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Ranking habitat patches by contribution to network connectivity: tradeoffs between processing time and spatial realisation

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Abstract: Habitat loss and fragmentation pose a major threat to flora and fauna worldwide. For those species that can move between habitat patches, it is important to consider the extent to which the patches are connected. This can be complex as many species may inhabit a given landscape, and the scale at which each one interacts with the landscape (and consequently its relative ability to move through it between patches) may differ. Nonetheless, designing effective conservation strategies requires prioritising patches for protection. One basis for doing so is the relative importance of patches to maintaining connectivity. This can be estimated by measuring the connectivity of the complete network, and then assessing the extent to which that connectivity changes when each patch in the network is removed in turn. Doing this manually is clearly not feasible for a landscape comprised of more than a few patches.

Obviously modeling landscapes in this way is inherently spatial. However, the volume of processing required to drop each patch from the network and measure how connectivity changes even when the process is automated creates a trade-off between the extent to which the spatial representation of the landscape is fully realized (spatial realisation) and processing time. For example, graph theory offers a very efficient method to assess connectivity by representing the landscape as a series of nodes (patches) and edges (links between patches) in Cartesian space. This can be extended ('spatial graphs') by geo-referencing the nodes. However, unless there is no resistance to how a given species moves between patches, it is necessary to weight the edges between nodes based on some model of dispersal. This can be made more spatially explicit by weighting edges based on least cost paths (distance between patches taking into account the difficulty of the species to move between them using detailed spatial representations of the landscape). However, doing so greatly increases processing times, and may not be feasible to run for large and complex study areas. Further, because of the variation in spatial realization between connectivity models, the results of these models, especially when considering the importance of individual patches to overall network connectivity, can differ substantially.

Thus, there is a need not only to be able to automate the ranking of patches based on their relative importance within the network (for which very few automated tools exist), but also to test the sensitivity of the results to the model (and the associated level of spatial realization) that is used. If patch rankings do vary considerably between models, it would make sense to use a model comparison approach to generate the final patch rankings (as is frequently done in other disciplines where considerable model uncertainty exists such as fire spread modeling or global climate change modeling) before making conservation decisions. This paper presents the Habitat Connectivity Research Software (HABCORES), a software toolbox written for ArcGIS 9.2, which incorporates three different modeling approaches to habitat connectivity that lie along the continuum of possible spatial realism. Preliminary testing of the tool for a case study of koala habitat in south-eastern NSW indicates that different model approaches yield quite different patch ranking results. Future work will include assessing the sensitivity of model results to key parameter settings, incorporating additional connectivity models into the HABCORES framework, conducting further tests of patch ranking sensitivity to the model choice using neutral models and testing connectivity predictions from the model for one or more case study species against field data of individual animal movements in a test landscape.

Keywords: *habitat connectivity, GIS, networks*

1. INTRODUCTION

Habitat loss, whether due to natural or anthropogenic causes, is widely recognised as an important threat to the survival of many faunal species worldwide (Lindenmayer & Fischer, 2006). As habitat is lost, once contiguous patches can be subdivided into smaller distributed patches, which can lead to extinctions in many species (Reed, 2004). Maintaining viable species populations within the network of widely distributed habitat patches that this creates requires that individuals disperse between the remnant patches. Habitat connectivity defines the connectedness, based on the degree which the intervening landscape facilitates or impedes movement, of habitat patches for individual species (Taylor et al., 1993) and is used to measure the potential for dispersal for a given species between patches (Taylor et al., 2006). GIS provides a simple yet effective method to quantify habitat connectivity where biological data is lacking (Santos et al., 2006) based on 'least-cost' modelling. This involves calculating the 'effective distance'; a measure of Euclidean distance modified for the effect of the landscape and species behaviour that quantifies the relative difficulty of individuals of a given species to traverse through the matrix between sets of habitat patches (Adriaensen et al., 2003). Although many studies have used this approach (for example, Drielsma et al., 2007a), few have done so to identify the relative importance of <u>individual patches</u> to overall habitat connectivity (for example, Saura and Pascual-Hortal 2007). Despite this, doing so is critical for prioritizing conservation decisions (Ovaskainen & Hanski, 2003).

2. HABITAT CONNECTIVITY RESEARCH SOFTWARE (HABCORES)

The Habitat Connectivity Research Software (HABCORES) is a toolbox extension scripted in Python v2.4 for use within ESRI ArcGIS v9.2 software for cost-weighted based habitat connectivity (connectivity) analysis. Figure 1 outlines the basic datasets and tools in HABCORES that can be used for such an analysis: the Identify Unique Patches toolset (1) is used to delineate patches of habitat for the chosen species and assign unique identification values to each patch (green boxes). The Cost Surface toolset (2, 3) is used to construct cost surfaces of the landscape inhabited by the chosen species (blue boxes). The Habitat Connectivity Analysis toolset (4, 5) provides the models to implement connectivity analysis (red boxes).

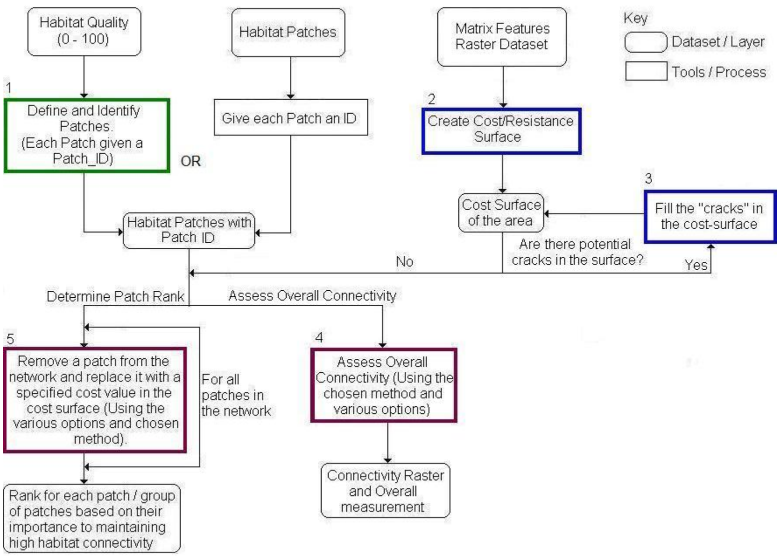

Figure 1. Stages of the methodology required to implement connectivity analysis. Square boxes represent a tool provided in HABCORES or a process which can be implemented within ArcGIS, while rounded boxes represent a raster dataset. The numbers appearing next to square boxes represent a tool provided in HABCORES.

HABCORES can be applied to a wide range of species across many landscapes where relevant data exists. For example, for a given landscape and species it must be possible to map habitat quality based on the requirements of that species and delineate these into patches. Further, enough about the species and landscape must be known in order to define and represent the cost(s) of that species moving between patches through the landscape matrix and to set a maximum dispersal limit (as a distance or energy expenditure).

2.1. Identify Unique Patches Toolset

This toolset assembles basic functions available in ArcGIS for delineating habitat patches from the perspective of a chosen species. This can either be done by reclassifying an existing habitat quality map into Boolean patches, or by taking an existing delineation of patches and assigning each patch a unique ID number needed for the rest of the processing.

2.2. Cost Surface Toolset

This toolset also uses basic functions available in ArcGIS to prompt the user to create a cost / resistance surface representing the spatial variation in the ease of dispersal of the chosen species between habitat patches within the landscape(s) it inhabits. Various raster data sets representing different costs to species movement are first defined, and then these are combined with relative weightings (if desired) to create the overall cost surface. Following Rothley (2005), HABCORES then identifies and fills 'cracks' in the cost surface. 'Cracks' in a cost surface occur when barriers (linear features, such as roads, which hinder the dispersal ability of the chosen species) are inadequately represented in raster format such that least cost calculations find shortcuts across these features along diagonals (Rothley, 2005).

2.3. Habitat Connectivity Analysis Toolset

This toolset implements three indicative cost-based connectivity models described in the literature, each of which provides an estimate of the overall connectivity of the network of patches (and is based on a hypothesis of how a species disperses through a given landscape). Once network connectivity has been measured initially, this can be repeated for iterations of the network whereby each patch is removed in turn. From this, each patch can be ranked based on its relative contribution to the overall network connectivity. HABCORES is one of few automated tools that exist to do this (for example, Saura and Pascual-Hortal 2007), and the only one that incorporates multiple habitat connectivity models within a single analysis framework. The three connectivity models implemented within HABCORES are: 1) Absolute Ecological Connectivity Index (ECI); 2) CONNECT and; 3) Least-Cost Path Graph-Theory (LCG Graph).

2.3.1 ECI model

The Absolute Connectivity Index (ECI) model (Marull & Mallarach, 2005) assigns an ECI value to each cell in an output raster dataset based on the least-cost distance of that cell to the nearest set of source cells (habitat patch). The ECI value is defined as:

$$ECI_a = 10 - 9\frac{\ln(1 + x_i)}{\ln(1 + x_t)}$$

where: x_i is the cost distance in a cell and x_t is the maximum possible cost distance.

The maximum possible cost distance is defined by the maximum dispersal distance of which the chosen species is capable. Resultant values range from 1 (minimal connectivity) to 10 (maximum connectivity). This results in an exponential decrease in connectivity values over increasing Euclidean distance from habitat patches. An advantage of this method is that connectivity estimates for a given species occupying different landscapes can be compared directly because values are normalised between 1 and 10.

2.3.2 CONNECT model

In contrast, the CONNECT model defines the connectivity of each cell to the overall habitat network as the amount of energy the chosen species has remaining to disperse to a habitat patch (Villalba et al., 1998). This assumes that a given species has a finite amount of energy to spend on dispersal between habitat patches. The amount of energy remaining for dispersal decreases as the species moves further away from the initial patch. The algorithm begins by assigning maximum amount of dispersal energy to the cells that make up each habitat patch. Connectivity calculations then commence from the edges of the patch. Calculating the connectivity value for each cell requires identifying the maximum connectivity value within the eight-cell neighbourhood surrounding a cell using neighbourhood models. The connectivity value for a cell is calculated by iterating the function for all destination cells away from a patch:

$U_n = U_{n-1} - (338 \times R_n)$, where U_n is the connectivity value of the cell n, U_{n-1} is the maximum connectivity value within the eight-cell neighbourhood surrounding cell n and R_n is the cost value of cell n.

The constant 338 adjusts for the geometry of the eight-cell neighbourhood used (Gulinck et al. 1993). These calculations continue in all directions from a source patch until all the maximum energy units are exhausted. This procedure is repeated for all patches in the extent. Thus, connectivity decreases linearly with increasing Euclidean distance from source patches. This may be a limitation of the method as an exponential decay may be more representative of species dispersal (Villalba et al., 1998; Moilanen & Hanski, 2001; Moilanen & Nieminen, 2002). In the HABCORES implementation of CONNECT, cell values in the final output dataset can be defined as either the maximum or the sum of all connectivity values calculated for individual cells from all patches. These two options have different implications for overall connectivity. The former provides the ‘best case scenario’ connectivity of each cell to the network (the connectivity of each cell to the closest least-costly patch), while the latter estimates the total connectivity of each cell to the network (the connectivity of each cell to all patches).

2.3.3 Least-Cost Path Graph Theory (LCP graph) model

Graph theory provides a very efficient means by which to analyse network connectivity for the initial landscape and after each patch has been removed in turn. This is done by representing habitat patches within a landscape as a series of nodes connected by edges (Urban & Keitt, 2001; Minor & Urban, 2008). The strength of the connection at a given edge is based on models of species dispersal. Although various functions can be used to generate edge connection values (for example, the larval dispersal kernals based on ocean currents used by Treml et al., 2008), HABCORES weights the edges with the least-cost path distance (LCPD) between patches. The overall connectivity of the graph is defined from three variables: 1) Recruitment, 2) Flux and 3) Traversability (Urban & Keitt, 2001).

<u>Recruitment</u> refers to the ability of patches across the landscape to recruit and accommodate individuals of the species (Urban & Keitt, 2001). A landscape dominated by large patches of high quality habitat can support more individuals, which then have a greater potential to disperse across the landscape (Liender et al., unpublished). Recruitment is defined as:

$$R = \sum_{i=1}^{n} s_i \times k_i$$

where n is the number of patches in the graph, s_i is the size of patch i and k_i is some scaling function representing habitat quality of patch i .

HABCORES defines the size of each patch as a fraction of the total specified environment extent.

<u>Flux</u> defines the degree to which patches across an extent are able to exchange individuals via dispersal by acting as sources and sinks (Liender et al., unpublished). Flux is defined as:

$$F = \sum_{i=1}^{n} \sum_{j=1;\, i \neq j}^{n} \frac{s_i \times k_i}{R} \times \frac{s_j \times k_j}{R} \times p_{ij}$$

where n is the number of patches, s_i and s_j are the sizes of patches i and j respectively, k_i and k_j is a scaling function indicating habitat quality of patches i and j respectively, R is the Recruitment and p_{ij} is the probability of dispersal between patches i and j.

The probability of dispersal, p_{ij}, is calculated in HABCORES by:

$$p_{ij} = \exp(\theta \times d_{ij})$$

where d_{ij} is the LCPD between patches i and j and θ is a distance-decay coefficient ($\theta < 0$) which describes the exponential decrease in connectivity over Euclidean distance. The distance-decay coefficient value is a user-defined parameter (see Okubo & Levin 2001).

Finally, <u>traversability</u> refers to the distance over which all patches are connected and is a measure of graph connectedness (Liender et al., unpublished). Traversability is defined by the diameter of the graph, which is defined as the longest weighted-path between any two nodes in a graph with weighted paths between nodes being the shortest possible weighted path distance. HABCORES calculates Graph Diameter using Dijkstra’s Algorithm (Dijkstra, 1959).

The efficiency of the graph data structure typically enables detailed analysis across broad areas for which other models may be too computationally intensive to be feasible (Urban & Keitt, 2001; Minor & Urban, 2008; Treml et al., 2008). However, the use of LCPD to weight edges within HABCORES partially offsets this advantage because calculating LCPDs is computationally intensive.

3. MODELLING KOALA HABITAT CONNECTIVITY WITH HABCORES

Multiple models exist for measuring habitat connectivity. If the connectivity estimated for a given network of habitat patches differs based on the model used (likely), then the most reliable way to prioritise patches based on their importance to network connectivity (in the absence of definitive field data that establishes which model most closely approximates reality) is to select those patches that rank highly across all models.

3.1. Case study setup

To test this, we used HABCORES to assess connectivity and rank patches based on their contribution to overall connectivity of koala habitat in the Upper Nepean-Avon region of south-eastern New South Wales (Figure 2). This area was chosen due to the large number of potential habitat patches for koala, ensuring a sufficient number of patches based on which to compare rankings. Detailed data on habitat quality (DECC 2007), as well as data relevant to koala movement costs (i.e. roads, water bodies, slope, and vegetation communities) were sourced from the New South Wales Department of Environment and Climate Change (DECC) and used to delineate habitat patches and construct a cost surface for dispersal (see Cook 2008).

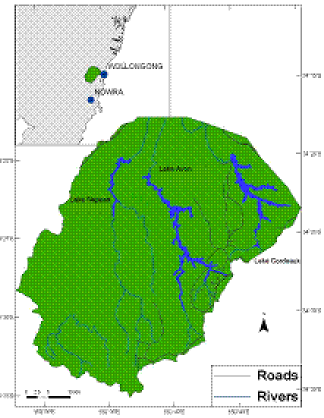

Figure 2. Case study area.

All three models in HABCORES were used to assess overall connectivity of koala habitat patches, with the maximum dispersal distance set to 4km (DECC 2003, Dique et al 2003, McAlpine et al 2007). The sum option within the CONNECT model was used (indicating the connectivity of each cell to all, rather than just the closest, habitat patches). For the LCP graph model, a negative distance-decay dispersal coefficient of -0.00017 was used (Rhodes et al 2006). Following this, patches were ranked based on their relative contribution to overall connectivity (with 1 as the most important) for each model. These results were then combined to generate an overall ranking based on agreement across all three models.

3.2. Case study results

HABCORES defined 30 individual koala habitat patches covering 30% of the study area (Figure 3-C). The patches are relatively evenly distributed with some large patches (largest patch covers 7% of the study area). The koala population was estimated to be highly connected by all three models (Figure 3).

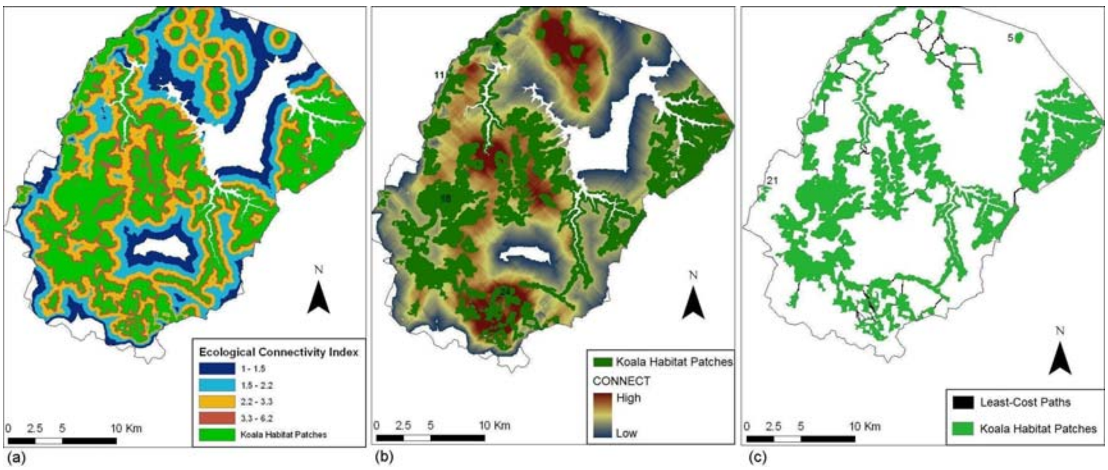

Figure 3. Koala habitat connectivity based on the: A - Absolute ECI, B – CONNECT, and C - LCP Graph models as implemented in HABCORES.

The average ECI value was 2.6383 with 87% of the study area accessible to koalas. Similarly, CONNECT found high connectivity overall (89% of the study extent is accessible to koalas), especially in the southern and central areas. Finally, the LCP graph model found koala patches to be highly connected as well, with only two of the 30 habitat patches completely isolated. It also showed that koala dispersal between the northern and southern habitat areas is possible via patches in the central or western areas. Ranking patches by their contribution to overall connectivity (with 1 as the greatest contribution) showed that patches in the centre of the study area contributed most (Figure 4), followed by those that link other patches to those in the central area (i.e. the fifth ranked

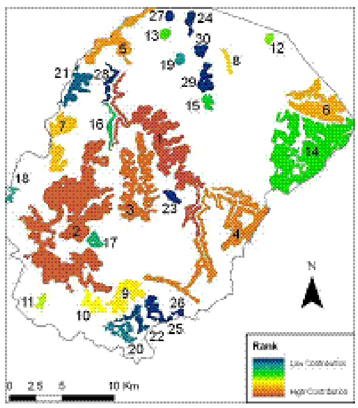

Figure 4. Koala habitat patch rankings.

patch). The highest ranked patch provides the connection between the northern and southern sections of the study area. Despite the fact that the models produced very similar overall results, for some patches the rankings varied quite substantially between the models (Table 1).

For example, the ranking for patch # 17 varied by 27 positions (out of 30 possible), from a rank of 3 (ECI) to 30 (LCP graph). ECI likely ranked this patch so highly due to its large size (removing extensive habitat results in fewer cells used as sources for calculations). In contrast, LCP graph considers the spatial context of each patch (via flux and traversabililty) as well as patch size. Flux increased considerably when this patch was removed, lowering its ranking. However, ECI may incorporate the hostility of the matrix into rankings in ways the LCP graph model may not. Consider a patch completely surrounded by a hostile section of the landscape. The LCP graph model will find a single least cost path through the hostile area, while ECI will consider connectivity in all directions.

Table 1. Notable differences between habitat patch rankings generated by the ECI and LCP graph models.

Patch ID	Rank from ECI model	Rank from LCP Graph Theory Model	Difference in rank (ECI rank - LCP rank)
2	29	18	11
4	27	3	24
11	12	28	-16
14	23	12	11
17	3	30	-27
22	28	14	14
23	25	13	12
29	30	16	14
30	14	26	-12

4. DISCUSSION AND CONCLUSIONS

This study demonstrates that using different models for estimating patch connectivity, even for a fairly homogeneous study area, can generate quite different results especially when patches are ranked for their relative contribution to network connectivity. This could be tested more rigorously using neutral models (Gardner and Urban 2007). Also, more models should be incorporated into HABCORES to represent the full range of approaches that exist – for example a graph theory approach where edges are weighted by other means is missing, as well as the interesting 'spatial links' approach (Drielsma et al 2007). Even the preliminary results evident from this study, however, suggest that conducting sensitivity analysis of these models in general (see Lilburne and Tarantola 2009), and the use of a model comparison approach when interpreting results, is advisable. One clear difference between the various models is the degree to which the spatial context within which dispersal operates (spatial realisation) is fully represented. A key problem here is the trade-off between the level of spatial realisation and processing times. For example, a graph theory approach where edges are weighted using a simple distance decay diffusion model is highly efficient and thus feasible to run for extensive and complex landscapes. This changes dramatically when the edges are weighted by LCPs, the calculation of which require very detailed depiction and processing of the spatial context of patches and factors that influence the ability of organisms to move between them through the matrix. Drielsma et al (2007) offer interesting ideas about how this might be addressed – for example, by analyzing subsets of the possible linkages between patches until the results stabilize at a likely pattern (similar to a genetic algorithm approach). Finally, efforts should be made to obtain actual field data of animal movements through a real landscape for use in testing the performance of connectivity predictions made by a range of models, each of which essentially provides a hypothesis about how species disperse.

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