include a) land use, b) regional ecosystems type, c) evapotranspiration, d) land cover and e) major vegetation group. Interestingly, these variables, except evapotranspiration, are all related to vegetation attributes, i.e. spatial association was found for classes pertaining to conservation (land use), native vegetation (land cover), and eucalypts woodlands (major vegetation group). On the contrary, as previously explained, the 'amount' of vegetation (as measured by foliage projective cover and NDVI) was found to have no spatial association with reptile occurrences.

Table 2. Map variables with high spatial association (C_s values > 1.96) with reptile occurrences

GIS Map Variable	High C_s Value(s)	Attributes of the High C_s Value(s)
1. Land use (different classes)	7.35	conservation
2. Regional ecosystems type (different classes)	5.80 – 6.57	RE11.3.25/11.3.2/11.5.5, RE11.5.1, RE11.4.3
3. Evapotranspiration	3.16 – 6.08	1736 – 1750 mm
4. Land cover (different classes)	5.64	native vegetation
5. Major vegetation group (different classes)	4.74 – 5.10	eucalypts woodlands, acacia forests and woodlands
6. Distance from water body (dams and lakes) (m)	4.48 – 4.65	265 – 278 m
7. Soils (different classes)	4.41	red sodosols
8. Incoming solar radiation	2.16 – 4.44	190 – 191 megajoules per day
9. Distance from road (m)	3.98 – 4.07	60 – 64 m ; 490 – 530 m
10. Geologic type (different classes)	3.76	arenite-mudrock
11. Distance from stream (m)	2.30 - 2.48	50 – 58 m

The variables related to proximity to water source (i.e. distance to water bodies and stream) produced comparatively moderate level of spatial association with reptile locations, with maximum C_s value of 4.65 and 2.48, respectively. While the snakes and lizards considered in this study do not particularly live in freshwater biomes, their association to such landscape attributes may be due to their food source. The food of these reptiles includes frogs, insects, birds, mice, etc. which thrive on or near water bodies such as creek, water holes, and lakes. With regards to the road factor (i.e. distance from road), the results indicate that it has a moderate spatial association with reptile occurrences (maximum C_s value of 4.07). Even as this road-related variable can be seen as “biased” (i.e. sightings may have occurred more near the roads due to relative access), their inclusion in the model was pursued and interpreted accordingly.

By combining the weighted evidence maps using Spatial Data Modeller in ArcGIS, several predictive habitat maps were created. The results (Table 3) show the different models tested, conditional independence test values and the prediction accuracies. Not surprisingly, the least number of predictor variables, i.e. two thematic maps, produced the lowest accuracy (i.e. 42%, 52% and 57% for the 0m, 100m and 300m buffer, respectively). On the other hand, the 4-map combination of *regional ecosystems type*, *distance from water*, *soils*, and *distance from stream* (Figure 2) produced the highest accuracy of prediction, i.e. 63%,

74% and 87% for the 0m, 100m and 300m buffer, respectively. Similarly, the test set (n=7) produced high results: 71%, 71%, and 86% for the three classes. For these predictive accuracy results, all values cited above were from the “high-moderate” predictive categories.

This 4-map model produced an acceptable value (42.6%) from the Agterberg & Cheng Conditional Independence Test. A value greater than 50% indicates that some conditional dependence occurs, which is not desirable for the model. The best result for the conditional independence test was achieved by the 6-map model (value of 18.1%), although its predictive accuracy is less than the 4-map model. With 8% difference in prediction accuracy, it appears that the road factor (distance from road) in the 6-map model did not contribute in producing significantly higher accuracy than the 5-map model. In fact, the 6-map model produced lower accuracy than the 4-map model.

Table 3. Different models tested, conditional independence test value and the accuracy of prediction

Habitat Potential Category	Calibration Set (n=30)			Test Set (n=7)		
	Buffer 0m	Buffer 100m	Buffer 300m	Buffer 0m	Buffer 100m	Buffer 300m
	(%)	(%)	(%)	(%)	(%)	(%)
1. High Predictive (A)	53	67	80	71	71	86
2. Moderate Predictive (B)	10	7	7	0	0	0
3. A + B	63	74	87	71	71	86
4. Low Predictive (C)	34	23	13	29	29	14
5. High Uncertainty (D)	3	3	0	0	0	0
Total (A-D)	100	100	100	100	100	100

The map of regional ecosystems (RE) type is the most important predictive variable with a confidence value of 9.14. This was followed by soils (4.41), distance from water body (3.99), and distance from stream (1.98). With that result, the importance of the regional ecosystems layer in the prediction model needs to be highlighted. RE map provides valuable information on the attributes of vegetation in a bioregion that are consistently associated with a particular combination of geology, landform and soil (Sattler and Williams, 1999). It differentiated vegetation communities into classes that depict vegetation type, composition, structure, and other characteristics. In turn, these attributes ‘captured’ the habitat preference of reptiles (Wilson 2005, 2008) considered in this study.

With a contrast (C) value of -2.34, the RE class “non-remnant vegetation” and reptile occurrences showed a negative spatial association. It indicates that reptiles considered in this study did not occur consistently in non-remnant vegetation areas. On the other hand,

other RE types (a total of 54 classes) have no spatial association with the observed reptile occurrences.

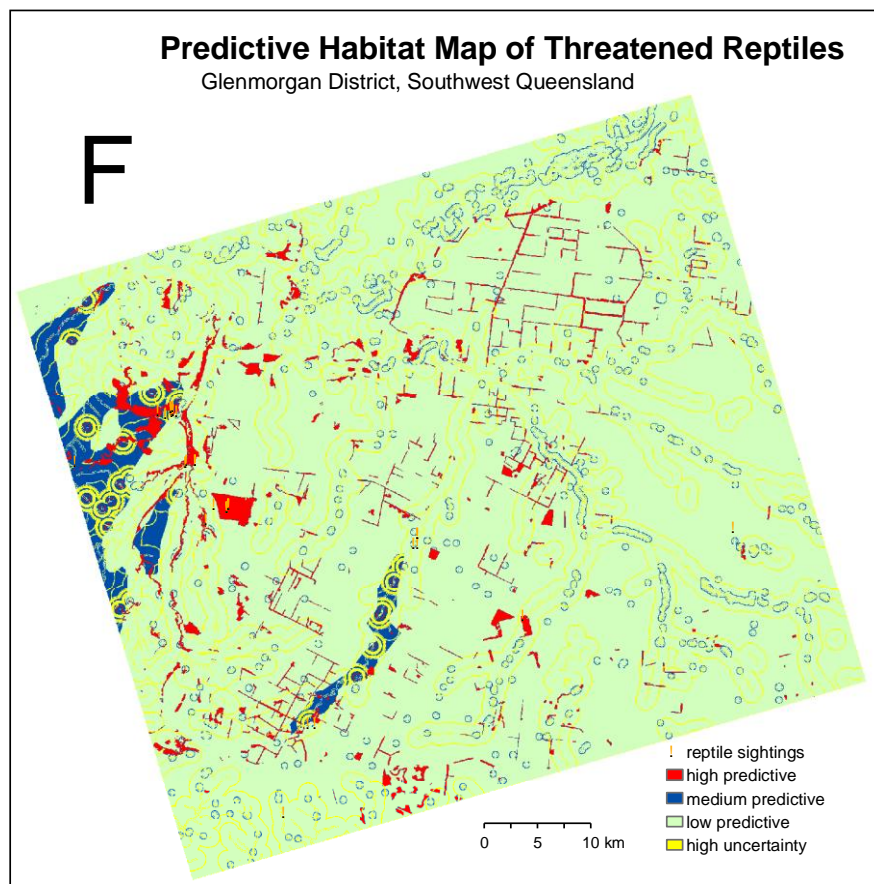


Figure 2. Predictive habitat map of threatened reptiles

The high Cs value (4.41) for the soil type is on red sodosols, signifying strong spatial association with reptile occurrences. Sodosols are soils with strong texture contrast between A horizons and sodic B horizons which are not strongly acid (Isbell 1996). Red Sodosols have reddish coloured upper subsoils that are often quite dense and coarsely structured (blocky, prismatic or columnar peds). These soil characteristics seem favourable with some of the snakes (e.g. Dunmall's snake and grey snake) under study, as they known to also dwell in soil cracks, soil cavities and other deep cavities (Wilson 2008). For the rest of soil types, the Cs values were all low, indicating their weak or lack of spatial association with reptile locations.

The predictive habitat map of threatened reptiles generated relevant some information. Of the total study area of approximately 377,283 hectares, only 4% (14,984 hectares) is considered as 'high predictive'. The 'moderate' and 'low' predictive areas correspond to 5% (20,617 hectares) and 82% (323,143), respectively. This indicates that only 9% of the total area has habitat attributes of high to moderate preferences for the reptiles. This is a very small area compared with the previous vegetation extent (Accad, et al. 2001) of the region prior to European settlement.

Since regional ecosystems (RE) map was identified as the most important habitat variable, and that reptiles are highly associated with selected vegetation (RE) classes, it is crucial that further vegetation clearing should be avoided to prevent new habitat loss. In addition, vegetation is inherently the most susceptible to alteration compared with other environmental predictors (i.e. soil, distance from water body and distance from stream) included in this study. The pressure to clear native vegetation will be high on these habitat areas due to potential development from the mining and energy industry. The Brigalow Belt is known to have substantial deposits of mineral and coal resources (Department of Natural Resources, Mines and Water 2006).

This study demonstrated the possibility of producing a habitat map for a group of threatened reptile species. This approach assumes that some species of reptiles in the region share certain common habitat requirements and preferences (see, for example, Wilson 2008; Drury 2001). For conservation planning and management, specifically in prioritising areas for protection and restoration, a habitat map for multiple species of reptiles can be more justified than the single-species approach. Whether a site is intended for rehabilitation or preservation, a shared habitat for several threatened species will present a stronger case. Furthermore, the map produced from this study can be refined further with new information on reptile occurrences. The weights-of-evidence approach was found to be versatile and robust for such potential enhancement.

Conclusion

Habitat model can be developed for a group of threatened reptiles in the Southern Brigalow Belt using the weights-of-evidence (WofE) approach in a GIS platform. Topography-related (slope, aspect, topographic wetness index, and elevation) and 'vegetation amount' variables (foliage projective cover and NDVI) exhibited weak spatial association with reptile occurrences and therefore excluded from the modelling. Conversely, land use, regional ecosystems type, evapotranspiration, land cover and major vegetation group variables exhibited strong spatial association with the observed reptile data. With several models tested, it was the 4-map combination of 'regional ecosystems type', 'distance from water', 'soils', and 'distance from stream' produced the highest accuracy of prediction.

The highest spatial association between regional ecosystems (RE) type and reptile occurrence was observed for selected eucalypt woodlands and shrubby open forest. 'Non-remnant vegetation' and reptile occurrences showed a negative spatial association, while other RE types have no spatial association with the reptile sightings data. With the importance of these selected vegetation communities as reptile habitat, and since only 9% of the total study area has habitat attributes of high to moderate preferences for the reptiles, further vegetation clearing should be avoided to prevent new habitat loss. Weights-of-evidence approach proved to be a suitable technique for habitat modelling of threatened reptiles.

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