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DEVELOPMENT OF A SPATIALY EXPLICIT HABITAT PATCH MODEL (C-PAN) AND COMPARATIVE ANALYSIS OF PATCH MODELING TECHNIQUES: THE CRAFTING OF A NEW TOOL FOR CONSERVATION PLANNERS

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AND COMPARATIVE ANALYSIS OF PATCH MODELING TECHNIQUES:

THE CRAFTING OF A NEW TOOL FOR CONSERVATION PLANNERS

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ABSTRACT

Ecological theories including island biogeography, intermediate disturbance, metapopulation and metacommunity all suggest that habitat patches of larger size and those comprised of substantial configurations of interior or core habitat possess the greatest potential for long-term species viability. As a direct means of mitigating edge encroachment and fragmentation's other adverse effects, there is a growing consensus among conservation planners that assembling larger, more cohesive tracts with substantial core area is of ecological value in conservation planning. Larger and more cohesive patches are believed to sustain larger and more viable local populations, enhance overall biodiversity, incorporate a wider array of natural disturbance regimes, and maintain more vulnerable, specialist species for the long term. Therefore, it is important that size and cohesion metrics be incorporated in patch and reserve modeling and design.

This research developed a spatially explicit patch modeling approach designed to incorporate these metrics. This new modeling tool is entitled the Cohesive-Patch Aggregation and Network (C-PAN) model. It was created using ArcMap 9.3 and the Spatial Modeler extension. The model was first tested at a pilot scale (the State of South Carolina) and then up-scaled to evaluate a much larger area (the Northern Appalachian/Acadian Ecoregion). The C-PAN approach is most appropriate for use on species requiring substantial core area and those sensitive to edge characteristics. It is also intended to serve as an alternative approach to heavily parameterized patch modeling methods when species-specific parameterization data are not available.

There exist a number of potential benefits associated with C-PAN usage. The C-PAN model searches landscapes for highly cohesive patches with substantial core area within an existing GIS framework. The aggregation and overlay processes used by the model also appeared to be an improvement over highly parameterized approaches which utilize region-growing components for generating patches. Additionally, the Landscape Cohesion Index (LCI) that is generated as part of the patch generation process proved beneficial for measuring fragmentation metrics across multiple sites and landscapes. This may be the first patch modeling approach to use landscape cohesion scores as a means of seeding patches based on their core area composition from the onset of the modeling process. The LCI allows users to delineate patches based on the statistical uniqueness of their core composition. This frees the user from selecting potentially unknown parameter settings when using other more complex approaches. Instead, it allows patches to be delineated and ranked based on how cohesive they are within the landscape. Both of these features may prove attractive to users as they ultimately make the tool more readily accessible to less technical practitioners.

The C-PAN model was then used to generate a unique set of patches in the Northern Appalachian/Acadian Ecoregion. C-PAN was then compared to two ArcGIS (v9.3) based commonly used patch generation tools. The tools, Corridor Designer (v1) and FunConn (v1) were used for this analysis because they represent two highly utilized approaches which are most similar to the C-PAN model in both modeling mechanics and process. The patch outputs from the three tools were then compared and evaluated. This analysis was aimed at addressing a void within the literature of comparing the results of

multiple patch modeling approaches. This analysis also served as a means of validating the C-PAN approach by comparing patch outputs of the three approaches.

C-PAN performed well when compared to the existing patch modeling tools of Corridor Design and FunConn. For all of the spatial and target capture metrics measured, C-PAN ranked first or second among all approaches. The results indicated that the C-PAN patch modeling approach performed as well, and better, in the patch metrics evaluated here (patch area, edge/area ratios, average nearest neighbor, average Human Footprint (HF)[1] score, Last of the Wild (LOW) capture, and patch commission. At relatively high patch selectiveness, the outputs of C-PAN and Corridor design were the most similar in size and distribution across the ecoregion-scale study area.

Furthermore, of the three patch delineation tools, C-PAN appears to provide users with greater site discrimination capabilities than Corridor Design or FunConn. This resulted in providing users with a more selective set of discrete patches than the FunConn approach. Both C-PAN and Corridor Design were effective in delineating highly homogenous patches. These results indicate that the C-PAN patch modeling approach outperforms Corridor Designer and FunConn when measures of patch cohesion and core area are of importance.

A graph theory based connectivity analysis was then conducted in order to identify and compare linkages between patches from the three patch modeling scenarios. The landscape networks modeled for each of the three scenarios indicated that while local

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[1] The Human Footprint dataset (Woolmer et al., 2008) was used as the input dataset for patch generation. Cells with low HF values are largely natural and were used to generate patches. Cells with high HF values are largely built and not suitable for generating natural patches. Averaging the HF score of each patch provided a measure of naturalness upon which patches could be compared further.

connectivity in portions of the ecoregion may exist, widespread connectivity across the ecoregion as a whole was less likely. This was apparent in the C-PAN and Corridor Design patch scenarios, as multiple connections were delineated across the majority of the study area. Alternatively, no connections were delineated linking portions of the large graphs located within the central portion of the ecoregion with smaller and more linear graphs located in the periphery of the region. This was attributable to natural bottlenecks and relatively high Human Footprint (HF)[2] values in those potential linkage areas. The landscape network derived as part of the FunConn patch scenario indicated even further diminished connectivity within portions of the ecoregion.

The C-PAN patch network scenario was comprised of the greatest number of patches. This ultimately resulted in the delineation of multiple and potentially functional redundancies in the landscape network. Increasing the number of patches also improved distance metrics within the minimum spanning tree for this scenario. More patches served as intermediate stepping stones which resulted in shorter linkage and edge lengths and smaller average area corridor requirements. The FunConn patch landscape network however connected significantly fewer patches. This resulted in the longest linkage and edge distances and the largest average corridors within the ecoregion. This represents an apparent tradeoff between the number of potentially beneficial redundant connections and total landscape network corridor area. While more connections may contribute to increased landscape connectivity and landscape function, the increased area requirement

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[2] The HF dataset was also used as the permeability surface for modeling structural linkages among the already modeled patches of the three modeling approaches. Areas with low HF scores are largely natural and thus desirable for modeling connectivity.

make it more costly to implement. On the other hand, fewer connections may be less costly from an implementation standpoint, but may also reduce landscape connectivity and ecological function.

The landscape networks were then used to test a simplifying assumption often used in conservation planning: that coarse-scale corridors may provide overlapping or "umbrella" effects for other scenarios. This was accomplished by conducting an analysis of corridor overlap among these three scenarios. This work is among the first corridor gap analyses to be conducted at the ecoregion-scale. The corridor gap analysis indicated that 5% of the corridor area for all 3 scenarios was spatially coincident, 34% was coincident over 2 scenarios, while the majority of corridor area (59%) was non-redundant. These results are intriguing for two reasons. First, this gap analysis proved to be a useful tool in identifying potential priority conservation areas. Areas held in common may prove to be no-regret areas for conservation action as they provide overlapping coverage across multiple conservation scenarios. Second, the significant coverage gaps among corridors from these three scenarios indicated that selecting "what" to connect at the ecoregion-scale has significant implications for selected corridors. As there was so little modeled corridor area in common among scenarios, there is little reason to believe alternate corridors would be functionally equivalent. This indicates that connecting any one set of habitat nodes would not likely serve as a corridor umbrella for all other scenarios.

The ecoregion-scale connectivity analysis conducted here was also useful in flagging areas for conservation prioritization based on their connectivity role within an

ecoregion-scale context. Connectivity analysis at this scale may also prove useful for evaluating connectivity at local scales. Any one of the subgraphs found within these modeled landscape networks could help inform local scale conservation efforts. Similarly, local scale connectivity and conservation actions could be added to the ecoregion-scale landscape network. As with many things, a successful landscape network is made up of the sum of its locally implemented parts.

Of additional interest, the large size and area requirements of ecoregion-scale corridors may prove to be potential mechanisms by which landscape scale gradients and processes can be included within present day networks of protected lands. While this research did not explore this explicitly, ecoregion-scale corridors may prove to be a provocative means by which natural disturbance regimes, environmental gradients, and shifting species ranges may be captured in conservation networks by virtue of their large size. As such, it may be worth considering ecoregion-scale corridors as implementable conservation components that may facilitate planning for persistence in the face of global climate change.

DEDICATION

I dedicate this work to my supportive family and friends. I never would have made it to this point in my journey without you. I also dedicate this work to all those who are striving to make our world a better place. We have much to do.

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I would like to start by acknowledging the unwavering support and dedication of my committee. I thank Dr. Chanse for providing the strong leadership necessary for guiding a truly interdisciplinary group of researchers and educators. I thank Dr. Baldwin for being the catalyst which has jumpstarted my collegial development as a researcher; I have made greater strides in our short time working together than in the years leading up to it. I thank Dr. Tonkyn for providing such a strong sense of scholastic enthusiasm throughout this work and elsewhere; it has provided me with the energy to forge forward when I felt like wavering. Finally, I would like to thank Dr. Lauria for his sage advice throughout my entire time here at Clemson; your commitment to me over the years has aided in my professional development like no other.

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CHAPTER ONE:

RESEARCH OVERVIEW

Accelerated rates of human-induced land-use change are producing potentially irreversible negative effects on the natural landscape. Chief among these, habitat loss and fragmentation are directly responsible for reducing species' populations and increasing species extinction among those sensitive to these changes (Sorrell 1997, Theobald 2001, Weber et al. 2005). A number of ecological theories however state that non-fragmented assemblages of habitat are necessary to ensure species survival; island biogeography, intermediate disturbance, metapopulation and metacommunity theories. These theories dictate that habitat patches of larger size and more interior or core habitat possess the most characteristics for ensuring the long term survival of species (Hilty et al., 2006).

A consensus is growing among conservation planners that assembling larger, more contiguous tracts of habitat, with substantial core area, is of ecological value in conservation planning. Larger patches have been linked to sustaining larger and more viable local populations, enhanced overall biodiversity, incorporating a wider array of natural disturbance regimes, and a heightened likelihood of maintaining greater numbers of more vulnerable specialist species (Simberloff 1992, Matter 1997, Haddad 1999, Conner et al. 2000, Beier et al. 2002, Weber et al. 2005, Falcy et al. 2007).

In an effort to address habitat fragmentation and the loss of species, much of the present day discussion associated with conservation management focuses on reserve selection and design. Numerous approaches have been developed aimed at providing

resource managers with reserve selection and design alternatives (Carroll et al. 1999 and 2001, Margules and Pressey 2000, Possingham et al. 2000, Noss et al. 2002, McDonnell et al. 2002, Church 2003, Leslie et al. 2003, Cadenasso et al. 2003, Lawler and Schumaker 2004, Fisher and Church 2005, Onal and Briers 2005, Williams et al. 2005, Noss et al. 2006, Theobald 2006, Copeland et al. 2007, Grand et al. 2007, Girvets and Greco 2007, McRae and Schumaker 2008 Game and Grantham 2009). Most notably, spatially explicit habitat modeling has made use of significant strides in computing technology and detailed data availability within the field of conservation biology. This is particularly relevant because it has led to the development of models that better describe and simulate the complex natural environments which they intend to emulate. Many of these approaches have focused on spatial parameter optimization in order to address the lack of spatial cohesion produced by earlier modeling efforts (McDonnell et al. 2002, Williams et al. 2005, Girvetz and Greco, 2007). Furthermore, state of the art reserve design and selection approaches are now combining aspects of spatial cohesion with Spatially Explicit Population Models (SEPMs)[3] to increase the likelihood of sustaining viable populations within the smallest or optimized amount of space.

These advanced approaches are not without shortcomings however. Some approaches designed to optimize spatial metrics tend to require detailed species-specific data regarding movement, foraging activities, and dispersal characteristics. Issues arise with these approaches when the data are questionable or unknown for the focal species in

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[3] SEPMs link survival and fecundity of individual species to mortality and habitat quality within individual patches. They typically track the demographics of species populations through time as individuals are born, disperse, reproduce, and die all while simultaneously predicting population size, time to extinction, and migration/recolonization rates within patches and across the landscape (Carroll et al., 2003).

question (Wilson et al. 2005, Copeland et al. 2007, Grand et al. 2007). Unfortunately, this is often the case. The added complexity of coupling spatial measures with SEPMs requires even greater knowledge of species-specific life history data. Such data include population birth and mortality rates, fecundity rates, and life history dispersal rates. Unfortunately these data are often not well known because of lack of species knowledge, complexities associated with large scale data collection, and issues with field data accuracy.

Furthermore, some of these approaches often use highly specialized software with significant barriers of entry to many with only basic technical skills and to practitioners in other fields. Several such approaches include: heuristic and metaheuristic reserve design models which employ greedy adding, simulated annealing, tabu searches, and genetic algorithms (Sessions 1992, Williams and ReVelle 1996, Clemens et al.1999, Rothley 1999, Possingham et al. 2000, Fischer and Church 2003). Excessive model complexity is of paramount concern because even the best models are of little value if only a handful of advanced technicians know how to use them.

In the absence of the technical knowhow to operate many of these programs, detailed species-specific data, and the necessary knowledge of how the potential error that is propagated by "guessing" to provide the inputs for needed modeling parameters, many practitioners may feel a sense of conservation modeling paralysis. For these reasons, this work stepped back to reevaluate and better incorporate several of the ecological and spatial fundamentals that are potentially being overlooked by many highly specific and overtly detailed approaches. Returning to the roots of the reserve selection

and design process may prove useful in making modeling tools more accessible to a wider group of researchers and practitioners. This may potentially be achieved by modeling patches based on these overarching theoretical themes instead of modeling patches based on detailed species-specific parameters.

As summarized by Diamond (1976), a handful of overarching spatial design guidelines for nature reserves exist: larger reserves are better than smaller ones, a single large reserve is better than several smaller ones of the same total area, reserves with close proximity to one another are better than those that are farther apart, reserves linked by corridors are better than unlinked reserves, and compact or circular reserves are better than stretched reserves.

There has been much backlash against a generalizable set of guidelines for representing inherently complex interspecies and geophysical processes. Most of this debate however has focused on the Single Large or Several Small (SLOSS), the Few Large or Many Small (FLOMS) reserves debate, and the discussion of corridors (Margules et al. 1982, Williams et al. 2005). As such, the discourses with Diamond's recommendations tended to deal with the spatial relationship amongst and between reserves rather than the spatial metrics of any single reserve itself. It seemed reasonable then to revisit the concepts of a single reserve's size and core cohesion in a more elegant or simplistic model than complex and data hungry approaches currently allow.

Addressing this need, this research developed a new and unique spatially explicit approach entitled the Cohesive-Patch Aggregation and Network (C-PAN) model. This model is discussed in Chapter Two and was developed to directly address and better

incorporate the fundamentals of patch size, core area, and cohesion into the modeling process. Development of this model was based on empirically supported ecological theory[4] as opposed to detailed parameterization of species-specific variables (Appendix A). Founding this model on ecological fundamentals rather than complex interactions potentially provides utility to a wide spectrum of practitioners within the conservation and planning related disciplines. This is achieved by providing significantly lower barriers of entry to potential users through employing widely understood and easily accessible geoprocessing tools already found within standard GIS platforms. This was done purposefully in an effort to provide a substantive alternative to complicated technical programs, modeling scripts, and unwieldy add-ons.

The C-PAN approach produces output datasets and patch metrics that are unique to other approaches (Landscape Cohesion Index, core area delineation, effective buffering of the patch core, and C-PAN value, quotient, and rank comparative metrics). These datasets are necessary if a solid argument is to be made for ranking and selecting potential sites based on optimal core area metrics and patch cohesion. Additionally, the simple aggregate, overlay, and extract process of patch generation used by C-PAN allows users to derive patches based on their statistical rareness in the landscape being evaluated. This researcher believes that this serves as a significant advantage of this approach over others as it does not require detailed and species-specific model parameterization.

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[4] Appendix A provides a collection of work which summarizes the ecological theories which C-PAN is designed to incorporate in its patch modeling outputs. Additionally, Appendix A also provides a collection of empirical evidence which supports establishing patches and/or reserves which are large, cohesive, and core rich. C-PAN was designed to model patches which exhibit high levels of these spatial metrics.

This research served dual purposes however. Producing a new modeling approach, while potentially beneficial, does little to untangle and discern the inherent strengths, weaknesses, and assumptions associated with the complex set of already existing approaches. In an effort to both evaluate currently existing modeling tools and validate the C-PAN approach, this research compared the patch outputs from the C-PAN approach to those generated from two currently highly utilized reserve selection and design tools, Corridor Design (Beier et al., 2007) and FunConn (Theobald et al., 2006). Taken together, these approaches comprise a significant proportion of the reserve selection and design work taking place today. Interestingly however, little inquiry has been initiated to compare and contrast their modeling outputs.

In addition to outlining the rationale for selecting these tools and describing their inner workings, the comparative analysis outlined in Chapter Three of this effort aids in bridging the relative modeling gap in patch modeling literature. For the first time, a systematic and categorical comparison of the patch outputs from these three tools has taken place. This was accomplished by evaluating the spatial metrics of the patch outputs and measuring how well each captured a set of pre-existing conservation targets. This knowledge is critical to users who find themselves choosing between varying approaches.

In summary, as conservation planning has evolved, so too have the approaches and technical tools being used within the discipline. While the benefits of these advances are significant, they have led to significant barriers of entry for many practitioners when attempting to employ these tools. Furthermore, many of the advanced approaches today require highly detailed species-specific data to be input as part the modeling process; in

many cases these data are simply not available. This in turn propagates potentially substantial error in the modeling process when 'best guessing' is used in the absence of known data. As such, the C-PAN habitat patch modeling approach developed here proved to be a useful tool for practitioners who currently find themselves paralyzed by the technical skill necessary and detailed data requirements needed to run many of the recently developed reserve selection and design tools.

The C-PAN approach was designed to use commonly understood tools within an existing GIS[5] as a means of reducing barriers of entry to the modeling process. Furthermore, as the results in Chapters Two and Three indicate, C-PAN has contributed significantly to the modeling of habitat patches. Specifically, C-PAN has demonstrated the ability to generate patch outputs with strong core area and spatial cohesion metrics without requiring additionally complex species-specific data.

Finally, the comparative phase of the analysis served two primary purposes. First, it addressed the lack of comparisons between each tool's respective outputs in the literature. This has shed light on each approach's potential strengths and weaknesses when attempting to reach certain conservation related goals and better understand spatial metrics of their respective patch outputs. Second, the success of C-PAN in this comparison has justified its use as a valid tool. This was accomplished in large part by comparing C-PAN derived patch outputs with those derived by its present day modeling peers.

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[5] ArcMap 9.3

Research Objectives and Rationale

The primary objective was to develop a new and innovative habitat patch modeling approach that focuses on the spatial metrics of reserve cohesion and core area. There existed a tiered rationale for developing this approach:

1) Rapid acceleration of land use change and natural land fragmentation is causing declines in species populations around the world and is potentially the greatest contributing factor to species' extinction.

2) There is substantial theoretical and empirical evidence that large expanses of core habitat and heightened patch cohesion are necessary for the conservation of a wide number of species (Appendix A).

3) Advances within spatially explicit reserve selection and design programs have become increasingly dependent on detailed species-specific data that is potentially inaccurate and not widely available.

4) Advances within these modeling programs have been increasingly technically demanding, leading to substantial barriers of entry for practitioners.

The C-PAN model is intended to delineate highly homogeneous patches which are core rich and largely cohesive. The C-PAN approach contributes to patch modeling by utilizing an aggregation, overlay, and extraction method for patch generation; to this author's knowledge, this is a new mechanism for patch generation. Through the

generation of its Landscape Cohesion Index (LCI)[6], the C-PAN model also provides a statistical means by which landscape fragmentation and patch selection can be evaluated. As a descriptive, structural based model, C-PAN aids in identifying those tracts of habitat that remain intact and pose potentially the greatest biodiversity related benefits for including in some sort of conservation scheme. Based in theory and empirical evidence, the aggregation process within the C-PAN model produces new spatial outputs for delineating core habitat areas, provides metrics for comparing core area between patches[7], and emphasizes patch cohesion through its iterative processing. Additionally, the C-PAN model is founded on ecological fundamentals rather than sparsely available detailed data (Appendix A). Finally, the C-PAN model poses potentially smaller barriers of entry to practitioners because it does not require complex model parameterization. It operates entirely within an existing GIS and uses commonly used tools which can be understood and communicated more effectively to practitioners (ArcMap 9.3 & Spatial Modeler Extensions).

The secondary objective was to provide rigorous validation of the C-PAN approach. This objective includes evaluating the C-PAN modeling approach and two additional reserve selection and design tools, Corridor Design (Beier et al., 2007) and FunConn (Theobald et al., 2006). As part of this objective, a more-detailed discussion of patch modeling techniques is included and the patch modeling portion of each approach

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[6] The LCI is a dataset generated by C-PAN which is used to measure landscape fragmentation and measure cohesion within and amongst patches.

[7] C-PAN patch metrics are discussed in greater detail in Chapter 2. For introductory purposes however, several metrics include: the Landscape Cohesion Index (LCI) score (a measure of patch cohesion characteristics in the landscape, C-PAN rank (a measure of ranking patches based on their core area and cohesion characteristics, and the C-PAN quotient (a measure of ranking individual patches when compared to the largest and most cohesive patch).

has been run independently within the specified study area. Patch outputs for each approach have been compared and contrasted. The patch outputs were evaluated based on two substantive categories: a) patch spatial metrics/cohesion and b) how well each approach captured several conservation targets.

The comparative phase of the analysis served two primary purposes. First, the comparative analysis outlined here served potential benefit in addressing the lack of relative comparison between each tool's respective outputs. This has shed light on each approach's potential strengths and weaknesses when attempting to reach certain conservation goals and better understand spatial metrics of their respective patch outputs. Secondly, the modeling success of C-PAN in this comparison has justified its usage as a valid and useful tool. This was accomplished in large part by comparing C-PAN derived patch outputs with those derived by its present day modeling peers.

The third objective was to apply and compare these three patch modeling techniques at the ecoregion-scale. A connectivity assessment for each was then conducted. Modeling connectivity between the patch outputs of these varying approaches aids in revealing the potential subtle differences of each approach's patch metrics and spatial dispersion at large scales. Furthermore, modeling connectivity at this scale is a critically important step in assessing the overall conservation planning implications of each approach. This resulted in identifying areas of conservation importance based on their connectivity role within the region.

Research Question Development

Resource managers are faced with the substantial task of planning, managing, and protecting a vast array of natural resources. Chief among them, the long term persistence of biodiversity and the natural systems required to support it. The first objective of this research aims to develop a new modeling approach that pulls upon substantially accumulated theoretical and empirically supported evidence. As such, an approach designed specifically to focus on assembling cohesive core habitat was sought. Similarly, this approach was developed to be sensitive to the fact that spatially explicit reserve selection and design programs have become increasingly technically demanding and dependent on detailed data. The C-PAN approach has been designed to avoid the pitfalls of heavy model parameterization.

Conceptually, the evolution and development of various reserve modeling approaches have potentially been confined to the following mold. Advances in ecological theory or technical capabilities have contributed to continual refinement of past approaches and the development of new modeling tools. In most cases, these new approaches are tested on specific species with unique spatial requirements. In other instances new approaches are simply tested at regional scales to help solve some reserve selection problem as part of management plan. In many cases, as with the Corridor Design and FunConn toolsets, these methods are picked up and used in many modeling and resource management efforts. Also common place within this mold is the desire to use new tools to provide stakeholders with multiple management scenarios. What has not

been the focus however, is an assessment that uses varying modeling approaches and multiple modeling platforms to evaluate several scenarios.

The second objective of this research effort aimed to help bridge this gap. Producing a new modeling approach, while potentially beneficial, does little to untangle and discern the inherent strengths, weaknesses, and assumptions associated with the complex set of already existing approaches. In fact, it falls into the potentially deficient mold that was just identified, as it has been developed to mitigate some of the potential shortcomings of the alternate approaches. In an effort to both validate the C-PAN approach and evaluate currently existing approaches within the context of each other, the patch outputs from the C-PAN approach were compared to those generated from Corridor Design and FunConn. Taken together, these approaches comprise a significant portion of the reserve selection and design work taking place today, conversely however, little to nothing has been done evaluate or compare their modeling outputs. This comparative analysis has aided in bridging a clear gap through outlining the spatial metrics, modeling efficiency, and relative success of each approach in capturing conservation-related targets such as patch core area and cohesion. Knowing the strengths, weaknesses, and differences in the patch metrics of each approach's outputs is essential for users who find themselves choosing between varying approaches.

Finally, the third research objective of modeling connectivity at the ecoregion-scale evaluated what effects the patch modeling method had on modeled connectivity. By modeling connectivity between the derived patches of each approach, an assessment was

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made regarding the overarching effectiveness of each approach's patches to serve as possible reserves as part of a conservation management plan.

Specific Research Questions

Research Objective 1: Develop the new C-PAN modeling approach.

    The development of C-PAN required the following questions to be explored:

    Research Question 1.1: Can ArcMap (v. 9.3) and its ModelBuilder work environment serve as a platform for developing, building, and packaging a set of tools designed to classify landscape fragmentation and identify highly cohesive patches of habitat?

    Research Question 1.2: Does the resulting C-PAN modeling approach provide useful metrics for classifying landscape fragmentation and generate spatially explicit outputs regarding highly cohesive habitat patches?

    It was hypothesized that assembling the C-PAN approach and subsequent patch modeling tools within ModelBuilder would be successful. The outputs of the C-PAN tools provide a unique means of evaluating the landscape matrix, quantifying landscape fragmentation, and identifying cohesive habitat patches.

Research Objective 2: Comparative analysis of additional habitat patch modeling

techniques and C-PAN Model validation.

The goal here was to run the C-PAN model and the patch modeling components of Corridor Design (Beier et al., 2007) and FunConn (Theobald et al., 2006). Suitable habitat patches were generated from each approach utilizing the same input data and the same model parameters whenever possible within the Northern Appalachian/Acadian Ecoregion. Comparing the outputs of these modeling approaches to those generated from the C-PAN model allowed for the following question to be answered:

Research Question 2.1: What differences exist among each modeling technique's spatial metrics and respective ability to capture the desired conservation targets?

Conservation targets that were evaluated for coverage within the patches included[8]:

1) Spatial metrics and cohesion of each patch.

2) Human Footprint (HF) scores

3) Last of the Wild (LOW) areas

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[8] HF scores are used for measuring the naturalness of each patches composition. LOW areas are have been previously established using highly natural HF scores (Woolmer et al., 2008). LOW areas represent the most natural areas within the ecoregion. As the patches modeled here are intended to be highly natural, it is useful to evaluate their average HF scores and LOW capture as a means of comparing the approaches.

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Capture was defined as the percent coverage of each conservation target distribution contained within the boundaries of each approach's patch outputs. In other words, what percentage of the conservation target's spatial distribution was found within each approach's patch boundaries?

It was expected that there would be differences in each approach's patch outputs. It was hypothesized that these differences would be attributable to the varying levels of spatial contiguity or cohesion built into each modeling approach. What was unclear was how variations in the spatial metrics of each patch will influence each approach's overall ability to capture conservation targets. For that reason, this researcher assumed differences in conservation target capture would exist.

Significant differences were measured in two ways:

1) The percentage of each conservation target's distribution that was found within each approach's patch boundaries.

2) The percentage of patch area that did not capture a conservation target area. This can be thought of as "wasted space" within the patch and has been reported as patch commission. This essentially renders the output less optimal because it captured area that did not contribute to a conservation related goal.

Patch outputs from each approach were compared quantitatively based on the spatial metrics of each patch and the ability to capture areas that contain the specified

conservation targets within their boundaries. By evaluating the modeled outputs of C-PAN and those of Corridor Design and FunConn, a determination was made as to the potential validity, strengths, weaknesses, and application of the C-PAN approach.

As the C-PAN approach differs from others in that it focuses on first identifying core and interior habitat with desired cohesion characteristics through the use of a new process, it was hypothesized that the C-PAN approach would perform at or above the levels of the Corridor Design and FunConn based patch generation tools[9]. It was also predicted that the habitat patches derived from the C-PAN modeling approach would reflect measures of spatial cohesion equal to, or better than, those exhibited by the Corridor Design and FunConn patch generation tools because it was designed to explicitly address this metric.

Research Objective 3: Connectivity assessment and modeling at the ecoregion-scale.

Modeling connectivity for the C-PAN, Corridor Design, and FunConn patch conservation scenarios has provided additional insight on:

Research Question 3.1: Does the patch generation approach result in varying levels of connectivity at the ecoregion-scale?

Research Question 3.2: What are the planning and conservation implications of each patch generation scenario on their resulting landscape networks? More specifically what coverage overlaps, if any, exist among scenarios?

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[9] The mechanisms by which each approach generates patches are discussed in Chapter 3.

A gap analysis of varying patch connectivity scenarios and resulting landscape networks for the same ecoregion indicated varying degrees of connectivity and minimal patch or corridor overlap (Perkl and Baldwin, in prep). As such, it was hypothesized that ecoregion-scale connectivity would vary between the three patch modeling scenarios that were evaluated here as well. Even subtle changes in patch configuration may lead to substantial connectivity alterations. It was expected that the resulting linkages and corridors for each scenario would provide little overlap and result in significant coverage gaps when compared to each other. Furthermore, it was anticipated that the resulting landscape networks and connectivity results of this analysis would aid in further evaluation of the strengths, weaknesses, and possible utility of each patch modeling approach within conservation planning.

Thesis Organization

Chapter Two assess the first two research questions: the effectiveness of ArcMap's ModelBuilder as a new tool development platform and the capability of the C-PAN approach to provide managers with meaningful outputs evaluating the landscape matrix, landscape fragmentation, and habitat patches. As the development and assessment of no new tool occurs within a vacuum, an introduction of existing patch modeling approaches is also discussed. Within this chapter, C-PAN development is discussed, tested, and calibrated on a pilot scale (state level) and its data requirements, processing, and outputs are discussed and evaluated. A full accounting of C-PANs strengths, weaknesses, assumptions, limitations, and possible applications is also discussed.

Chapter Three addresses the third research question: which habitat patch modeling approach best captured conservation targets and how did the resulting spatial metrics of each patch output compare to one another? This chapter serves as the primary means for validating the C-PAN approach through quantitatively evaluating its outputs with those of its peers. The patch modeling analysis conducted in this chapter also increased the scale upon which C-PAN was applied (ecoregion-scale). This chapter also provides a new and unique assessment of landscape fragmentation and core habitat areas within a large scale landscape.

In Chapter Four, the final two research questions are evaluated: does selecting one patch generation approach over another influence ecoregion-scale connectivity and, if so, what are the planning and conservation implications of the resulting landscape networks and how they overlap? This chapter provides commentary on ecoregion-scale connectivity modeling and resulted in the derivation of multiple large scale conservation planning scenarios. Additionally, the ground covered in this chapter also sheds additional light on the strengths, weaknesses, and possible utility of each patch modeling approach within ecoregion-scale conservation planning. The structural connectivity between individual patches is also evaluated in this chapter.

CHAPTER TWO:

DEVELOPMENT OF THE COHESIVE-PATCH AGGREGATION AND NETWORK

(C-PAN) MODEL

Patch Modeling and Reserve Selection Overview

The main objective of this chapter was to provide a new method of generating patches. Patches can be thought of as biologically viable planning units from which to choose when designing, selecting, and creating linkages that could be used as part of a comprehensive conservation plan. As such, a habitat patch modeling approach which focuses on emphasizing the spatial metrics of reserve cohesion and core area with minimal user parameterization was developed. The C-PAN approach discussed in this chapter quantifies landscape pattern and emphasizes structural connectivity with the habitat patches it generates.

The chapter starts with an overview of modeling approaches that have historically been used and built upon for generating reserves and designing modeled habitat patches. These approaches are ordered based on their modeling complexity. This overview ultimately concludes that current patch modeling approaches have become overly technically demanding, data and parameter hungry and unwieldy for many practitioners. The C-PAN modeling approach was designed to specifically address these issues.

An overview of the C-PAN patch model is then presented and it is tested on a pilot scale landscape (South Carolina) with a randomly selected species distribution dataset (*Pseudacris crucifer*, Spring Peeper, frog). The specific habitat requirements of the Spring Peeper are ancillary to this work as the dataset was only used for calibrating and testing the model, not developing species specific habitat patches for conservation action. Intermediate steps and graphics of the modeling process are provided in order to better explain the automated and behind the scenes mechanics of the model. Patch outputs are provided and patch classification metrics unique to the C-PAN approach are also discussed.

This chapter finishes with discussion regarding possible usage of the C-PAN model as a decision support tool. Additionally, the strengths, weaknesses, assumptions, and limitations of the C-PAN approach are also discussed. A comparative analysis which discusses the patch modeling mechanics of C-PAN and other patch modeling tools can be found in Chapter Three which follows.

Reserve Selection Approaches

The advent of computing technology coupled with large remotely-sensed datasets has drastically improved the means by which resource managers inventory, measure, and analyze landscape patterns and processes. This improvement has contributed directly to the goal of better maintaining species diversity through the implementation of better reserves. Early heuristic reserve selection models served as a catalyst for ensuring that species distributions were captured in networks of protected lands. Adoption of these

modeling techniques ultimately became known as the "minimum reserve set" problem in which the smallest set of reserve sites was identified while still capturing desired species distributions (Kirkpatrick 1983, Margules et al. 1988, Cabeza and Moilanen 2001). In these modeling algorithms, no consideration was given to patch metrics such as shape, edge, number of patches, or their relative connectivity or proximity to each other (Williams et al. 2005). C-PAN was developed in part to address these shortcomings.

The respective outputs of these early approaches are often assemblages of disjunctive sites that lack spatial cohesion both within and between patches. While this has proven useful in ensuring short-term species coverage, the long term persistence of species within spatially incoherent patches is problematic. Studies by Margules et al. (1994), Virolainen et al. (1999), Rodrigues et al. (2000), and Cabeza and Moilanen (2003) have all documented species decline in implemented cases of the "minimum reserve set" modeling approach (Williams et al., 2005). This is attributable to the lack of reserve design components such as size and cohesion within reserve selection approaches. C-PAN adds these measures of reserve design into the modeling process.

Reserve Design Approaches

In an effort to better incorporate natural ecological processes and species persistence, reserve selection models have been largely improved upon by reserve design models. A reserve design model explicitly incorporates spatial attributes of patches such as their size, shape, and connectivity. Spatially coherent patches are likely to be important to species population persistence because they exhibit the spatial attributes (adequate

size, proximity, connectivity, shape, and core area) that are believed to support larger populations while in the face of environmental variations (Williams et al. 2005). Such spatial attributes are generally addressed in two ways within reserve design models: through establishing maximization/minimization objectives for achieving as much or as little of the spatial metric as desired, or with structural constraints that ensure that a specified level of an attribute is achieved (Williams, et al. 2005).

These inclusions enable the modeled reserve systems to be comprised of patches that exhibit the spatial metrics needed for spatial coherence. Heuristic and metaheuristic reserve design models such as those that employ greedy adding, simulated annealing, tabu searches, and genetic algorithms, have been used to varying effect for identifying approximate reserve solutions or global optimums by Sessions (1992), Hof and Flather (1996), Williams and ReVelle (1996), Andelman et al (1999), Clemens et al. (1999), Rothley (1999), Possingham et al. (2000), McDonnell et al. (2002), Nalle et al. (2002), Fischer and Church (2003), Leslie et al. (2003), and Williams et al. (2003).

Still, inherent in all of these adaptations, is their fixed temporal nature. Each of the above reserve selection and design approaches represent site-selection decisions that are but single snapshots in time. As such, the next generation of reserve selection and design modeling includes metrics designed to also model species population fluctuations over time.

Spatially Explicit Population Approaches

Spatially Explicit Population Models or (SEPMs) have been designed to project species population dynamics in patches across a given landscape (Schumaker, 1998). SEPMs link survival and fecundity of individual animals to mortality and habitat quality within individual patches. They typically track the demographics of populations through time as individuals are born, disperse, reproduce, and die all while simultaneously predicting population size, time to extinction, and migration/recolonization rates within patches and across the landscape (Carroll et al., 2003). Williams et al. (2005) has further classified SEPMs into three modeling paradigms: diffusion approaches (Okubo and Levin, 2001), metapopulation approaches (Levins 1969, Levin 1976), and individual-based approaches (DeAngelis and Gross 1992, and Pacala et al. 1996). As the level of detail implicit in these approaches suggests, they are typically complex, data hungry, and require heavily parameterized calibration for each species being modeled.

Patch Modeling Mechanics

Basic Patch Generation

Landscapes are comprised of a number of building blocks, none potentially more fundamental for species survival than the patch. Patches can be thought of as areas in the landscape that are comprised of characteristics suitable for the persistence of a species. Wiens (2006) adds that these areas will exhibit high levels of connectivity for an organism of focus. So central to landscape composition and the management of species

populations, virtually every form of reserve selection, design, and optimization model formulated to date is dependent on the delineation, attributes, and distribution of patches as a central component of their function. As such, methods of patch generation become one of the essential components central to modeling any landscape.

Put simply, modeled habitat patches are generally derived from "extracting" grid cells or polygons from a dataset which exhibits some desired landscape characteristic. Landscape characteristics of interest for patch generation may include habitat suitability scores, land cover types, species presence or absence, or geophysical features to name a few. Eastman et al. (1995) utilized this basic extraction technique for identifying sites for specific uses. In their work, cells with suitability values greater than a predefined threshold were identified. Suitability values were tightened or relaxed to reflect the desired total land area being sought. While this process is particularly straight forward, it does not include mechanisms to ensure that the selected cells were clustered or connected in any way. In the absence of these mechanisms, sites or patches of a specified size could not be identified, sites were not subject to meet shape or compactness requirements, and sites or patches could contain holes or be highly fragmented (Brookes, 1997).

Rules of Contiguity in Patch Generation

In order to address the issues of disjunctive cells and sites, others have applied rules of contiguity to ensure that those cells being identified share some level of spatial adjacency to one another. By applying rules of contiguity, sets of suitable contiguous cells which touch neighboring cells can be identified and selected, thus ensuring some

level of connectedness in the sites being generated. Contiguity approaches vary in their neighborhood sizes and can range from cell neighborhoods which require suitable adjacent cells to touch on at least one side in any of the cardinal directions (4 cells), expand to search for adjacent cells that touch on the sides and/or corners (8 cells), and can even expand further to include larger groupings of cells (With 1997, Gardner 1999, Turner et al. 2001, McGargal et al. 2002).

As outlined by Girvetz and Greco (2007) however, there are several drawbacks to using rules of contiguity alone in patch generation. First, these rules are somewhat limited by the minimum mapping unit or cell size of the input dataset (coarse scale datasets will not be appropriate for fine scale applications and fine scale datasets result in the excessive delineation of many small sites). Second, they have demonstrated that rules of contiguity do not adequately characterize patches for a particular focal species they studied. In their work they determined that small gaps in habitat should be considered part of the patch, and sections of narrow edge that extend outwards from the larger patch should be excluded. Finally, rules of contiguity alone do not account for density or quality of habitat in a given area.

Region-Growing Patch Generation

Addressing a number of the drawbacks associated with applying rules of contiguity, Brookes (1997) developed a parameterized region-growing algorithm (PRG) which included basic region-growing and parameterized shape-growing components. In this approach, the region-growing component initiates with a single "seed cell" and then

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adjacent suitable cells are then iteratively added until the region has grown to a desired size. Regions are not grown if adding a neighboring cell would create a hole in the final region. Similarly, the parameterized shape-growing component starts by calculating the shape suitability score based on edge and core area for each of the neighboring cells and finishes each iteration by including the cell with the best shape suitability score (Brookes, 1997).

Similarly, Church et al. (2003) developed a patch-growing process (PGP) that was based on the adaptations of Brookes (1997). In his approach a seed cell is first identified and then neighboring cells of the highest habitat suitability are added for expanding the boundary. The PGP uses a patch connectivity multiplier to help keep total edge relatively low, is independent of any pre-specified shape, and generates patches that meet predefined criteria (Church et al. 2003). The limitations of this approach are in its restricted accessibility since it was constructed outside of a commercial GIS. As such, the tool remains largely inaccessible to practitioners and its use is hindered by potentially significant barriers of entry. It is worth pointing out here that rules of contiguity provide the basic foundation for any region-growing patch modeling approach within or outside of a GIS.

Hybrid Patch Generation

Three additional patch modeling approaches are discussed in greater detail here in order to illustrate the relatively detailed level of parameterization, species-specific data, and technical expertise that is required for their utilization. First, PatchMorph (Girvetz

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and Greco, 2007) provides useful advances to both rules of contiguity and region-growing approaches. It starts with a moving window which applies a habitat quality threshold for seeding the patch. Next, thin breaks or areas that are not suitable are added to the patch based on a user-defined threshold thickness. Third, areas of suitable habitat that are thinner than a user-defined threshold thickness are removed. Finally, patches are removed that do not meet a user-defined minimum threshold size.

While PatchMorph has the benefit of adding a measure of habitat quality to patch delineation, it requires heavy user-defined parameterization in the remaining steps of its approach. User-defined minimum patch break distances vary largely with the species being modeled, may not be documented or known for many of those species, and may even prove inappropriate for edge-sensitive or core-dwelling species. Additionally, parameterization of minimum "spur" thicknesses and patch size thresholds will also vary greatly based on the species in question and may not be known.

Specific Patch Generation Tools: Corridor Designer

Finally, the Patch Generation tool within Corridor Designer (Beier et al., 2007) requires user-defined input parameters which include: the moving window neighborhood size, habitat suitability scores, and minimum patch areas for supporting a population and breeding occurrence. Each of these parameters can be thought of as a selection criterion that continually culls all available patches leaving only those that meet all of the required functional characteristics. The habitat suitability score establishes the minimum habitat quality value that will be considered for region-grouping or assembling the first cut of

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habitat patches. Higher suitability scores result in more restrictive patch selection. The minimum patch size parameter is also used to eliminate patches that are not large enough to sustain the species. Unique to Corridor Designer, the moving window size setting allows the user to define the size of the area being averaged for inclusion in the patch, the larger the moving window, the more restrictive the patch becomes to less suitable values, eliminating them from the patch.

As the level of detail in these inputs suggests, they are largely species-specific, vary greatly among species, and require substantial user parameterization. Additional discussion and evaluation of the Corridor Designer Patch Generation tool is provided in Chapter Three.

Specific Patch Generation Tools: FunConn

The Define Functional Patches tool within FunConn (Theobald et al., 2006) represents an additional patch generation tool which uses a number of the modeling techniques outlined above. Tool parameters include a resource quality threshold, the minimum patch size, the maximum foraging radius for an animal, and the core habitat percentage. From a modeling perspective, the foraging radius aims to identify patches that meet certain minimum size requirements necessary for sustaining the species. Finally, the core habitat percentage parameter refines again which patches are functionally suitable by aiming to add a measure of the species interior versus edge

habitat requirements (Theobald et al. 2006). This parameter is similar to a boundary

length modifier (BLM)[10] used by Leslie et al. (2003).

Again, these input parameters are largely species-specific, vary greatly, and

require substantial user parameterization. Additional discussion of the Define Functional

Patches tool within FunConn is provided in Chapter Three as this tool is one of those

evaluated in the comparative analysis.

Specific Patch Generation Tools: C-PAN

The C-PAN modeling approach developed here purposely varies in several key

ways from the patch modeling approaches discussed thus far. First, C-PAN uses tools and

modeling components found within ArcGIS commercial GIS software, drastically

reducing technical barriers of entry. Second, while it is based on rules of contiguity as

part of the patch design, it does not rely on any region-growing algorithms for expanding

and delineating patches. This is a significant departure from other approaches as it

eliminates issues of patch spurs, drastically elongated or highly irregular shaped patches,

holes, and excessive edge that require heavy user parameterization in order to be

removed. Instead, the aggregation and overlay process that C-PAN model uses provides a

more streamlined alternative. To this author's knowledge, this is the first patch modeling

approach to use these processes as the primary means of patch delineation.

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[10] The BLM is a model parameter which can be used to specify the desired level of edge/area ratios
exhibited by the modeled patches.

Additionally, the Landscape Cohesion Index (LCI) that is generated as a result of the C-PAN model allows for patches to be generated based on the statistical distribution of landscape characteristics. This allows the user to determine at what point patches of a certain size and core area composition become statistically unique in a landscape. This frees the user from having to choose parameters such as foraging distances, spur thicknesses, and moving window sizes which are required in the previously discussed approaches. The LCI is unique to this approach alone and may additionally be a valuable means by which connectivity can be evaluated and compared within and across landscapes. Development of the LCI is potentially a significant improvement over other patch modeling approaches as it focuses on delineating the most spatially optimum patches (i.e., top 10% most cohesive) as opposed to less optimally shaped and highly parameterized patches that require detailed knowledge of a specific species and advanced technical skills.

C-PAN Model Development Overview

A less technical introduction to the C-PAN modeling method is provided here. It is intended for those readers less interested in the technical aspects and process of model development and more curious in the overarching concept. The section that follows however discusses in great detail the C-PAN modeling process. This is necessary because the technical inner workings of the C-PAN model must be transparent if it is to be entirely understood and evaluated. The technical discussion and figures that follow are

intended to show how the C-PAN model works and provide the reader with snapshots of intermediate modeling data in order to discuss the overall process of this approach.

The C-PAN model was developed to identify habitat patches that exhibit spatial characteristics known to support core dependent species and promote overall biodiversity. Using only common geoprocessing tools found within ArcMap's ArcToolbox, a model was constructed in order to identify habitat patches of progressively larger size with high core area and highly cohesive characteristics.

Data requirements for this model are non-demanding as it only requires an input dataset that reflects the environmental parameter from which the patches will be generated (i.e., a land cover dataset, suitable habitat type, or species range dataset). Once the input dataset is established, the vast majority of the remaining process is automated.

Once the C-PAN modeling process is initiated (by simply providing the input dataset and clicking "start"), the GIS begins to search the input dataset for clusters of adjacent cells that exhibit the same data value (i.e., a specific land cover type, suitable habitat, or range presence). If a 2 by 2 block of adjacent and similar cells is encountered, those 4 grid cells are aggregated together to form one larger grid cell. The output that results from this process is a dataset that depicts only aggregated grid cells which represents patches of the data that meet or exceed the 4 cell requirement. This process automatically restarts to again re-search the original input dataset for clusters of adjacent grid cells that exhibit the same data value. This time however, during the second run, the GIS is searching for a 3 by 3 block of adjacent cells. If a 3 by 3 block of cells is encountered, those 9 cells are aggregated together forming a new dataset that depicts all

of the patches that meet or exceed this size requirement. This process continues over and over again where each time the GIS is searching for only those patches that meet or exceed the next size requirement. Eventually, no more adjacent cells that meet the required size remain. After a specified number of these encounters, the aggregation portion of the C-PAN model terminates itself.

Next, the model automatically layers the subsequent datasets that depict these progressively larger patches. Using an overlay technique, each time a cell on the surface encounters a new layer placed on top of it, the total is tallied as a sum. This dataset represents the total number of times that each of the original grid cells was included in a larger patch aggregate. Individual cells that were part of very large patches are in-turn reflected by higher cell values. The higher the value, the more valuable that cell is in terms of core area and patch cohesion in the larger landscape. This step results in developing the LCI for every cell within the study area. Once the LCI values are assigned to the cells their distribution is quantified in a graph. The user then chooses an LCI score (which corresponds to the desired level of "uniqueness" that the user desires, top 10% etc.) to delineate patches. The user then selects another less restrictive LCI value (top 20% etc.) to grow the patch to include adjacent suitable cells. These are the only two parameters that the model requires and they are selected from the modeled LCI. The results of this process are a series of individual patches that are identified and ranked based on their respective cohesion and heightened core area characteristics. Furthermore, these two parameters are easily adjusted for exploratory purposes in a way that is completely transparent and more easily understood to more practitioners.

A simplified accounting of the C-PAN patch modeling process can be summarized as:

1) Landscape Aggregation → Identifies patches of different sizes (user provides
   input dataset)

2) Patch Combination → Overlays patches for generating the Landscape
   Cohesion Index (LCI) (automated)

3) Patch Classification → Delineates patch core area metrics (user selects two
   LCI values for patch delineation)

4) Spatial Joining → Grows the patch to the desired cohesion parameter
   (automated)

These outputs offer a new perspective on modeling habitat patches as they are defined based on spatial cohesion metrics and contiguous core area. It may prove advantageous to model patches in this way in order to incorporate many of the known ecological benefits associated with patch size, cohesion, and higher core area that were discussed earlier.

Detailed C-PAN Model Development Methods

A spatially explicit patch modeling approach entitled the Cohesive-Patch Aggregation and Network (C-PAN) model was developed utilizing ArcMap 9.3 with the Spatial Modeler extension. A USGS derived GAP Analysis species distribution dataset

for the State of South Carolina served as the input for the piloting stage of this modeling

approach (SC GAP, 2001). Range datasets consisted of a raster based binary

classification schema depicting values of "1" (predicting a species to be present in a

given cell) and "0" (predicting a species to be absent from a given cell). For the state of

South Carolina, some 455 different vertebrate species have been mapped using this

approach. Range datasets were evaluated to identify those species which had statewide

distributions (335). One randomly selected distribution was then chosen from this group

and utilized in refining the Cohesive-Patch Aggregation and Network (C-PAN) modeling

process as a "proof of principal" or "proof of concept" in this pilot work. The species

range dataset that was used here represented the potential distribution of a frog, Spring

Peeper (*Pseudacris crucifer*)[11]. The range distribution is found in Figure 2.1 (left).

The original range distribution data used as the input to the C-PAN model

consisted of 90 x 90 meter cells depicting suitable habitat (see SC GAP 2001 for

classification and categorization rules). Suitable habitat cells were aggregated to identify

homogeneous habitat patches of progressively larger size, this concept is diagrammed in

Figure 2.1 (right).

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[11] The use of this dataset is not intended to imply that this analysis is specific to this species. The patches generated using this dataset have intentionally not been parameterized to meet any spatial or habitat requirements of this particular species. Instead, this species distribution dataset is simply used as an example of a dataset that could be used as an input for C-PAN patch generation. Additional input datasets could include habitat suitability values, specific land cover types, and measures of landscape naturalness among others. Chapter Three of this work for example uses Human Footprint (HF) scores for generating highly natural patches.

Figure 2.1 – Species Distribution and Patch Aggregation Concept
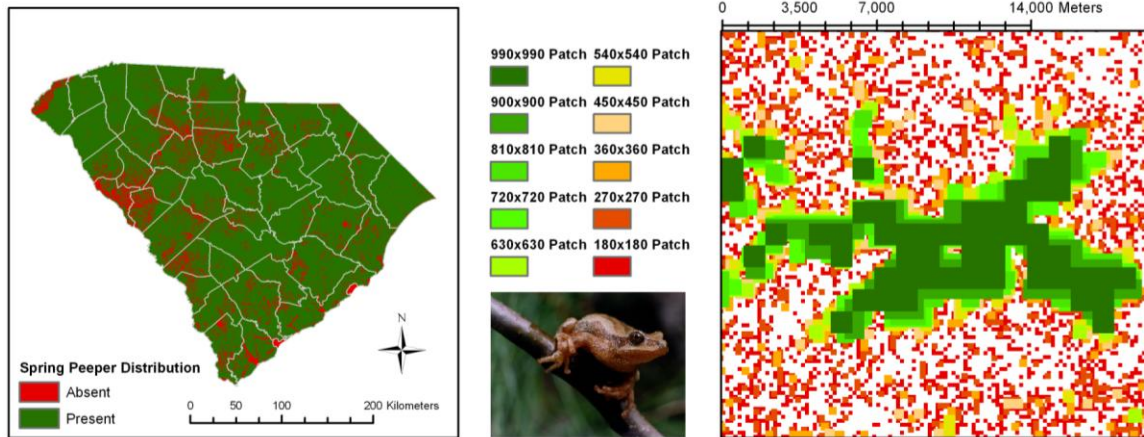
Figure 2.1 (Left): Represents SC GAP range distribution for *Pseudacris crucifer.* This served as input data for the C-PAN modeling process. Individual cells are classified as "Present" for those that are suitable habitat and "Absent" for those cells that are not suitable to support this species. The C-PAN Model will be "searching" for clusters of suitable cells.

Figure 2.1 (Right): Depicts suitable habitat aggregation into progressively larger patches. Small, highly fragmented patches are indicated in red while larger, less fragmented patches are indicated in green. This represents the backbone of the C-PAN modeling process because it systematically identifies progressively larger clusters of suitable habitat cells. Ecologically speaking, this is directly related to the patch size and core area argument. Thinking in this way, those patches in red, while suitable, are not likely sufficient to support a core-dwelling species because they are small and fragmented. Those in green however are of larger size and contain greater core area and pose a better chance for the persistence of edge-sensitive species.

The data presented in Figure 2.2 represents an intermediate iteration that derived 990 x 990 meter habitat aggregates. Each 990 x 990 meter patch was comprised of 121 90 x 90 meter cells. These aggregates were assigned values depicting the total number of contiguous suitable habitat cells within the 990 x 990 meter aggregate. The model carries this process out for a total of 121 iterations at 90 meter increments until a final size of 10,980 x 10,980 meters was achieved. This is the foundation from which patches are generated later on in the modeling process.

Figure 2.2 – C-PAN Modeling Process: Initial Landscape Cohesion Classification
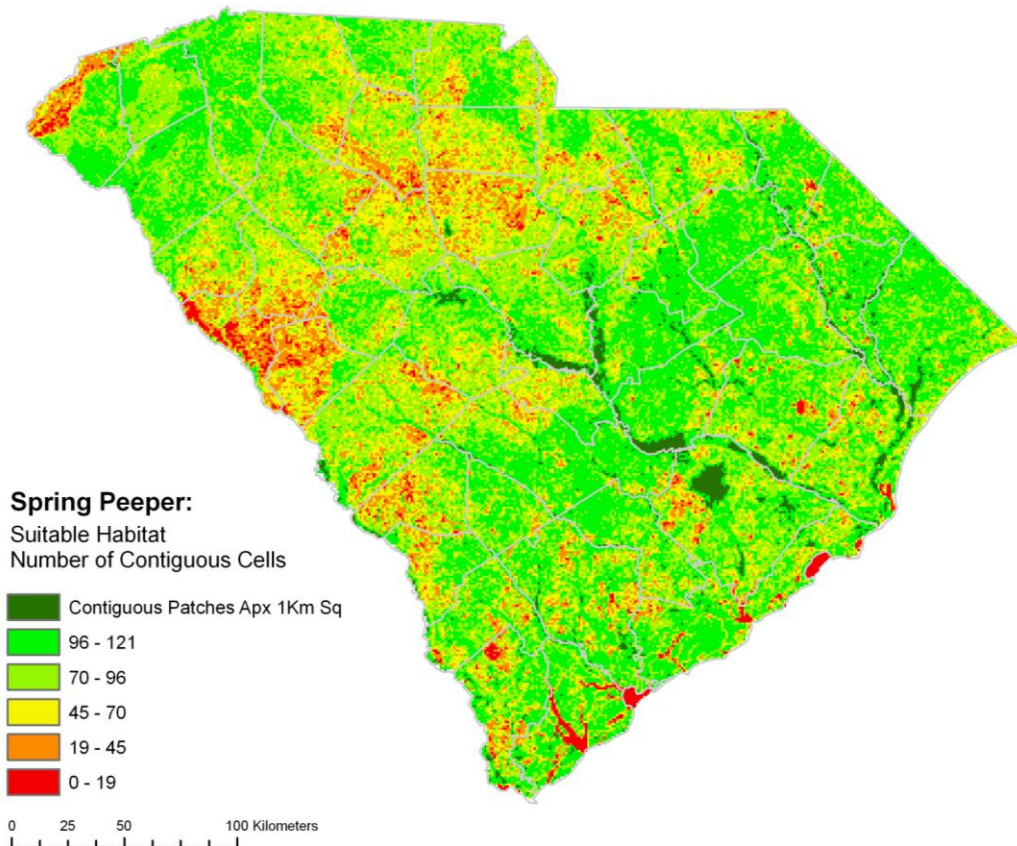
Figure 2.2: Represents the total number of 90 x 90 meter cells within a 990 x 990 meter aggregate. Areas in red represent regions in which small fragmented patches dominate. Those depicted in green represent largely contiguous and cohesive tracts of suitable habitat. This figure represents a snapshot from an intermediate output of the C-PAN modeling process. It is included here because it depicts how the model begins to categorize and classify the landscape based on patch size and cohesion. From a management standpoint, those areas in green represent portions of the natural landscape that are largely intact and thus suitable for this species. They may prove to be prime areas for conservation.

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An aggregate of 1,800 x 1,800 for example, has an aggregate value (the sum of all "present" binary coded cells within the aggregate) ranging from 0 to 441. These values represent the total number of 90 x 90 meter cells within that aggregate that are suitable habitat. Each C-PAN model iteration eliminates patches of smaller sizes from any further analysis and identifies only those that meet or exceed the minimum patch size for that respective iteration (Figure 2.3).

Figure 2.3 – C-PAN Modeling Process: Patch Size Sieving

Figure 2.3: Depicts the first 20 iterations or runs of the C-PAN model. Each run produces a new set of habitat patches that meet or exceed the minimum size requirements for that run. Starting in the upper left, you can see that there is a significant number of patches that meet this relatively small patch size requirement (180 meters by 180 meters). Continuing on with additional runs and increasing the minimum size however, identifies fewer and fewer patches of the required size. As the patch size requirement increases, fewer and fewer sites are identified. After 20 runs, the lower right box indicates that there are significantly fewer patches that are 1,890 meters by 1,890 meters or greater. Again, identifying larger patches is of ecological importance because they include the characteristics (low edge/area ratio and high cohesion) necessary for sustaining core dwelling species.

Each aggregate is reclassified to represent a patch that is comprised solely of contiguous and cohesive cells. This is achieved by setting the highest value observed within that respective aggregate (441 in the case of the example) to a binary value of 1 and all other values to 0. This results in the derivation of aggregated grid cells that are comprised solely of contiguous and cohesive habitat cells. The total value depicted in Figure 2.4 represents the number of progressively larger patch overlaps that are present on a cell by cell basis for the first C-PAN model combination. This combination consisted of 20 progressively larger patches ranging from 180 x 180 meters to 3,600 x 3,600 meters. This process continues for a total of 6 times until a final combine function within the model is executed.

Figure 2.4 – C-PAN Modeling Process: Patch Aggregate Overlays
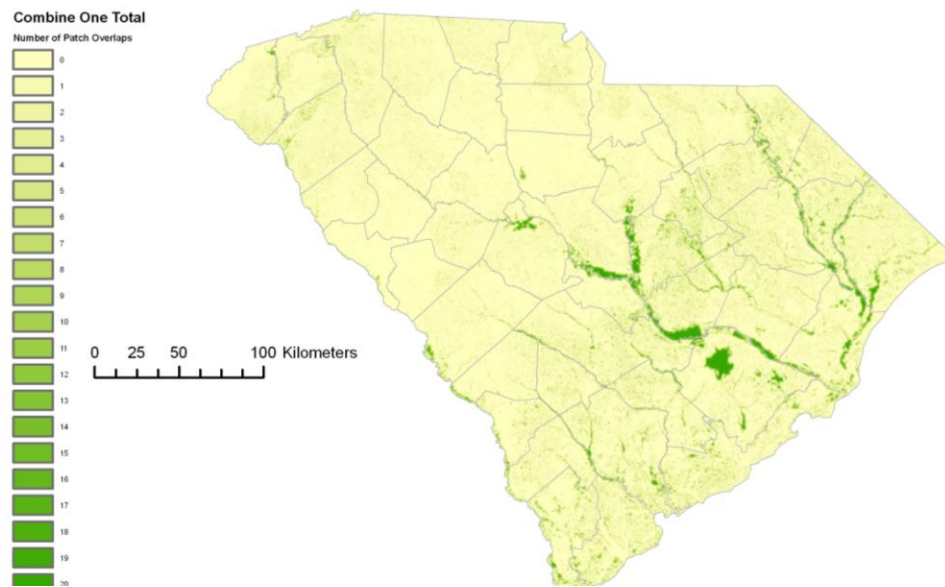
Figure 2.4: Depicts the results of the first 20 patch size combinations. Areas in yellow have very few patch overlaps, representing areas comprised of high fragmentation and relatively small patch sizes. Those areas depicted in green however represent regions in which progressively larger patches overlap, representing largely cohesive regions of suitable habitat. These areas are comprised of cells that are largely buffered from edge effects associated with the fringe of small patches. Conceptually, they represent areas of suitable habitat that are on the interior or near the core of the patch. These areas represent possible candidate sites for core area conservation. This however represents an intermediate step within the overall C-PAN Modeling process. This process continues in order to further refine and rank the remaining core areas of larger patches.

Data layers depicting the range of patch sizes are combined in batches of 20 (the maximum number of layers allowed by the tool at any one time). Once combined, a new dataset is created that indicates all of the possible unique combinations of cell values for the varying patch size inputs (Figure 2.4 and upper left of Figure 2.5). Totaling the value of each row identifies those patches that meet the patch size requirements for all 20 input layers. A value of 18 for example indicates that the requirements were met for 18 of the groups patch sizes but not the larger 2. A value of 20 indicates those areas that meet all patch size requirements in that grouping for each respective patch size. The total fields from the 6 combination groupings are then combined one final time. A final total field is added and calculated based on the sum of the 6 input layers (top Figure 2.5), this value represents the C-PAN value or Landscape Cohesion Index (LCI) score. The C-PAN value represents the total sum of all overlapping patches. A C-PAN value of 120 for example represents a cell that was part of all progressively larger patch sizes (180 x 180 - 10,980 x 10,980). This however would require a cohesive patch of 11 sq km. The largest C-PAN value observed here was 98 overlaps (Figure 2.5).

The cells exhibiting the highest C-PAN values were then identified and extracted by their value attributes. The highest C-PAN values represent the most patch overlaps and are depicted on the left in Figure 2.6. Those cells with the highest values represent the respective center of the Largest Contiguous and Most Cohesive (LCMC) patch[12]. The cells identified as the center of LCMC patch are then reclassified to a binary value of 1 to

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[12] The Largest Contiguous and Most Cohesive (LCMC) patch represents the biggest and most clustered assemblage of suitable patch cells within the landscape being evaluated. Taken together these cells delineate the patch with the most enhanced size, cohesion, and core characteristics of any in the landscape.

indicate their presence; all other values are set to No Data. The binary cells are then

converted to a vector data format. All other habitat areas (Figure 2.6, right) are also

converted to a vector data format so that they can be spatially joined to the center of the

patch (Figure 2.7).

Figure 2.5 – C-PAN Modeling Process: Continued Landscape Overlays
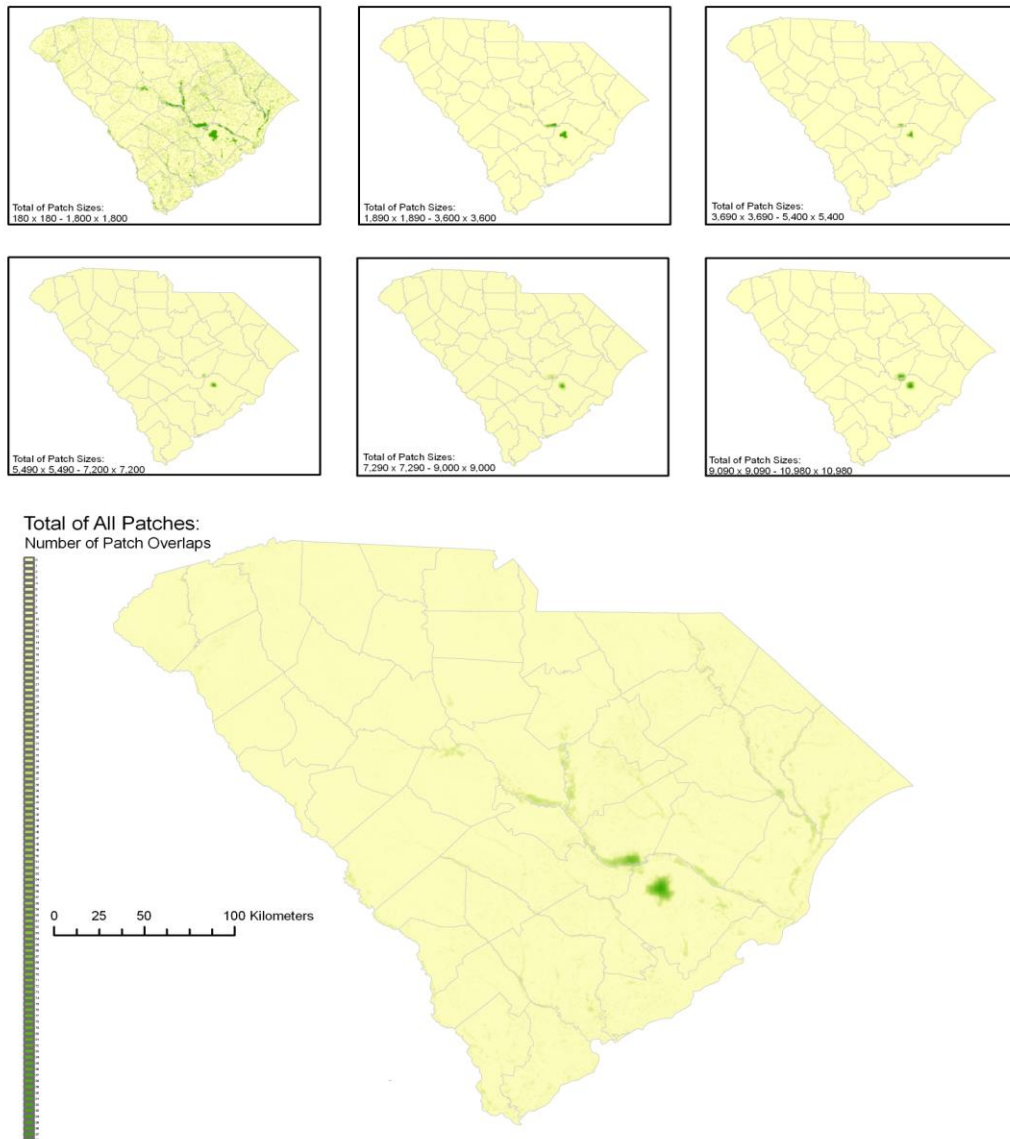
Figure 2.5: As the patch core refinement process continues, areas previously identified as core within relatively small patches become less apparent. While the resulting output depicts all areas of core that have been delineated, it emphasizes the core area that is identified as part of the largest and most cohesive patches. This is evident in the bottom graphic.

Figure 2.6 (Left): This is potentially the most useful output generated by the C-PAN model as it represents a ranking of the core area associated with every patch within the landscape as a measure of cohesion. From the Landscape Cohesion Index (LCI), a selection query can be initiated in order to select only those patches that contain the desired level of core habitat cohesion. Areas in green for example represent the core area associated with the largest patch within the State, it is depicted here as an example. When compared to the land cover for the region on the right, this process becomes more apparent as the large, contiguous, un-fragmented yellow patch contains the largest amount of interior or core habitat.

Figure 2.6 – C-PAN Modeling Process: Landscape Cohesion Index (LCI)
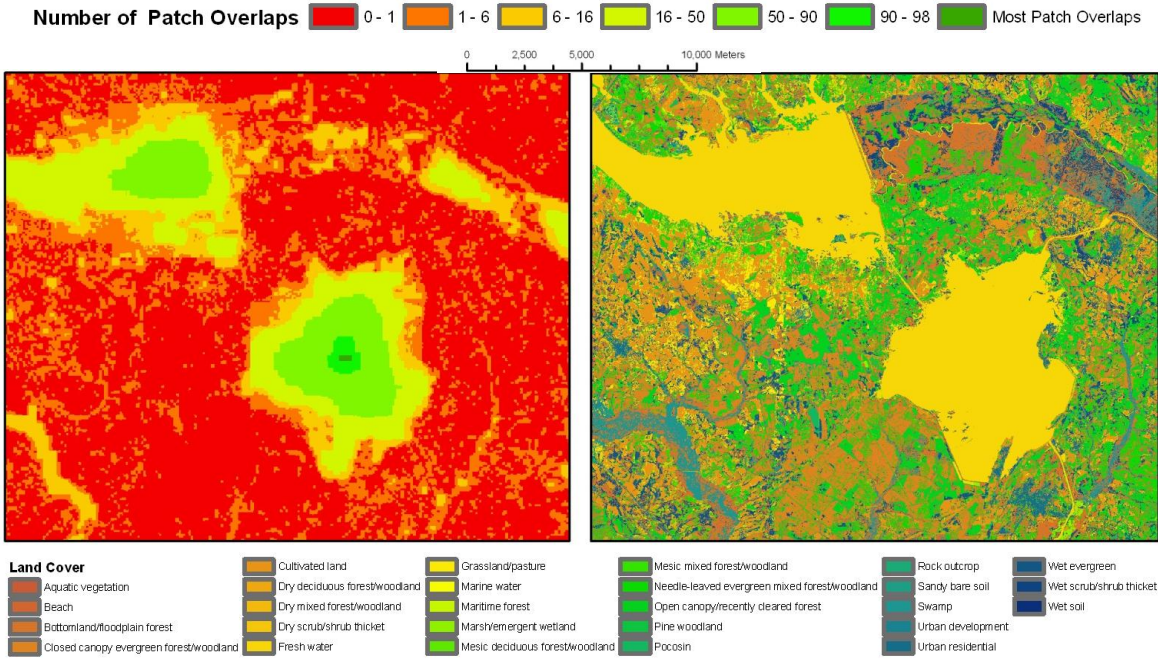
Figure 2.6 (Right): Depicts land cover of the largest contiguous patch and its surrounding network. Land cover types that are deemed suitable habitat are determined by the SC GAP. The suitable habitat adjacent to the largest contiguous patch represents the network of suitable habitat adjacent to that site. Comparing the land cover to the core area output on the left, it is apparent that fragmented land cover types results in relatively little core area. Conversely however, larger and more contiguous tracts are depicted by increased areas of core and interior habitat. The patches that represent the desired level of core and interior habitat then become prime candidate sites for conservation; this is the unique aspect of the C-PAN modeling approach.

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Once the center of the LCMC patch has been spatially joined to all statewide suitable habitats, a selection query is initiated to identify the suitable habitat surrounding the center of the largest patch. The selection query identifies the suitable habitat feature that contains the center of the largest patch. Once this patch has been identified and selected, its boundary grows to include the adjacent network of contiguous suitable habitat. The output of this analysis identifies the LCMC patch of habitat (which using raster format data, the optimal shape of this patch is square) and grows that region to include its adjacent habitat network (Figure 2.7).

It is worth pointing out that for the development purposes outlined here, the C-PAN model was used to identify the LCMC patch as a means of calibrating the model. In practice however, it would be used to identify any number of smaller user-defined patches to initiate the reserve selection process (Chapter Three). It is also worth pointing out, that while a SC GAP species distribution dataset was used here for model development, this modeling approach is not constrained to the use of GAP data or this region. By design, the C-PAN approach would use the most readily available and accurate habitat suitability data as an input for any user-defined study area.

Figure 2.7 - C-PAN Modeling Process: Largest Contiguous & Most Cohesive Patch
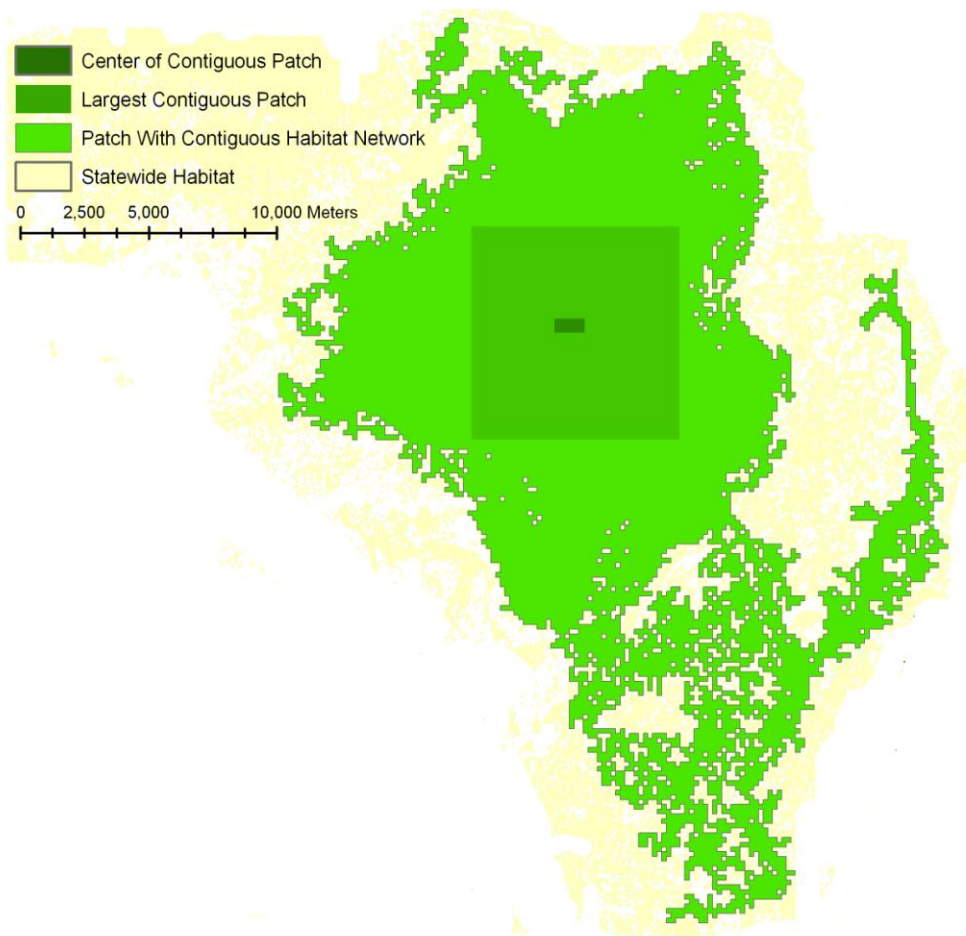
Figure 2.7: Represents a final output of the C-PAN modeling effort. In this case, the model was used to identify and depict the Largest Contiguous and Most Cohesive (LCMC) patch (apx. 6,556 ha). The patch center is represented by the highest LCI value while the core of the patch is represented by largest contiguous and most cohesive patch aggregate from the analysis. An example surrounding habitat network (which may be less optimal as it is impacted by edge effects) is also depicted and utilized here to grow the patch (apx. 34,196 ha). A more restrictive patch grow LCI value could be selected to address this. From a reserve design and selection standpoint, this output delineates the most cohesive habitat patch for this species and thus could serve as a candidate site for conservation. This site for example is of ecological importance because it exhibits the best core area and patch cohesion of all patches across the landscape.

C-PAN Model Development Results

A number of potentially useful outputs were derived throughout the C-PAN modeling process. They included spatially explicit graphics and tabular data associated with cohesion value[13] and area. Each model iteration resulted in the identification of continuously larger cohesive habitat patches. Those outputs alone could prove useful for identifying areas that meet minimum size and range requirements for a particular species of interest. While the results depicted in Figure 2.7 illustrate the largest patch, the model can be calibrated to identify patches of any user-defined cohesion value and space requirement by selecting a lower LCI value. This is an important aspect of any reserve selection and design program because it allows users to make choices on which patches to include within the overall reserve system. Specific and unique to the C-PAN approach, patches can be evaluated and selected based on their core cohesion requirements, a known factor of ecological importance.

Although the exercise of identifying the largest patch of Spring Peeper habitat may not be of the utmost importance (because range requirements for this species are mostly small), the range and distribution of this species was particularly appropriate for calibrating this model. Most landscapes in the southeastern U.S. are fragmented to the extent that one would not expect to find a contiguous tract of entirely suitable habitat as large as 11 km on a side (the calibrated end patch size of the pilot model, this was increased to 20 km upon pilot completion for evaluation in larger landscapes). It just so

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[13] The cohesion value (LCI score) represents a value which counts how many times an individual cell participates in patches of increased size. Higher values indicated high cohesion among adjacent cells and represent core areas within derived patches.

happens however that the largest contiguous tracts of any one land cover class within South Carolina included open water, a land cover class tied to distributions of the Spring Peeper. This connection allowed for the model to be tested at much larger scales than one would normally encounter for any other land cover type in the region. The results effectively identified the largest cohesive patch aggregate to be approximately 8,100 x 8,100 meters in size. This represented a cell of cohesive habitat that is approximately 6,556 hectares in size (16,200 acres). When the contiguous adjacent habitat network that surrounds this cell is included, the total habitat area swells to approximately 34,196 hectares (84,500 acres). This output delineates the LCMC patch, the patch with the greatest core or interior habitat, and the patch with relatively little edge effects compared to other suitable patches.

While there is utility in identifying the C-PAN derived Largest Contiguous and Most Cohesive (LCMC) patch (which was simply included here because it is an interesting example), there are potentially greater benefits to be derived from ranking sites of smaller scales. The C-PAN approach of ranking candidate patches based on core area cohesion is potentially useful as it provides yet another means to inform the reserve selection process. Such an evaluation would allow for priority conservation areas to be delineated based on the relative valuation of interior habitat within the smaller patches when compared to that of the LCMC patch. For this site ranking/prioritization method, the C-PAN value is particularly useful as it can be easily converted into a C-PAN quotient that can aid in prioritizing smaller sites. The largest C-PAN value observed in this analysis was 98 (which corresponded with the Largest Contiguous and Most

Contiguous patch of suitable habitat). The C-PAN value of 98 represents a C-PAN quotient of 1 (C-Pan value / largest C-PAN value). Other sites may then be ranked based on the quantity of interior habitat relative to the largest patch using the C-PAN quotient.

Consider this example: habitat patch A consists of 1,000 hectares while habitat patch B also consists of 1,000 acres. All else being equal, this would indicate that both sites are of equal conservation value. What is less known however is that habitat patch B contains less interior or core habitat because it is more linear in nature than is habitat patch A. Using the C-PAN values and quotient however, one could easily determine this and come to an arguably more selective alternative conservation conclusion that accounts for the quantity of interior or core habitat. Habitat patch A has a C-PAN value of 56 and a C-PAN quotient of 0.57 (56 / 98) and Habitat patch B has a C-PAN value of 24 and a C-PAN quotient of 0.24 (24 / 98). Based on the quantity of interior habitat, habitat patch A is more valuable than habitat patch B.

Similarly, the C-PAN quotient can be used to compare and rank sites of varying sizes. Consider this example: Habitat patch A is 1,000 hectares while habitat patch B is 1,250 hectares in size. All else being equal, size alone would indicate that there is potentially greater ecological value in conserving or preserving habitat patch B. Again however, when taking the cohesive nature of the patch and the quantity of interior habitat into account an alternative conclusion can be drawn. Habitat patch A has a C-PAN quotient of 0.67 while habitat patch B has a C-PAN quotient of 0.41. When taken together, the C-PAN quotient and the area of the patch can be used to derive the C-PAN rank. The C-PAN rank is derived by multiplying the C-PAN quotient for the patch with

the patch area. For habitat patch A, the C-PAN rank is 670 (0.67 x 1,000) while the C-PAN rank for habitat patch B is 513 (0.41 x 1,250) thus reversing the initial conservation decision by taking the cohesive nature of interior habitat into account. An additional graphic example of this is provided in Figure 2.8.

Additionally, the binary file structure of C-PAN modeling outputs also allows for possible future coupling with population viability models. This has potential utility because such models require a spatial component that can be tied to real-world geographic space. This is achievable because the outputs of this modeling method are recorded on a cell by cell basis that ranks their relative importance based on the number of times each cell participates in a progressively larger patch size.

C-PAN Model Development Discussion

The C-PAN modeling method differs from others in that it is centered on identifying habitat areas of a highly cohesive nature. This ultimately leads to the design of patches that are more suitable for sustaining edge-sensitive or core-dwelling species. The planning implications of this are important because modeled patches are often a starting point for implementing conservation or protection action.

Other spatial tools such as Region Group[14], and simple area calculations associated with vector based data files do not take aspects such as edge-to-area ratio into account when identifying the largest patches without additional selection processing. The

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[14] This tool is ArcGIS equivalent to the region-grouping process used by the models discussed earlier in this chapter.

Region Group tool for example is effective in identifying connected suitable habitat but does not provide a ranking of the patches for conservation prioritization based on their respective edge spatial pattern, quantity of interior habitat, or contribution to spatial cohesion of the patch (this is discussed in greater detail in Chapter 3 when alternate approaches are compared). Furthermore, additional measures of spatial cohesion, or the relative pattern of adjacent habitat cells, are not easily taken into account. The C-PAN method however is driven by first categorizing and ranking patches based on the level of spatial cohesion within their core habitat, a fundamental difference from other approaches.

Size and cohesion do matter; patches of greater size and cohesion exhibit reduced microclimate extremes, lower susceptibility to catastrophic disturbances, decreased abundance of common disturbance-tolerating species, and reduced effects from exploitation of human land uses (Anderson and Jenkins, 2006). The size of internal or core habitat matters most however. Two habitat patches of equal area are not necessarily equal. One may be concentric in shape, boasting large expanses of interior habitat (cohesive). The other while being contiguous, may be linear, narrow, and resemble a corridor more than a cohesive habitat patch. Edge encroachment on the second patch will have much greater effects on its inhabitants as the edge-to-area ratio is vastly greater and the effective patch size for edge-intolerant species is much lower. Thus there is utility in identifying, and subsequently enrolling, patches with heightened levels of core habitat in conservation management. Furthermore, there may be utility in identifying these patches

so that surrounding land uses may be targeted for restoration and thus become part of the core habitat network.

Take the example illustrated in Figure 2.8 using C-PAN quotients as a measure of interior habitat. This example uses actual C-PAN modeling outputs for evaluating two suitable patches for Red Fox (*Vulpes vulpes*)[15]. Patch A is of larger total size (approximately 988 hectares), has a larger perimeter (approximately 40.3 km), exhibits a C-PAN quotient of 0.59 (10/17), and a C-PAN rank of 583 (0.59 x 988). Patch B however is smaller (approximately 975 hectares), has a slightly smaller perimeter (approximately 38.2 km), but exhibits a larger C-PAN quotient of 0.82 (14/17), and a larger C-PAN rank of 800 (0.82 x 975). All else being equal, patch A may very well be identified as prime for conservation because it is larger. When interior habitat is taken into account however, patch B presents itself as a more favorable alternative as both the C-PAN quotient and rank (which are measures of core area and patch cohesion) are higher. This is of particular importance in conservation planning as resource managers are often faced with finding the optimal conservation solutions or reserve locations with very limited resources (i.e., funds to purchase land).

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[15] This was also a SC GAP Analysis species distribution dataset (SC GAP, 2001). It was comprised of cells which were capable of supporting Red Fox and cells which were not. Using this dataset as an input for C-PAN resulted identifying clusters of these cells for patch generation. This dataset was simply selected for demonstrative purposes.

In this example (Figure 2.8), the C-PAN modeling approach actually optimizes this decision making process by determining which patch is more cohesive and exhibits the greatest quantity of interior habitat per total area. Using this example, the smaller of the two patches is actually more optimal because it not only exhibits higher core area characteristics, but would likely be more cost effective to acquire because it is smaller in total size.

Figure 2.8 – C-PAN Quotient & Rank Metric Comparisons
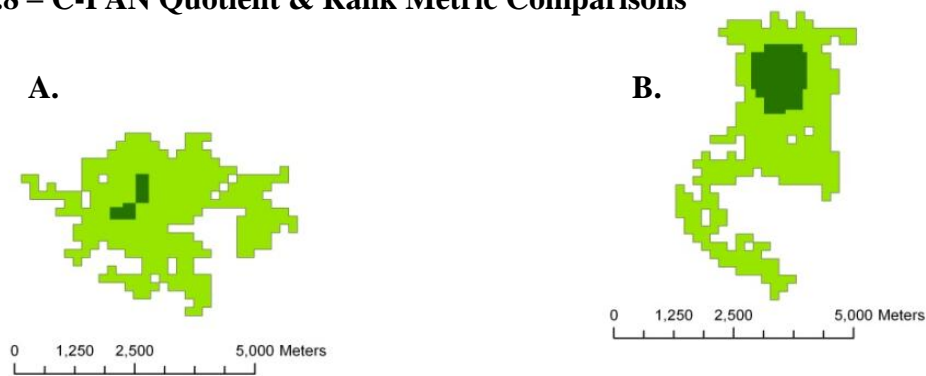
Figure 2.8: Patch A (left) is larger, has greater perimeter, and has a C-PAN quotient and rank of 0.59 and 583 respectively. Patch size alone would dictate it is more favorable over patch B (right) because it is larger. When C-PAN modeling is conducted and interior habitat is accounted for, it becomes less favorable to patch B. Figure 8 (Right): Patch B is smaller, has a shorter perimeter, but exhibits a higher C-PAN quotient and rank of 0.82 and 800 respectively when compared to patch A. In ranking the two suitable habitat patches, patch B becomes a more optimal alternative because it exhibits greater interior habitat yet is potentially more feasible to enroll in some form of conservation effort because it is smaller in size.

In addition to the empirical and theoretical underpinnings and benefits from identifying cohesive habitat patches of the largest size, there is perhaps greater utility in ranking sites of intermediate size using this modeling method. Such ranking may allow users to determine optimal scales for conserving particular species and also identify thresholds at which patches of a certain size become statistically unique on a given landscape using the LCI. The C-PAN value and C-PAN quotient may also prove to be

useful metrics for ranking sites based on core habitat requirements and priority. The C-PAN quotient could also be coupled with a wide variety of additional evaluative landscape matrices. Leitao et al. (2006) outlines numerous measures[16] which could prove useful in helping resource managers select and prioritize amongst sites/patches for conservation action. Habitat patches of any user-defined size derived from this modeling method could easily be evaluated using the C-PAN quotient and any combination of these measuring techniques. Moreover, the data structure and file type of this methods outputs would not require the use of additionally complicated programs such as FRAGSTATS; each of these landscape matrices could be evaluated locally within the GIS.

C-PAN as a Decision Support Tool

This modeling method also has the potential to be used as a decision support tool by any number of users. The C-PAN patch model provides users with the ability to rank candidate sites based spatial metrics of core area and patch cohesion. Such ranking could be used for identifying optimal conservation reserves or provide anchor patches as part of a conservation network. Outputs from this modeling method that identify candidate patches could easily be layered using widely accepted suitability techniques. Such an analysis may prove useful in identifying optimal areas for protecting multiple species

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[16] Some of which include: patch richness (PR), class area proportion (CAP), patch number / patch density (PN / PD), mean patch size (AREA_MN / AREA_AM, shape (SHAPE), radius of gyration (GYRATE), contagion (CONTAG), edge contrast (ECON), euclidean nearest neighbor (ENN), and proximity (PROX). These are metrics which can be used to rank and select among sites.

with particular patch size or range requirements; this would be analogous to processes used in reserve selection optimization models[17].

Ranking sites based on the C-PAN quotient also ensures that the characteristics of core interior habitat are accounted for and included in the conservation area design process. The C-PAN approach could also be employed for other applications in conservation planning. Several such applications could include deriving conservation schemes associated with land tenure and pinpointing candidate sites for habitat restoration or triage. Additionally, C-PAN could even be used to aid planners in identifying habitat areas that may be at risk to further habitat fragmentation, threatened by pollution, or diminished by encroachment of competing land uses.

Finally, the C-PAN modeling pilot work that has been presented here represents yet another unique application and use of GAP related data. Using species range distributions as input datasets is potentially useful for this modeling method because they often incorporate all suitable land cover types for the species in question. That being said however, virtually any dataset could serve as the input for the C-PAN methodology. Simple land cover may well be inserted to identify the largest and most cohesive patch of any one class or combination of classes. Similarly, possible applications exist outside of the resource conservation discipline. One could easily use datasets such as impervious surface or vacant land as inputs. The results of such a modeling effort could aid users of

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[17] C-PAN patches are by design, highly cohesive and core rich. These are known characteristics in ecological theory and empirically supported research critical to sustaining viable populations of edge-sensitive species. Coupling these modeled boundaries with additional characteristics such as habitat quality, species distributions etc. could be potentially beneficial in further ranking sites based on their ability to optimize these characteristics within a conservation network.

other disciplines in identifying cohesive regions of a particular size that exhibit a wide range of user-defined attributes.

Based on these concepts, the C-PAN modeling approach may add utility to conservation reserve design through the prioritization of candidate sites by centering patch modeling on core/interior habitat. Once identified, the C-PAN modeling approach expands from the concentric core to include the contiguous network of suitable habitat associated with the patch. The C-PAN quotient and rank metrics then make it possible to grade habitat patches based on the respective proportion of cohesive interior habitat and total area. The C-PAN modeling approach of assessing habitat patches from the core outward using an overlay technique represents a fundamentally different alternative for modeling patches. As the remainder of this work indicates, it has the definite potential to aid resource managers in discerning which patches are the most optimal based on interior core habitat, patch cohesion, and size.

C-PAN Model Strengths, Weaknesses, Assumptions and Limitations

By design, the C-PAN approach is most appropriate for use on species requiring substantial core area and those sensitive to edge characteristics. This model searches the landscape for highly cohesive patches with substantial core area within an existing GIS framework. The elegant aggregation and overlay process used by the model allows for patches core rich and cohesive patches to be derived. This appears to be an improvement over highly parameterized approaches which utilize region-growing components for generating patches (discussed in detail in Chapter 3).

The C-PAN approach is also intended to serve as an alternative approach to heavily parameterized patch modeling methods when species-specific parameterization data are little or not known. Additionally the Landscape Cohesion Index (LCI) that is generated as part of the patch generation proves potentially beneficial for those also attempting to measure fragmentation metrics across multiple sites or landscapes and delineate patches based on the "statistical uniqueness" of their core composition. This frees the user from selecting potentially unknown parameter settings when using other approaches and allows for a choice to be made based on a measure of patch uniqueness in the landscape.

As the C-PAN approach is highly iterative and computationally intense, processing time is worth discussing here. Using a 90 x 90 meter habitat dataset spanning a study area over 330,000 square kilometers, the C-PAN model took approximately 7 hours of processing time on a 2 gigahertz dual core Windows based lab machine (512 mb ram). The majority of this processing time however is devoted to generating the LCI dataset from which patches are generated. Once this dataset is created, patches with any desired core composition can be generated in a matter of seconds. Also worth pointing out here, the C-PAN approach was fed into a cloud computing program (CONDOR, http://www.cs.wisc.edu/condor/) which parsed out the parallel iterative sequences of the model; this reduced the total processing time from 7 hours to 7 minutes[18].

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[18] CONDOR is a cloud computing program which allows for parallel processing of large problems. The C-PAN model is highly iterative in its aggregation process which establishes LCI scores. Providing CONDOR with the underlying C-PAN modeling script allows for the parallel process of the model to be computed simultaneously. This improves processing time by orders of magnitude.

The moving window used during the aggregation and searching processes of the C-PAN model is potentially sensitive to the starting position of the search and the boundary of the study area being evaluated. This means that habitat cohesion is potentially underrepresented at the immediate fringe of the study area being evaluated. The extent of this potential impact is a function of the input dataset scale or cell size. In fine scale datasets this potential underrepresentation will be only a few meters while in coarse scale datasets underrepresentation of patches may persist at greater distances from the study area boundary. It is worth pointing out however that this issue persists in any analysis which uses a moving window and is not a limitation unique to this approach. Here it can be addressed by relaxing the LCI patch growing parameter, which will expand the patch to include areas with lower continuity values that resulted from their study area edge proximity.

The C-PAN approach quantifies landscape pattern and emphasizes structural connectivity within the habitat patches. As a structurally based modeling approach, it is not intended to model landscape processes beyond the theoretical and empirically supported evidence that many landscape processes are captured in large and cohesive reserves. This approach is not intended to be used as substitute for PVA or SEPM analysis which evaluates processes such as species populations within patches and dispersal of individuals between them. Finally, like any other patch generation tool, the C-PAN approach cannot create a potentially viable biological reserve network on its own, only the reserve's fundamental component parts, the patch. Thus this author's main objective was to provide a more elegant means of generating biologically viable planning

units from which to choose when designing, selecting, and connecting patches that could be used as part of a comprehensive conservation plan.

C-PAN Model Conclusions

The primary goal of this objective was to develop a habitat patch modeling approach that focuses on maximizing the spatial metrics of reserve cohesion and core area with minimal user parameterization. While continual refinement of any model is necessary, this goal has largely been met. As a descriptive and structural based model, it will aid in identifying those tracts of habitat that remain intact and pose potentially the greatest biodiversity related benefits for including in some sort of conservation scheme. Based in theory and empirical evidence, the aggregation process within C-PAN produces new spatial outputs for delineating core habitat areas, provides metrics for comparing core area between patches, and maximizes patch cohesion through its iterative processing. Additionally, the C-PAN model is founded on ecological fundamentals rather than sparsely available detailed data. Finally, the C-PAN model presents potentially smaller barriers of entry to practitioners because it does not require complex model parameterization and operates entirely within existing GISs with commonly used tools (ArcMap 9.3 & Spatial Modeler Extensions); conservation planners need only provide an input dataset and select two LCI values (which the model generates) for delineating patches.

In order further evaluate the C-PAN approach, the work that follows tested C-PAN within the context of its modeling peers. The comparative analysis that follows in

Chapter Three served two primary purposes: 1) it addressed a gap within the patch

modeling literature comparing currently utilized approaches and 2) it validated C-PAN

by evaluating how its patch outputs compared to those of currently used tools.

CHAPTER THREE:

COMPARATIVE ANALYSIS OF PATCH MODELING APPROACHES

AND C-PAN VALIDATION

Comparative Analysis Overview

Chapter Three first outlines a number of patch modeling approaches, each increasing in their level of complexity[19]. From these approaches, two patch modeling tools were chosen to compare with the C-PAN approach. Patches were generated using each approach within the Northern Appalachian/Acadian Ecoregion and the modeling outputs compared.

The comparative phase of the analysis served two primary purposes. First, it addressed the lack of relative comparison between each tool's respective outputs within the literature. As it currently stands, no such evaluation exists. Having evaluated the metrics of each approach's outputs has shed light on their potential strengths and weaknesses. Second, the analysis conducted aided in the validation of the C-PAN modeling approach as a potentially valid and useful tool. This is accomplished in large part by comparing C-PAN derived patch outputs with those derived by its present day modeling peers.

Patch metrics of area, edge/area ratio, average nearest neighbor, and a measure of patch naturalness were evaluated. The comparative analysis also evaluated how well each

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[19] Model complexity ranges both in terms of the technical knowhow and the data requirements required for parameterization and use of a particular model.

approach's patches captured the last remaining wild places within the ecoregion. These metrics are discussed and the Chapter concludes with an assessment of C-PANs performance when compared to the other two approaches.

Introduction to Patch Modeling Approaches

Modeling approaches often substitute potential usefulness with complexity and vice versa. Sisk et al. (2002) observed that when simpler modeling alternatives adequately rank and discriminate among alternative outcomes they are more likely to be used to help solve actual problems. Basic patch/reserve design approaches focus primarily on the spatial attributes of the patch such as size, quantity, proximity, connectivity, shape, and core area that are believed to support natural population dynamics and maintain the resiliency of populations to environmental variations (Williams et al. 2005). In these approaches (Brookes 1997, With 1997, Gardner 1999, Turner et al. 2001, McGargal et al. 2002, Church et al. 2003, Theobald 2006, Beier 2007, and Girvetz and Greco, 2007), parameterization of patch occupancy or population viability components are not present. Instead, these studies rely to varying degrees on a simplifying assumption: that metrics such as size, shape, and core, in suitable form, can support the viability of certain populations. In other cases however, greater complexity may be sought.

Patch Occupancy, PVA, and SEPM Models

Patch occupancy models provide the next level of complexity and can be used to provide crude assessments of population viability (Akcakaya and Brook, 2009). These approaches (Levins 1969, Hanski et al. 1996, Lindenmayer et al. 1999) evaluate the presence or absence of a species within a patch. Some applications (Grimm et al. 2004, Moilanen 2004) added patch design parameters for spatial optimization (Akcakaya and Brook, 2009). Population Viability Models (PVAs) and/or Spatially Explicit Population Models (SEPMs) provide the highest level of modeling complexity to date. Demographically structured metapopulation models (Breininger et al. 2004, Kindvall and Bergman 2004, Ruckelshaus et al. 2004, Brook and Whitehead 2005, Wintle et al. 2005, Bowman et al. 2006, Haines et al. 2006, Maschinski and Duquesnel 2006) are most commonly used for modeling declining populations, locally abundant organisms, large dynamic landscapes, and require significant demographic data (Akcakaya and Brook, 2009).

Individual Based Models (IBMs)

Individual-based models (IBMs) further incorporate environmental stochasticity, habitat quality, and density dependencies for modeling the providence of each individual in a population. IBMs are typically utilized for analyzing very small populations, large-bodied territorial species, genetic threats, or emerging behaviors (Akcakaya and Brook, 2009). Again, however, while these complex models can provide perhaps the most detailed level of analysis within conservation planning, they are potentially limited in

application because they are reliant upon detailed demographic and behavioral data and are computationally intense for larger populations.

Patch Modeling, Comparative Analysis and C-PAN Validation Overview

The C-PAN model and the patch modeling components of Corridor Design and FunConn have been run independently as part of this work within the newly defined and scaled study area. Patch outputs for each approach have been compared and contrasted. The patch outputs have been evaluated based on two substantive categories: a) patch spatial metrics/cohesion and b) the respective ability of each approach to capture conservation targets; these are discussed in greater detail in the methods section.

Approach Selection

These approaches were chosen based on a number of factors. First, the C-PAN method was created in order to overcome potential barriers of entry found by many practitioners to spatially explicit habitat modeling and to address issues of modeling core area and spatial cohesion found in other approaches. The C-PAN approach is included here so that it can be tested at the ecoregion-scale and be validated as a potentially useful tool. The other two approaches (Corridor Design and FunConn)[20] however are widely used in present day conservation planning and have been embraced as valid patch design tools. It is believed that these approaches represent a satisfactory sampling of the current tools being used today because each employs different patch modeling techniques and parameters and each is based on varying theoretical underpinnings for addressing

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[20] Corridor Design in the Arizona Wildlands Project. FunConn in (Baldwin et al., In Press).

connectivity. Additionally, they have varying levels of modeling complexity, and they incorporate spatial metrics of patch design in their delineation of patches without incorporating parameters such as occupancy or population viability found in more complex approaches.

A conscious decision was made to compare spatial metric approaches only as C-PAN does not have any presence/absence or explicitly modeled population components. Having compared spatial metric approaches only, inferences should not be drawn regarding the occupancy or population viability potential of the patches defined by any of these approaches beyond the general theoretical assumptions that bigger, spatially coherent, and core rich patches may better support populations of edge-sensitive/core-dependent species.

Ecoregion-scale Study Area

The project study area is the Northern Appalachian/Acadian Ecoregion (Figure 3.1). This region includes significant portions of New York, Vermont, New Hampshire, and Maine within the U.S. and portions of Quebec, New Brunswick, Prince Edward Island, and Nova Scotia in Canada. Elevation within the region ranges from sea-level to over 1,500 meters. Additionally, this region is uniquely situated along a significant latitudinal gradient which separates the boreal forests of the north from the deciduous forests of the south (Trombulak, et al., 2008). Taken together, the region includes an estimated 3, 844 species of plants and animals, some 148 rare endemics, and is one of the continents top 20 ecoregions for vertebrate diversity (Trombulak et al., 2008).

Figure 3.1 – Ecoregion Study Area
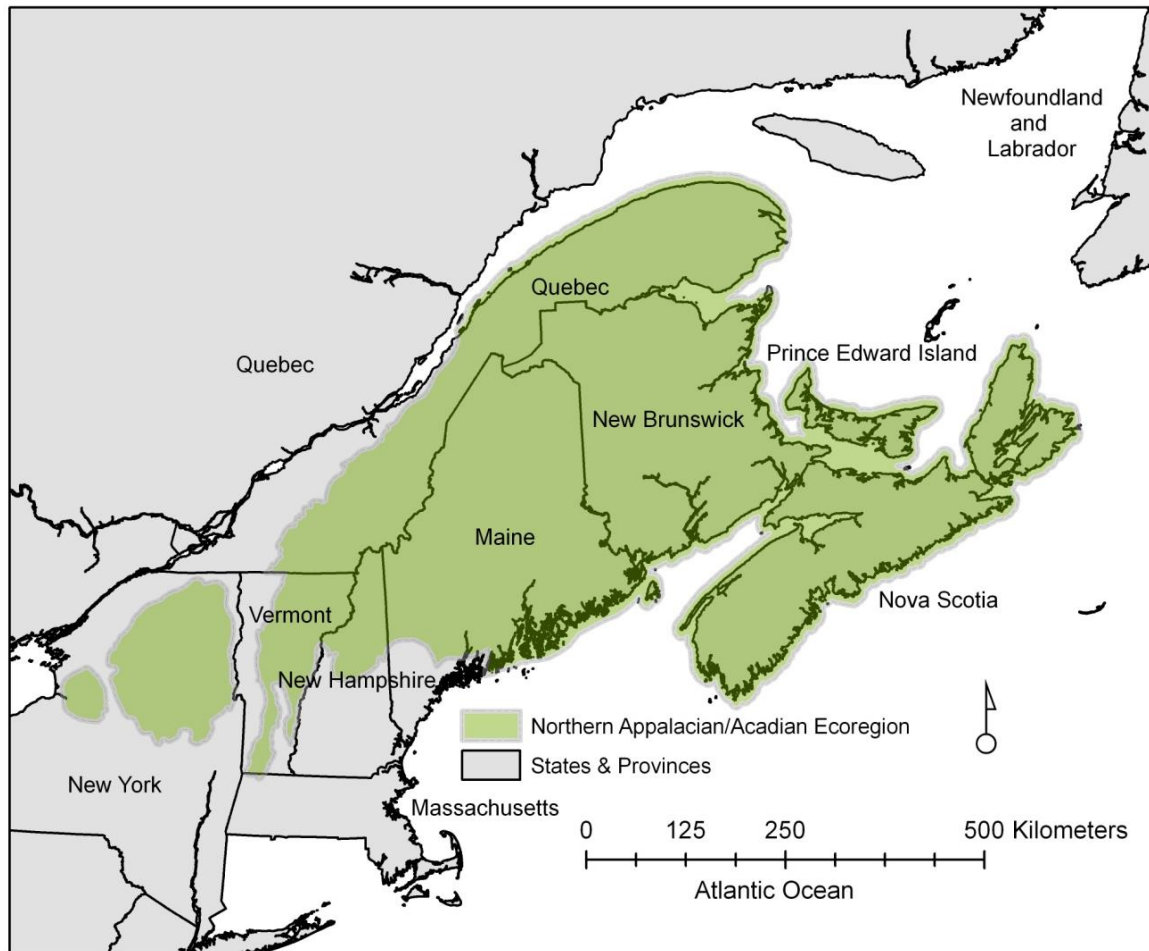
This region was selected for a number of reasons. First, and perhaps most

appropriately for any spatial analysis, the region has been widely studied and includes a

vast library of digital datasets that can be used within a GIS. Many of these datasets have

been used for past and ongoing research endeavors and have been widely evaluated to

satisfactory levels within a number of peer reviewed settings (Foster et al. 2002, Baldwin

et al. 2007, Carroll 2007, Baldwin et al. 2008, Woolmer et al. 2008, and Trombulak et al

2008). Several high quality datasets unique to this region and held by the Nature

Conservancy and cooperative researchers include, human footprint data, high resolution

land cover, geophysical characteristics, and empirically supported habitat suitability

analysis for a number of high profile vertebrate species including the Canada lynx. This

region also posses unique land use characteristics that include highly urban centers, vast

assemblages of virtually untouched wilderness, and intensely managed blocks of multi-

use land enrolled in agricultural and timber production. Additionally, consensus that

conservation efforts at the ecoregion level, as opposed to smaller scales, are most

appropriately sized to ensure the long term persistence of the greatest number of species

and ecosystems is growing (Hoctor et al. 2000, Phua and Minowa, 2005, Rouget et al.

2006, Knight et al. 2007, Trombulak et al. 2008).

Patch Modeling Methods

Each modeling approach uses different methodologies and tools for generating

modeled patch outputs. In order for a comparative analysis of these tools to take place, all

data, model parameters, and inputs must be controlled. This was accomplished by using

the same data as inputs and normalizing model parameters whenever possible. These

details are discussed more thoroughly in the methods section of each approach.

C-PAN

In addition to identifying patches of any user-defined size, the C-PAN output

delineates the LCMC patch, the patches with the greatest expanse of core or interior

habitat, and the patches with relatively little edge effects and the metrics for comparing

all other potential patches. This approach differs from other modeling approaches in that

it first identifies core and interior habitat and then extends the patch boundary outward to

encompass the surrounding habitat network. It provides the metrics of the C-PAN value, quotient, and rank for comparing habitat patches of any size with each other and the largest patch so that decision makers may optimize the inclusion of core and interior habitat into reserve design. Utilizing the C-PAN derived LCI, users can determine optimal scales for conserving specified species and ultimately thresholds at which patches of certain sizes become statistically unique on a given landscape. Based on these concepts, the C-PAN modeling approach may add utility to conservation reserve design and the prioritization of candidate sites by centering patch modeling on concentric core interior habitat and heightened patch cohesion.

The C-PAN model results represent the first set of unique patch outputs to be evaluated. Taken individually, the outputs from these 3 approaches could serve as possible candidate sites in the reserve design, selection, and/or the derivation of patches from which a more detailed population viability analysis could take place. Taken together however, they can be compared and their differences surmised. This ultimately aids in assessing the relative performance of each approach.

C-PAN Parameterization

A raster human footprint dataset (Woolmer et al. 2008) for the ecoregion was used as the input dataset for patch generation. The human footprint dataset serves as a measure of landscape "naturalness" and has been used by others in the identification of "last of the wild" areas, or those areas within the ecoregion with minimal human impact (Sanderson et al. 2002, Woolmer et al. 2008). Using this dataset for patch generation has several benefits. First, it implies that the patches being modeled may be appropriate for

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those species sensitive to landscape fragmentation (core-dwelling), this is closely aligned with the recommended use of the C-PAN approach. Secondly, utilizing an index of "naturalness" for defining patches removes species-specific data and patch parameterization assumptions found in typical focal species analysis. Third, the dataset has been peer reviewed, provides ecoregion-scale coverage, and is fine resolution (90 x 90 meters) for modeling at this scale (Sanderson et al. 2002, Woolmer et al. 2008). Finally, as "last of the wild" (LOW) patches have been generated from the results of past research, they can provide yet another set of modeled patches for comparison here. Human footprint scores ranged from 100 (high human impact) to 0 (mostly wild). Scores of 10 or less were selected as suitable cells from which patches could be generated; this is the same cutoff value that was used by Woolmer et al. (2008) for establishing the ecoregions LOW patches. Suitable cells were then reclassified to a value of 1 and all other cells converted to 0. This binary "suitable/unsuitable" dataset served as the input to the C-PAN model.

Starting the C-PAN model initiates the Landscape Cohesion Indexing (LCI) of the study area. LCI scores range from 0 (cells are not found in patches) to 200 (cells which participate in many highly cohesive patches). Upon completion, the user evaluates a histogram which illustrates scores depicting how many times a particular grid cell participates in patches of progressively larger sizes. Lower scores indicate that the cell and its neighbors are relatively fragmented and are found in smaller patches with minimal interior habitat. Conversely, higher LCI scores illustrate cells and their neighbors which are largely cohesive in their landscape distribution. Evaluating the LCI histogram allows the user to identify at what score cells become statistically unique in the landscape. This

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score is then chosen as a starting point for generating highly cohesive patches. For proposes here, the top 10% of the ecoregions LCI scores (LCI = 29) were used for delineating the core seeds of each patch. This selection generates the top 10% most cohesive patch core areas in the ecoregion.

Additionally, the C-PAN model allows for the user to establish a second cohesion parameter which constrains or expands how adjacent cells are treated when growing the patch core seeds. Cells with the top 20% LCI scores (LCI = 20) were selected for expanding the core of the patch to its full size. Scaling this parameter up or down will tighten or expand the resulting patches. Setting these two parameters results in an output that consists of patches with a LCI score of 29 (top 10%) for the core and 20 (top 20%) for adjacent cells to expand the patch. C-PAN parameters are displayed in Table 3.1.

Corridor Design

Created by Beier et al. (2007) at the University of Northern Arizona, Corridor Design has been widely used as part of the Arizona "Wildlands Project" throughout the American southwest. Designed primarily to promote connectivity conservation, Corridor Designer developed a set of spatial modeling tools. The workflow of this approach involves defining an analysis area, identifying focal species, choosing GIS factors, estimating suitability, combining factors, modeling habitat patches, modifying habitat maps, defining corridor endpoints, generating a cost surface, and evaluating corridors. This approach uses "least cost path" methods for generating the likely path an organism might take based on the cost or impedance of moving through the landscape matrix (Beier, et al., 2007).

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For purposes here, only the patch modeling component of Corridor Design has been used. Input parameters required for this process include the moving window neighborhood size, habitat suitability scores, and minimum patch areas for supporting a population and breeding occurrence. The patch delineation process used by Corridor Designer is relatively straightforward. The habitat suitability dataset serves as the input from which patches are derived. The moving window then averages suitability scores based on a user-defined size and threshold value. Cells with average scores above the user-defined quality threshold are used to delineate patches. Clusters of those cells that exceed the user-defined minimum size threshold are then assembled into patches. The output of this analysis provides the second unique set of patches within the study area.

Corridor Designer Parameterization

The corridor design patch modeling tool was parameterized to mirror the settings of the C-PAN tool as closely as possible. Coincidentally, this resulted in the tool being set to be as edge-sensitive (most discriminatory) as the tool recommends when delineating patches. First, the input HF dataset was the same as that used in the C-PAN approach. Second, the moving window was set to 27 x 27 cells (the maximum size recommended by the tool) which parameterizes the tool to be edge-sensitive. The habitat quality threshold was set to 1, which ensured that patches are comprised entirely of suitable habitat. Finally, the minimum breeding and population patch sizes were set to 661 hectares, the smallest size patch that was delineated by the C-PAN model. Parameterization of this approach is provided in Table 3.1.

FunConn

Developed by Theobald et al. (2006) at Colorado State University, FunConn aims to delineate functional patches based on organism-specific parameters. This method identifies functional patches based on an organism's foraging habits and its ability to move between patches (Girvetz and Greco, 2007). The workflow for FunConn begins with creating a habitat quality surface, defining functional patches, building a landscape network, delineating a points, lines, and polygons network, developing the minimum spanning tree, calculating edge, neighborhood and node calculations, shortest path derivation, and generating a node-edge-node / node-path-node distance matrix. FunConn utilizes graph theory as its basis for addressing issues of connectivity between individual patches (Theobald, et al., 2006).

Again, only the patch modeling components of this approach was used for this comparative analysis. The input parameters required for this process include the maximum foraging radius, minimum patch size, core habitat percentage, and a resource quality threshold. The outputs of this approach's patch modeling component provides the third set of unique patches to be evaluated.

The Define Functional Patches tool within FunConn aims to delineate functional patches based on organism-specific parameters. This tool relies on several user-defined parameters to be input which includes a resource quality threshold, the minimum patch size, the maximum foraging radius, and the core habitat percentage. Each of these parameters can be thought of as a selection criterion that continually culls all available patches leaving only those that meet all of the required structural characteristics.

FunConn Parameterization

To the extent possible, each parameter value was set to mimic those of the C-PAN and Corridor Design approaches. The resource quality threshold establishes the minimum habitat quality to be considered for region-grouping or assembling the first cut of habitat patches. The higher the threshold value (necessary for species that are more restrictive in their habitat requirements) the more restrictive the patch selection process will become; this was set to 1 as in the other approaches.

The minimum patch size parameter is also used as a measure for eliminating patches that are not large enough to sustain the focal species; this was set to 661 hectares just as in the other approaches. Similarly, the maximum foraging radius parameter attempts to incorporate a measure of how far an animal travels during foraging, to aid in identifying patches that meet minimum size requirements. The minimum foraging radius was set to 1,215 meters to match half the approximate width of 27 x 27 window utilized in the Corridor Design approach.

Finally, the core habitat percentage parameter refines again which patches are functionally suitable by aiming to add a measure of the species interior versus edge habitat requirements. Those species negatively affected by edge (edge negative species: lynx) would require a higher value to be entered, while those species that are indifferent to edge (edge neutral: bobcat) and positively affected by edge (edge positive: mountain lion) would require lower values to be entered as the patches for these species need not be as restrictive (Theobald et al. 2006). A value of 100 was selected to maximize this measure. Parameterization of this approach is provided in Table 3.1.

Table 3.1 – Patch Modeling Parameterization

Patch Modeling Parameterization			
	C-PAN	Corridor Design	FunConn
LCI Core Value	29	NA	NA
LCI Grow Value	20	NA	NA
Habitat Quality Threshold	1	1	1
Min Patch Size	661	661	661
Moving Window Size	NA	27 x 27	1,215
Core Habitat Requirement	NA	NA	100

Efforts were taken to parameterize all three patch modeling approaches as closely as possible. The habitat quality threshold of (1) was utilized for all three approaches. The minimum patch size (661 hectares) was also set to be equal across approaches; this represented the smallest patch size delineated from the C-PAN model. The maximum recommended moving window from Corridor Designer (27 x 27) was scaled to a value of 1,215 meters for the FunConn approach; this represents the minimum foraging radius that the model requires. All other parameters that were unique to one approach and not the others are represented as NA.

Comparative Analysis and C-PAN Validation Methods

The comparative, quantitative analysis highlighted some of the inherent strengths, weaknesses, and assumptions associated with each of these modeling approaches. This was accomplished by evaluating two primary components of each approach's patch outputs: 1) patch spatial metrics/cohesion and 2) how well each approach captured conservation targets.

Spatial Metrics and Cohesion

The spatial metrics analysis included an evaluation of the physical attributes and dimensions associated with each individual patch. Spatial statistics were generated for each individual patch and for the average of all patches from each approach. These metrics were used to discern which approach provides patch outputs that are optimally

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orientated from a spatial perspective. This work evaluated patch area, edge/area ratios, and average nearest neighbor metrics. These metrics are reported in the following summary section that discusses and evaluates each model's patch cohesion performance.

Ability to Capture Conservation Targets

The conservation targets evaluated here were derived from preexisting datasets that have been widely accepted in a number of peer reviewed and conservation planning initiatives for the Northern Appalachian/Acadian Ecoregion (Woolmer et al. 2008, Trombulak et al. 2008). They include average human footprint scores within the patch, LOW capture, and omission/commission values for capturing LOW areas. These preexisting targets were all derived from the Human Footprint (HF) dataset; the HF dataset was used in this research as the input for patch derivation in each scenario. This common link led to an analysis of conservation target capture. The target capture analysis determined what proportions of these distributions were captured within the boundaries of the modeled patch outputs. This analysis determined which approach best met the goals of protecting these resources within this region.

Conservation targets were reported in three ways: first, as the total percentage captured by each patch output; second, the amount of conservation target related land not captured by the patch (omission); third, the amount of non-conservation target related land within each patch (commission). These output values were evaluated within a matrix depicting the reported results of each approach. From the evaluation conducted as part of this work, a conclusion was drawn regarding each approach's ability to meet and include

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specific conservation-related goals and compared the relative effectiveness and efficiency of each model.

Conservation Target Distributions

Wild areas within the ecoregion were delineated by Woolmer et al. (2008) through extracting HF scores of ≤ 10. While these areas ranged in size from < 1 to 1,930 km^2, most of them (80.7%) are ≤ 1 km^2 in size and are highly fragmented. Last of the Wild (LOW) areas were then delineated by extracting the top 10% largest blocks of wild areas for each sub-region within the ecoregion. These areas are delineated in Figure 3.2.

Figure 3.2 – Last of the Wild (LOW) Areas
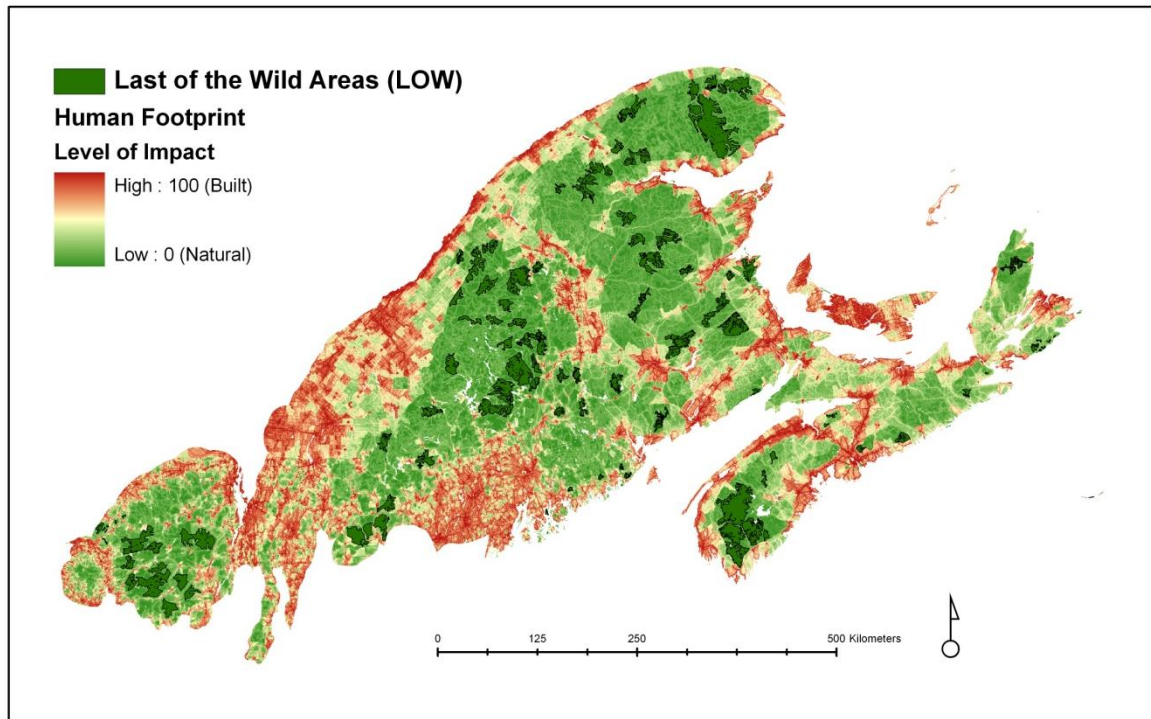
LOW areas represent the top 10% largest areas of HF scores ≤10 within each subregion. There are 120 LOW areas delineated ranging in size from 237 to 193,108 ha. The average size of LOW areas is 17,111 ha.

Patch Modeling Results

   Patch modeling results for each approach have been provided here separately. Spatial metric and conservation target capture comparisons have been provided in the following section. This was done as part of this work because no such comparison currently exists among these approaches.

C-PAN

The C-PAN derived LCI indicated that scores ≥ 29 were among the top 10% for the ecoregion while scores ≥ 20 were in the top 20%. The highest LCI score observed in the ecoregion was 176, which represents cells in regions that were highly cohesive and largely unfragmented. LCI Scores are depicted in tabular form (Figures 3.3) and graphic form (Figure 3.4). C-PAN patches are depicted in Figure 3.5 followed by Corridor Designer patches (Figure 3.6) and FunConn patches (Figure 3.7).

Figure 3.3 – Landscape Cohesion Index (LCI) Distribution
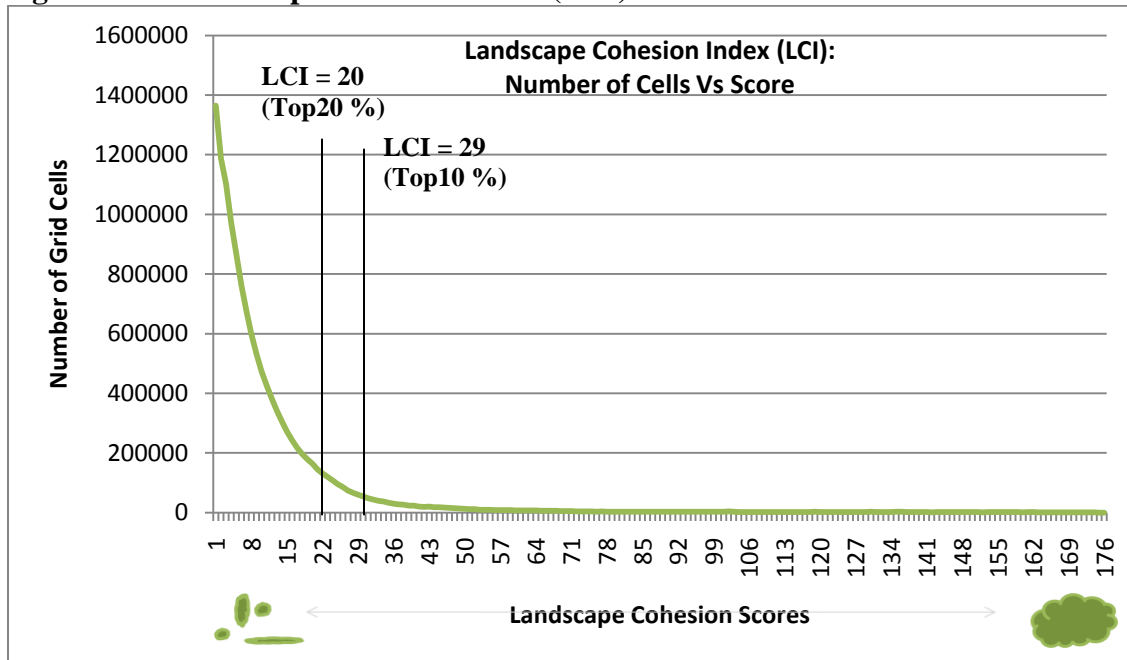
Represents the Landscape Cohesion Index scores for the ecoregion. Small values to the left represent numerous grid cells that are part of small and fragmented patches. Large values to the right represent relatively few grid cells that are part of largely contiguous and cohesive patches with substantial core area. These LCI scores allow the user to evaluate landscape fragmentation and determine potentially useful statistical thresholds (top 10% etc) for determining patch delineation parameters. Establishing patch delineation measures this way allows for patches to be delineated based on how "unique" their characteristics are throughout the landscape as opposed to species-specific parameterization.

Figure 3.4 – Landscape Contiguity Index (LCI) Spatial Distribution
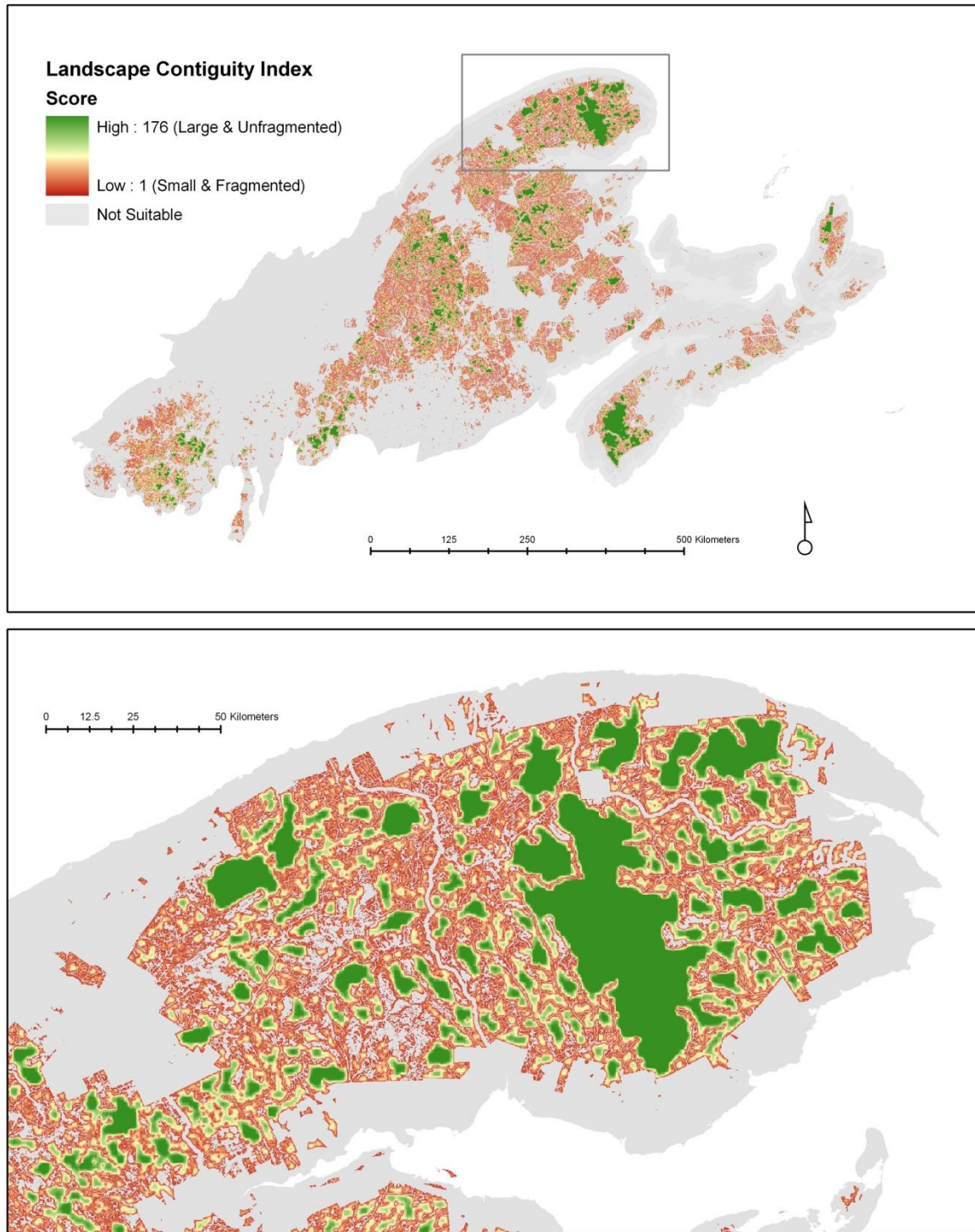
Top: LCI scores range from 0 to 176 for the ecoregion. Areas with low scores are comprised of relatively small and fragmented patches. Areas with high scores are comprised of larger more contiguous patches. Areas in gray are highly fragmented and are not part of any patch.
Bottom: Inset of landscape fragmentation and LCI scores.

Figure 3.5 – C-PAN Patches
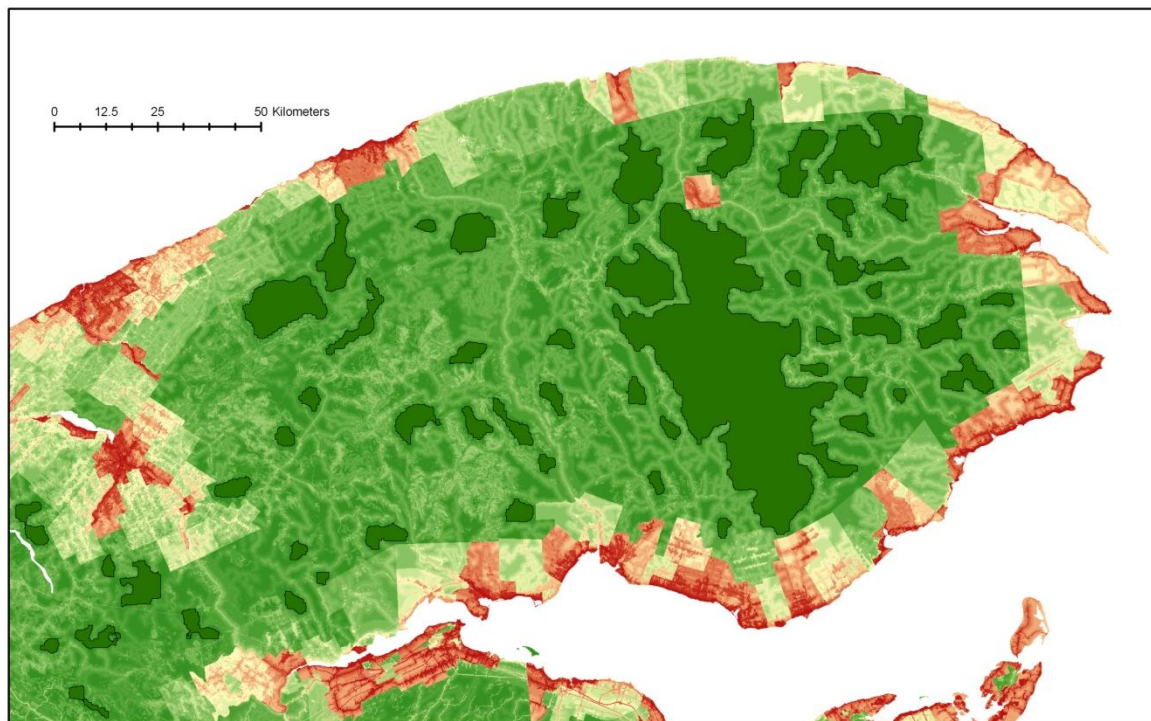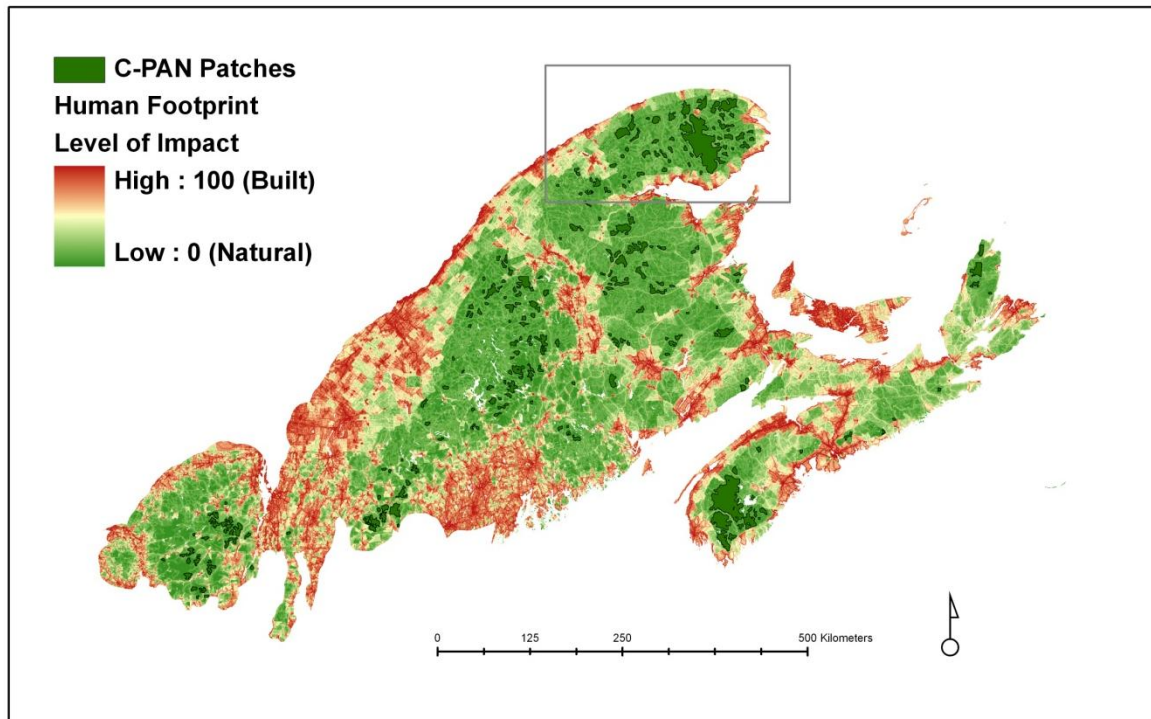
C-PAN derived patches for the ecoregion (N = 225). Patches range in size from 661 to 178,212 ha with an average size of 5,883 ha.

Corridor Design

Figure 3.6 – Corridor Design Patches
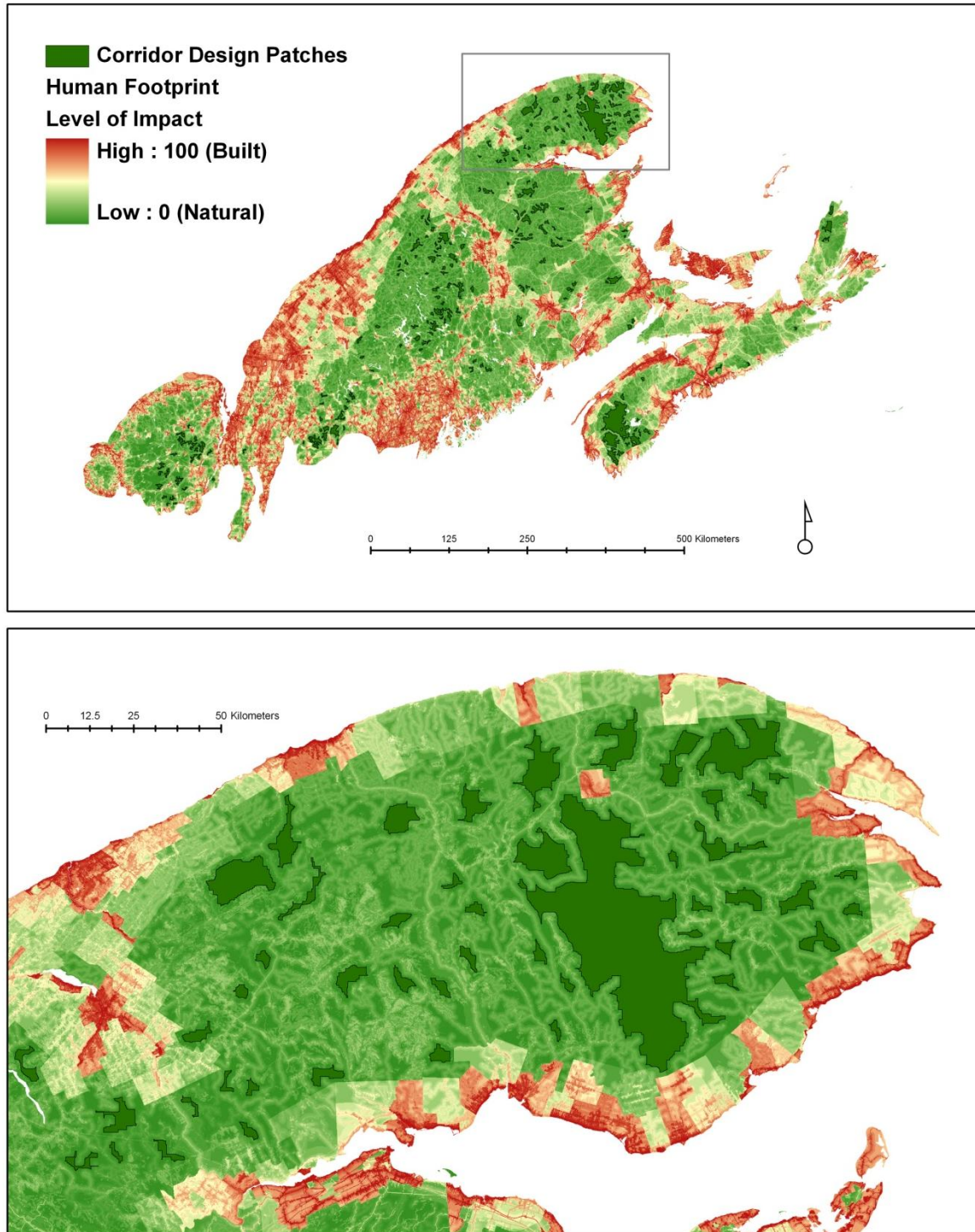
Corridor Design derived patches for the ecoregion (N = 209). Patches range in size from 664 to 156,799 ha with an average size of 4,502 ha.

FunConn

Figure 3.7 – FunConn Patches
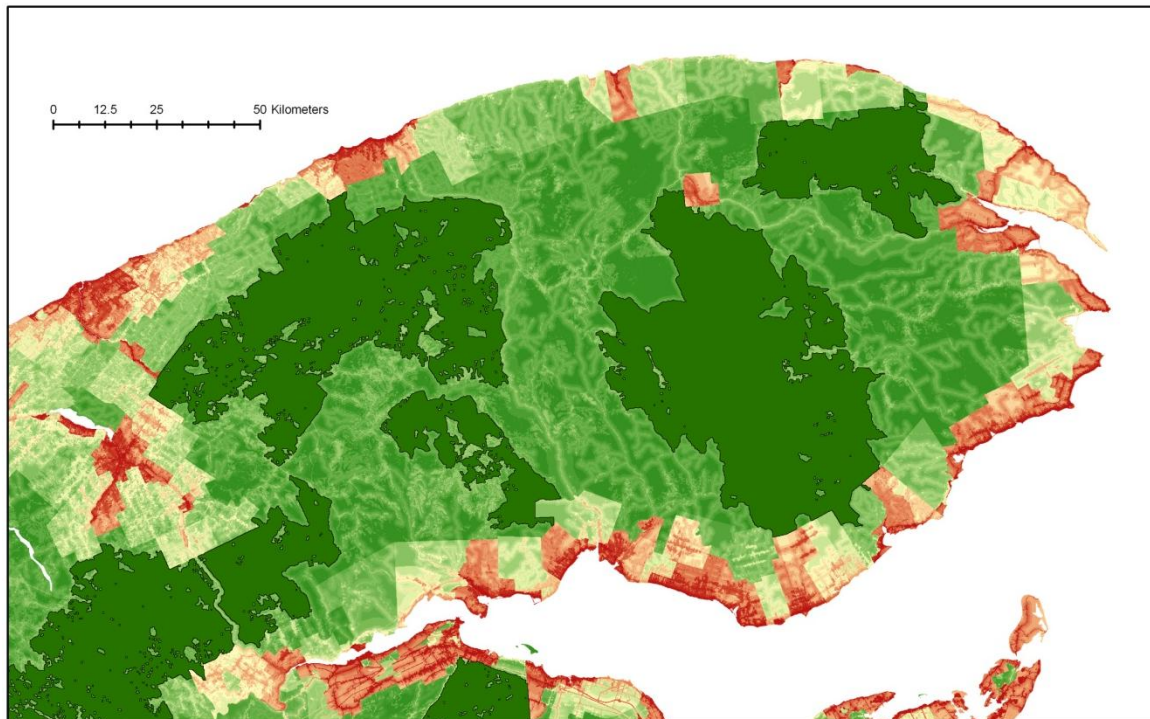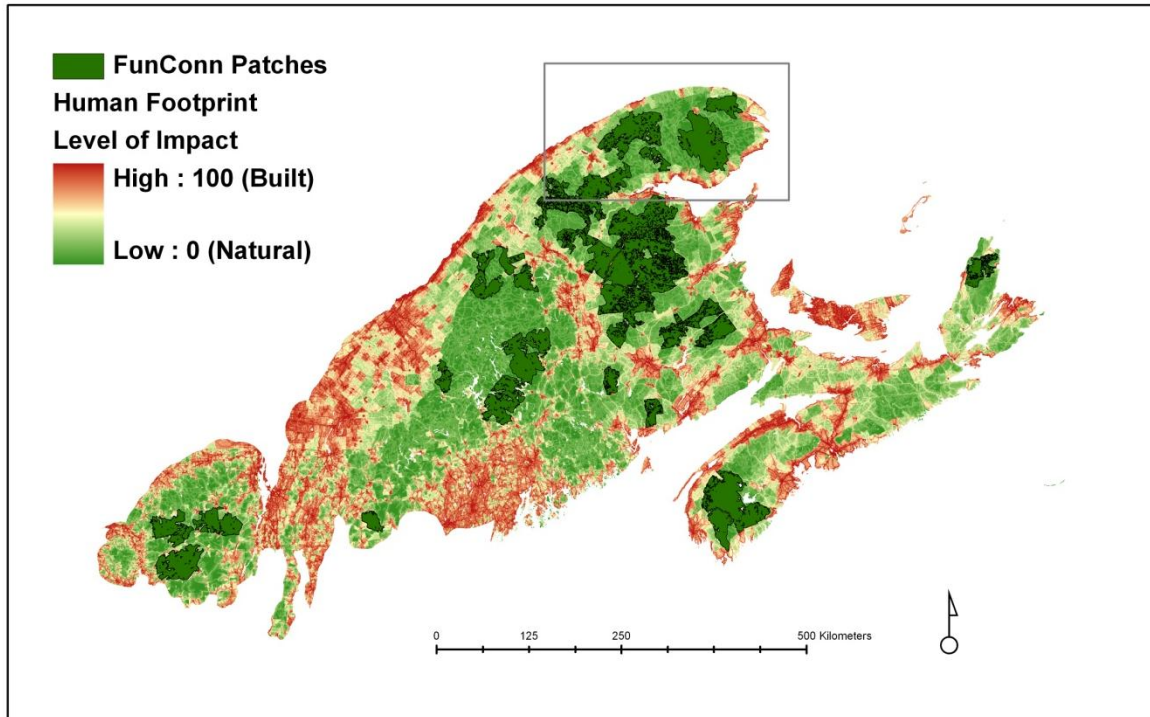
C-PAN derived patches for the ecoregion (N = 31). Patches range in size from 1,444 to 4,609,512 ha with an average size of 148,693 ha.

Comparative Analysis: C-PAN, Corridor Design, and FunConn

The spatial results of the C-PAN patch modeling approach were compared to those of Corridor Design and FunConn. Spatial metrics associated with patch area included the minimum, maximum, and average patch size, total patch area, and patch area standard deviation. Edge/area ratio metrics of minimum, maximum, and average edge/area ratios were also compared[21]. An average nearest neighbor analysis of patch distributions was also conducted. The results of this comparative analysis are discussed below.

Spatial Metrics and Cohesion: Patch Area

The minimum patch area observed for C-PAN (N = 225) was 661 ha, Corridor Design (N = 209) was 66 ha, and FunConn (N = 31) was 1,444 ha. As the C-PAN approach was run first, the observed patch size of 661 ha was set as the minimum patch size for the other approaches. Corridor design delineated a nearly identical patch size (664 ha) while the minimum patch size delineated by FunConn was more than twice as large (1,444 ha). Corridor Design exhibited the smallest maximum patch size (156,799 ha) followed closely by C-PAN (178,212 ha). The maximum patch size for FunConn however was over three times greater (561,099 ha). Corridor Design also reported the smallest total patch area (940,950 ha) followed by C-PAN (1,323,755 ha) and FunConn (4,609,512 ha). Similarly, Corridor design exhibited the smallest average patch area (4,502 ha) and standard deviation (14,331 ha), followed by C-PAN (5,883 ha, std dev

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[21] These metrics are appropriate for measuring the cohesive nature of patches. More cohesive patches will exhibit lower edge/area rations and vice versa.

16,787) and FunConn (148, 693 ha and std dev 119,459). These values are provided in

Table 3.2 and further compared in Figure 3.8.

Table 3.2 - Patch Metrics: Patch Area Comparison

Patch Metrics: Patch Area			
	C-PAN	Corridor Design	FunConn
N	225	209	31
Min	661	664	1,444
Max	178,212	156,799	561,099
Sum	1,323,755	940,950	4,609,512
Mean	5,883	4,502	148,693
Std Dev	16,787	14,331	119,459

While C-PAN produced the greatest number of patches, tighter parameterization would result in additional patch discrimination. Corridor Design however was parameterized as tightly as the tool recommends indicating that honing in on a more select group of patches may be limited. Similarly, FunConn was also very tightly parameterized, this resulted in very few, and very large patches being delineated. While FunConn delineated fewer patches, their large size may pose difficulties for selecting priority sites for implementation.

Figure 3.8 - Patch Metrics: Patch Area Comparison
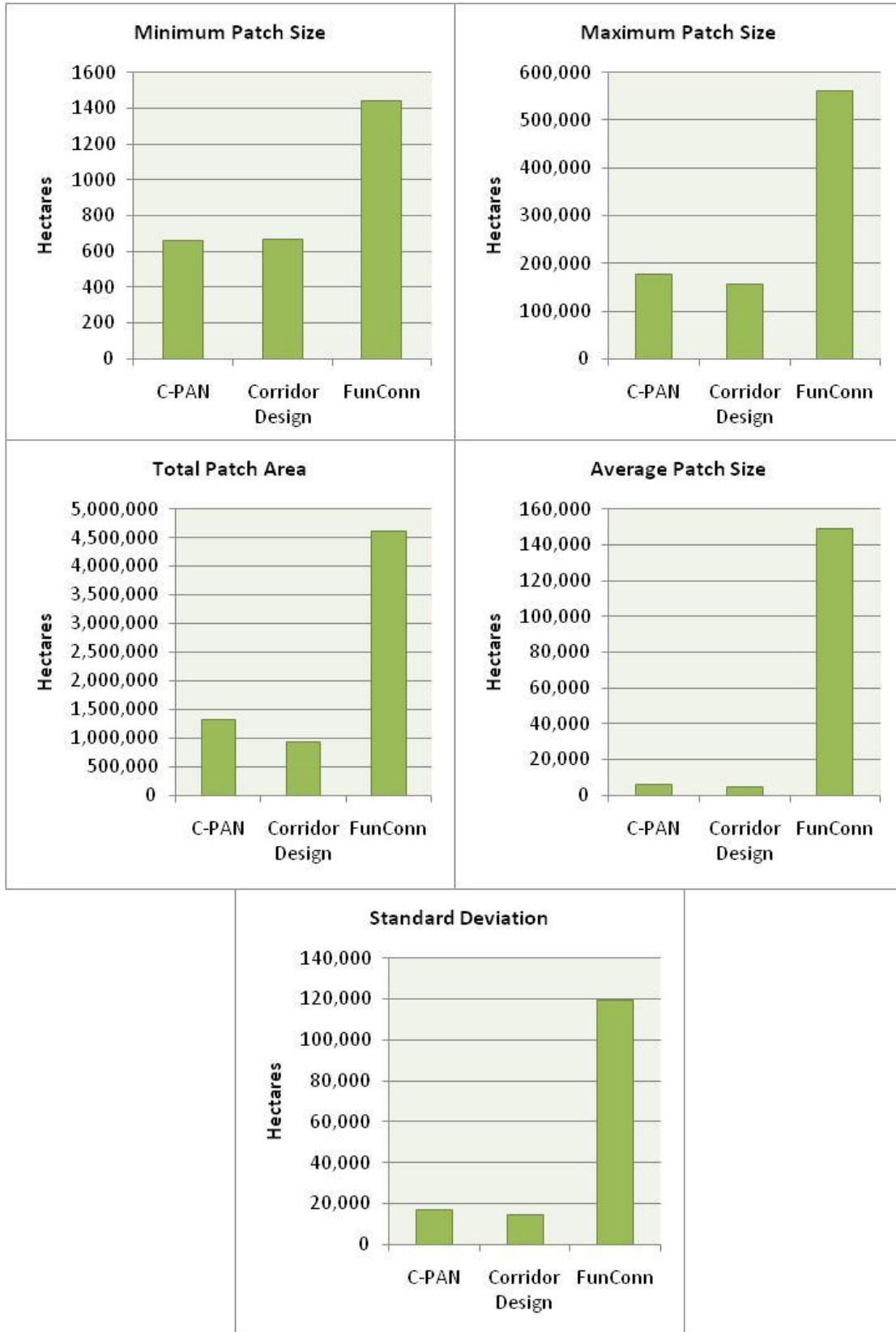
Spatial Metrics and Cohesion: Edge/Area Ratio

Edge/Area (EA) ratio comparisons indicate that the C-PAN approach exhibits the

best minimum (0.000238) compared to FunConn (0.000254) and Corridor Design

(0.000286). FunConn reported the best maximum EA ratio for any one patch (0.001695)

followed by C-PAN (0.001912) and Corridor Design (0.003805). The average EA ratio

for C-PAN was 0.00117 (std dev. 0.000348), 0.00177 (std dev. 0.000695) for Corridor

Design and 0.00068 (0.000303) for FunConn. FunConn reported the best average EA

ration when compared to C-PAN and Corridor Design. This is attributable to the very

large average patch size (148, 693 ha) compared to 5,883 ha for C-PAN and 4,502 ha for

Corridor Design. For patches of similar size derived by Corridor Design, C-PAN

produced patches with better EA ratios. These values are provided in Table 3.3 and

further compared in Figure 3.9.

Table 3.3 – Patch Metrics: Edge/Area Ratio Comparison

Patch Metrics: Edge/Area Ratio			
	C-PAN	Corridor Design	FunConn
N	225	209	31
Min	0.000238	0.000286	0.000254
Max	0.001912	0.003805	0.001695
Sum	0.263201	0.36985	0.021066
Mean	0.00117	0.00177	0.00068
Std Dev	0.000348	0.000695	0.000303

Smaller values indicate potentially less edge effects within a patch. At high discrimination, C-PAN reported the patch with the best EA ratio from all approaches. While FunConn performed best followed by C-PAN and Corridor Design in other metrics of EA ratio, this is attributable to the very large size of the FunConn patches. Parameterized this way, FunConn was not able to derive patches of small size like the other approaches. Relaxing the parameterization of C-PAN and Corridor Design however would lead to EA results more similar to FunConn.

Figure 3.9 – Patch Metrics: Edge/Area Ration Comparison

Spatial Metrics and Cohesion: Average Nearest Neighbor

The average nearest neighbor analysis indicated that the C-PAN and Corridor Design patches were highly clustered with Z-scores of -11.68 and -12.29 respectively. C-PAN and Corridor design patch distributions each exhibited a significance level of 0.01 and a critical value of -2.58 (highly clustered). The patch distribution for FunConn exhibited a Z-score of -0.1, indicating a random distribution across the landscape. This data is presented in Table 3.4.

Table 3.4 – Patch Metrics: Average Nearest Neighbor Analysis

Patch Metrics: Average Nearest Neighbor				
	Observed Mean Distance / Expected Mean Distance	Z Score	Significance Level	Critical Value
C-PAN	0.59	-11.68	0.01	-2.58
Corridor Design	0.56	-12.29	0.01	-2.58
FunConn	0.99	-0.1	x	X

Patch distributions for C-PAN and Corridor Design were highly clustered. There is less than a 1% likelihood that this clustered pattern could be the result of random chance. The FunConn patch distribution was randomly distributed across the landscape.

Conservation Target Capture: Average Human Footprint Score

The average HF score is a measure of patch naturalness. As HF scores of ≤ 10 were used for patch generation in all three approaches, the average HF score of the resulting patches should be, by design, low. C-PAN and Corridor Design patches had the lowest average HF scores (1.76 and 1.51 respectively). FunConn patches exhibited a slightly higher average HF score (5.10). This indicated that C-PAN and Corridor design

patches were "more natural" and less impacted by anthropocentric activities than were

FunConn patches. HF metrics can be found in Table 3.5 and Figure 3.10.

Table 3.5 – Conservation Target Capture: Average Human Footprint Score

Conservation Target Capture: Average Human Footprint Score				
	Min	Max	Mean	Std Dev
C-PAN	0	10	1.76	2.17
Corridor Design	0	10	1.51	1.95
FunConn	0	99	5.10	6.04

C-PAN and Corridor Design patches exhibited the most "natural" characteristics. FunConn patches exhibited higher HF scores within them. This is attributable to the less selective region growing process that is unique to the FunConn approach.

Figure 3.10 – Conservation Target Capture: Average Human Footprint Score
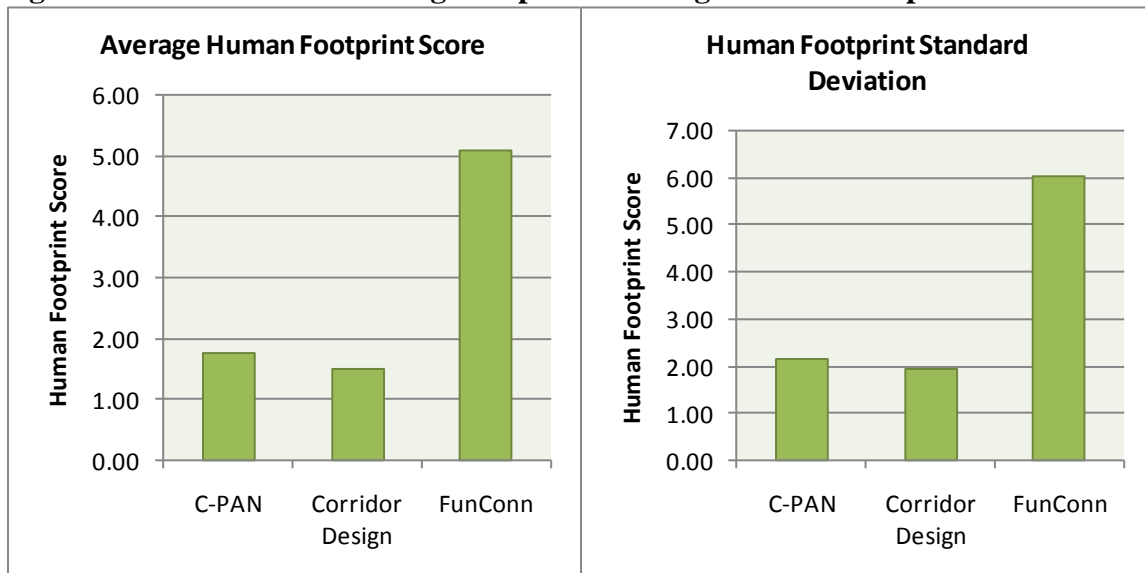
Conservation Target Capture: Last of the Wild

Under highly selective patch edge parameterization, FunConn captured 72.07% of the last of LOW areas followed by C-PAN at 40.46% and Corridor Design at 37.24%. As with the patch area and EA ratios reported earlier, the higher capture rate achieved by FunConn is attributable to the large, less discriminatory patches; whereas C-PAN and Corridor design achieve less LOW capture because their respective patches tended to be smaller and more selective. This is also directly analogous to target omission across the three approaches. FunConn exhibits the smallest LOW omission followed by C-PAN and Corridor Design at 59.54% and 68.80% respectively. Conversely however, the large patches delineated by FunConn contributed to the greatest commission area among the three approaches. Commission area (patch area that does not contribute to capturing the conservation target) for FunConn (67.90%) was nearly twice that of C-PAN and Corridor Design at 37.24% and 31.91% respectively.

Figure 3.11 on the following page provides a conceptual diagram of patch target capture, omission, and commission. Additionally, a measure of model efficiency was developed by dividing the total target captured area with the total commission area for each approach. The "capture to commission ratio" (CC) indicates hectares of target capture for every hectare of commission area. Corridor Design reported the best CC ratio at 2.13 followed by C-PAN at 1.68 and FunConn at 0.68. A measure of overall modeling effectiveness was also developed by dividing total target captured area with the total omission area for each approach. The "capture to omission ratio" (CO) indicates hectares of target capture for every hectare of omission area. FunConn reported the best CO ratio

of 2.58 compared to 0.68 for C-PAN and 0.45 for Corridor Design. These comparisons

are outlined in Table 3.6.

Figure 3.11 – Patch & Target Capture Concept
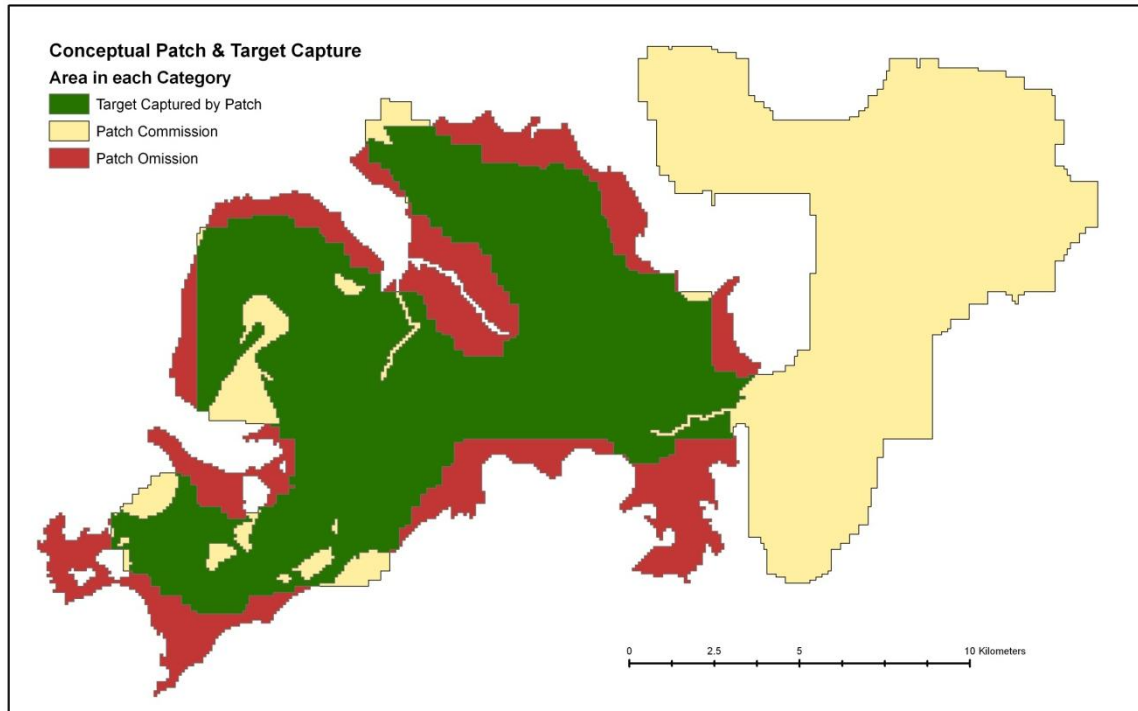
Target capture, patch commission, and patch omission is derived via performing a union with the patch outputs of each approach and the LOW target areas. Areas in green represent portions of the LOW that were captured within the boundaries of a patch modeling approach. Areas in tan indicate areas delineated by the patch modeling approach that do not capture a LOW area (commission). Areas in red indicate LOW areas that were not captured by the modeling approaches patch output (omission).

Table 3.6 – Conservation Target Capture: Commission & Omission

Conservation Target Capture: Last of the Wild (LOW)			
	Target Captured	Commission	Target Omission
C-PAN	830,728	493,026	122,2636
	40.46%	37.24%	59.54%
Corridor Design	640,707	300,242	1,412,657
	31.20%	31.91%	68.80%
FunConn	1,479,807	3,129,704	573,557
	72.07%	67.90%	27.93%
	(Patch and LOW)	(Patch Only)	(LOW Only)
	Capture to Commission Ratio (Capture / Commission)		Capture to Omission Ratio (Capture / Omission)
C-PAN (High)	1.68		0.68
Corridor Design	2.13		0.45
FunConn	0.47		2.58

At high selectivity, C-PAN and Corridor Design captured less conservation target area but also reported smaller patch commission. Higher CC values indicate better model efficiency; value represents hectares captured per 1 hectare with no contribution. Higher CO values indicate better model effectiveness; value represents hectares captured per 1 hectare un-captured. C-PAN performed at intermediate levels when measuring these metrics, never last. C-PAN outperformed or performed as well as FunConn when parameters were relaxed to more closely mimic those patches (Table 3.7)

Patch Modeling Discussion

The three patch delineation tools evaluated here incorporate parameters that place selective criteria on the spatial metrics of the patch. More complex approaches which evaluate patch occupancy and PVA include additional parameterization that the C-PAN model is not intended to evaluate. As such, the C-PAN approach was evaluated with two of its most closely related patch modeling peers, Corridor Design and FunConn. The parameterization of each approach proved critical in comparing their modeled patch outputs. Each approach uses varying algorithms and spatial mechanics for delineating

patches. Corridor Design primary mechanism for patch generation relies on a moving window which averages habitat quality at a user-defined scale. This allows the user to determine how edge-sensitive the patch delineation process becomes; an increase in the moving window size for example parameterizes the model to be more selective in patch generation. The Corridor Design patch modeling tool was tightly parameterized for comparison with C-PAN and FunConn.

The FunConn patch modeling tool relies on a region-growing processes coupled with core habitat requirements and a minimum foraging radios. The region-growing process within the FunConn approach is a common means of selecting contiguous suitable cells. The core habitat requirement and minimum foraging radius are parameters that place selection criteria on the region-grouped cells. The FunConn approach was also tightly parameterized for patch modeling comparisons.

Similar to other patch modeling approaches, C-PAN uses a moving window in the early stages of landscape sampling for generating LCI scores. C-PAN varies from others however in that it does not use the moving window or a region growing process in its delineation of patches. Instead, C-PAN uses an iterative aggregation, overly, and extraction process to generate patches. To this author's knowledge, this process is unique to this approach alone. Additionally, the C-PAN approach provides LCI scores for evaluating fragmentation within the landscape and provides a statistically means for determining patch selection criteria. Together, the mechanically unique methods, utilization of LCI scores, and ease of model parameterization, make C-PAN a distinctive and potentially beneficial alternative means of patch generation.

Comparative Analysis and C-PAN Validation Discussion

C-PAN performs markedly well when compared to the patch modeling tools of Corridor Design and FunConn. C-PAN ranked first or second among all spatial and target capture metrics measured. Furthermore, C-PAN appears to provide users with greater site discrimination capabilities than Corridor Design or FunConn. At high patch selectiveness, the outputs of C-PAN and Corridor design were the most similar in size and distribution across the study area and provided users with a more selective set of discrete patches than the FunConn approach (Figure 3.12). The C-PAN approach could be parameterized to be even more selective by selecting a higher LCI value from which to derive patches[22]. Tighter parameterization of Corridor Design however may be more difficult as it was already parameterized as selective as the tool recommends. Increasing site selectivity is particularly beneficial from a conservation management perspective as it allows users to identify discrete locations as opposed to wide areas upon which to direct efforts.

The FunConn approach delineated very few patches when compared to the others (N = 31) but the average patch size was orders of magnitude higher (average area 148,693 ha vs. 5,883 ha for C-PAN and 4,502 for Corridor Design). This resulted in FunConn performing fairly well in capturing LOW wild areas (72.07%) within the study area when compared to the other two approaches. When model parameters were relaxed in the C-PAN approach (to derive fewer patches of larger size) the results resembled that of FunConn more closely. In order to achieve this, the C-PAN LCI core value was increased to identify patches within the top 5% of LCI scores (reducing the number of

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[22] Example: the top 5% LCI values could be selected instead of the 10% as was modeled here.

patches identified) and the LCI grow value was decreased to a value of 1 (increasing the size of those patches). Parameterization of C-PAN in this way resulted in fewer, larger, patches that more closely resembled the output of FunConn. C-PAN conservation target capture was increased to 69.13% to nearly the same as FunConn (72.07%). While patch commission also increased to 56.60%, it was considerably less than that observed by FunConn 67.90%. While the CC efficiency ratio decreased markedly from the results of the more tightly parameterization run (1.68), it remained slightly better than the efficiency ratio reported by FunConn (0.77 to 0.47 respectively). The CO ratio of C-PAN increased to nearly the same value reported by FunConn (2.24 and 2.58 respectively).

These results demonstrate that relaxing the patch selection requirements of C-PAN resulted in patches that are comparable to those delineated by FunConn. Parameterizing C-PAN in this way derived patches that outperformed or mimicked closely FunConn patches on measures of conservation target capture, target omission, commission, and model effectiveness and efficiency. These values are reported in Table 3.7.

Table 3.7 – Conservation Target Capture (FunConn): Commission & Omission

Conservation Target Capture: Last of the Wild (LOW)			
	Target Captured	Commission	Target Omission
C-PAN	1,419,551	1,851,762	633,813
	69.13%	56.60%	30.87%
FunConn	1,479,807	3,129,704	573,557
	72.07%	67.90%	27.93%
	(Patch and LOW)	(Patch Only)	(LOW Only)
	Capture to Commission Ratio (Capture / Commission)		Capture to Omission Ratio (Captured / Omission)
C-PAN	0.77		2.24
FunConn	0.47		2.58

Relaxing C-PAN parameters resulted in decreased patch modeling efficiency (increasing commission) and increased conservation target capture effectiveness (reducing target omission). This was done for comparative purposes to derive patches of similar metrics to those delineated by FunConn. Doing so resulted in C-PAN outperforming or performing as well as FunConn on these metrics.

Figure 3.12 – Modeled Patch Comparisons

■ **C-PAN Patches**

C-PAN patches tended to delineate discrete locations with high core area characteristics. C-PAN patches exhibited better EA ratios than Corridor Design patches. The C-PAN approach also appears to have higher patch discrimination capabilities when compared to the others.

■ **Corridor Design Patches**

Corridor Design patches also delineated discrete locations with high core area characteristics. Additional patch discrimination may be difficult however as it was parameterized as tightly as the tool recommends. Increasing the moving window size is the primary means of addressing patch edge.

■ **FunConn Patches**

FunConn patches were generally large, heterogeneous, and comprised of less suitable HF scores. When C-PAN parameters were relaxed, the patch outputs closely resembled that of FunConn (below). FunConn could not be parameterized to achieve the same site discrimination of C-PAN or Corridor Design however.

■ **C-PAN Patches (Less Selective)**
Human Footprint
Level of Impact

High : 100 (Built)

Low : 0 (Natural)

0   25   50   100 Kilometers

Evaluation Conclusions

The comparative phase of the analysis served two primary purposes. First, the comparative analysis outlined here served potential benefit in addressing the lack of relative comparison between each tool's respective outputs. This has shed light on each approach's potential patch modeling strengths and weaknesses when attempting to reach particular conservation related goals associated with patch cohesion and conservation target capture.

Of the three approaches, C-PAN achieved the highest level of discrimination amongst sites. Both C-PAN and Corridor Design were effective in delineating highly homogenous patches. Corridor Design was also effective in delineating relatively acute patch locations. Additional patch discrimination may prove difficult however as the tool was set to maximum discrimination for this analysis. Increasing the size of the moving window and the core area percentage parameters were key to delineating patches that were sensitive to edge characteristics. The FunConn approach delineated much larger and heterogeneous patches even at high discrimination. Relaxing C-PAN parameterization resulted in patches that were comparable to those of FunConn. FunConn however could not be parameterized to generate patches that resembled the highly selective nature of C-PAN and Corridor Design.

Secondly, this analysis validated the C-PAN modeling approach as a potentially compelling and useful patch modeling tool. This was accomplished in large part by comparing C-PAN derived patch outputs with those derived by its present day modeling peers. C-PAN patches closely resembled those derived by Corridor Design in the number

of patches generated and metrics of size. C-PAN also delineated the patch with the best EA ratio and reports better average EA ratios than Corridor Design derived patches.

Comparing the average HF scores within the patches of each approach indicated that Corridor Design and C-PAN approaches exhibited higher levels of "naturalness" than did FunConn patches. While the large FunConn patches captured LOW areas rather effectively, it also exhibited the highest patch commission of the approaches. C-PAN captured more LOW area than did Corridor Design and was able to capture nearly as much LOW area as FunConn, with less commission area, when its patch modeling parameters were relaxed.

These results indicate that C-PAN patch modeling approach performs as well, and better, in the patch metrics evaluated here (patch area, EA ratios, average nearest neighbor, average HF score, LOW capture, and patch commission). Additionally, the use of the statistical distribution of LCI scores for tool parameterization (i.e., top 10% etc.) represents a significant and potentially beneficial departure from other approaches. Using LCI scores allows users to parameterize patches in the landscape based on their statistical uniqueness in the landscape as opposed to species-specific parameterization.

In summary, the C-PAN patch modeling approach exhibits the ability to delineate discrete patches with higher discrimination capabilities than the other tools evaluated here. It has proven successful in delineating highly homogenous patches with significant core area, at high resolution, and at a large scale. Resource managers may find the use of this tool useful when species-specific parameterization of other approaches is lacking, there is a desire to identify patches that are the most unique in the landscape being evaluated, and when attention to core area and patch cohesion is of particular importance.

CHAPTER FOUR:

PATCH AND CONNECTIVITY MODELING

AT THE ECOREGION-SCALE

Landscape Connectivity Overview

The goal for the remaining portion of this work is to develop a system of ecoregion-scale corridors for the provision of connectivity between the patches that were delineated earlier in this work. In order to achieve this, an overview of large-scale landscape connectivity was provided. Additionally, an overview which outlines the role that corridors can play in facilitating connectedness and the persistence of species has also been provided.

Specific aspects of landscape connectivity were then discussed. This involved an overview of graph theory and the landscape modeling tool (FunConn) that was used for generating corridors. An in-depth discussion of the FunConn modeling process and ecoregion-scale modeling methods has been provided. Landscape networks for each of the three patch modeling scenarios were then generated and their respective spatial metrics evaluated.

The landscape networks were then used to test a simplifying assumption often used in conservation planning: that coarse-scale corridors may provide overlapping or "umbrella" effects for other scenarios. To examine this assumption a gap analysis of the three modeled landscape networks was conducted. Stemming from this analysis, a discussion focused on connectivity modeling and ecoregion-scale implications has been

provided. This chapter concludes with the derivation of four priority connection and linkage areas within the ecoregion.

Introduction to Landscape Connectivity

As the consensus around assembling larger more cohesive patches or reserves has coalesced, a parallel debate focusing on how they function together at large scales has also been taking place. Central to this debate is the role that connectivity among patches plays in facilitating species persistence at these scales. While multiple definitions of connectivity have been formulated and refined (Merriam 1984, Taylor et al. 1993, With et al. 1997, Singleton et al. 2002), Hilty et al. (2006) provides a useful definition for use here: a measure of the ability of organisms to move among separated patches of suitable habitat, it is related to differences in vagility between species, and is dependent on a species' perception of the landscape.

It is largely believed that as landscape fragmentation increases and connectivity is decreased, patches that weather the initial storm of land transformation become increasingly isolated from one another causing additional species' decline (Schumaker, 1996). This concept is largely discussed within the context of a binary landscape made up of habitat patches and the landscape matrix (non suitable habitat surrounding the patches of interest) (MacArthur and Wilson 1966, Ehrlich and Murphy 1987, Harrison et al. 1988, Soule' et al. 1992, Hanski 1998). The matrix which surrounds habitat patches is often composed of a complex mosaic of other land cover and land use types, which may vary greatly in their permeability to individual species moving between patches (Ricketts,

2001). In this way, the matrix can significantly influence the effective isolation of habitat patches, rendering some more or less isolated based on their surrounding matrix.

As such, a good deal of effort was directed early on with the fusion of conservation biology and landscape ecology by developing better methods of predicting species persistence following habitat fragmentation (O'Neill et al. 1988, Turner 1989, Ripple et al. 1991, Pulliam et al. 1992, McKelvey et al. 1993). Additionally, Schumaker (1996) points out that numerous indices of landscape pattern have been linked to ecological function (Merriam 1984, Frankin and Forman 1987, Burel 1989, Miller et al. 1989, Turner et al. 1989, Keller 1990, Noss 1990, Shaw and Atkinson 1990, Ripple et al. 1991, Hansen and Urban 1992, Johnson et al. 1992, Taylor et al. 1993, Tischendorf and Fahrig 2000, Moilanen and Hanski 2001, Moilanen and Nieminen 2002). Calabrese and Fagan (2004) explain that it is therefore desirable to quantify connectivity and integrate its measures into reserve design. This integration has been used in several reserve design applications to date and has been useful in further refining the patch selection process (Siitonen et al. 2002, Singleton et al. 2002, Cabeza 2003).

In general, there exist three classes of connectivity metrics for focal species in a landscape: structural, potential, and actual, each of which increases in complexity (Calabrese and Fagan, 2004). As part of this research, a synergistic accounting of connectivity metric approaches categorized by Calabrese and Fagan (2004) and Singleton (2002) has been compiled and adapted and is provided here. This is intended to serve as a brief overview of major connectivity approaches and some key aspects of them. Each approach has been classified based on the type of connectivity being modeled (structural, potential, actual), the level of landscape analysis performed by the approach (minimal vs.

maximum), data input requirements (few of low detail vs. many of high detail), the level

of modeling assumption found within each approach (fewer: implicit vs. more: explicit)

the relative key limitations associated with each approach (fewer vs. greater) and key

points regarding the approaches utility in practice (lower vs. greater). A compilation of

this information is provided in Table 4.1.

Table 4.1 – Summary of Connectivity Metric Approaches

Summary of Connectivity Metric Approaches

Connectivity Approach	Type of Connectivity (Structural)	Landscape Analysis Provision (Minimal)	Data Requirements (Few, Low Detail)	Key Model Assumptions (Fewer : Implicit)	Key Model Limitations (Greater)	Key Model Utility (Lower)	Examples
Nearest Neighbor Distance	Structural	Patch isolation measure	Patch distribution	Matrix quality is homogenous	Poor predictor of connectivity	Exceptionally simplistic and has minimal data requirements	Moilanen and Neman 2002, Bender et al. 2003
Spatial Landscape Metrics	Structural	Quantifies landscape pattern	Patch characteristics (e.g., number, size, core, area, edge/area ratio)	Spatial pattern indices show potential predictable relationships with actual connectivity	Lacks expected movement patterns and dispersal success varies (poor to good predictability) across metrics, species and landscapes	Can describe landscape variability over time, change monitoring, and is useful for comparing landscapes	Haines-Young and Chopping 1996, Schumaker 1996, Tischendorf 2001, McGarigal et al. 2002
Scale-Area Slope	Structural	Fragmentation measure of an individual focal species distribution	species occurrence, presence/ absence	Proximity is the major determinate of connectivity among occurrences	Relationships between this approach and actual connectivity have yet to be	Provides potential means of quantifying risk of local extinction across a landscape.	Kunin 1998, Fagen et al. 2002
Graph Theoretic	Potential	Quantifies relationships between patches and their attributes	Spatially explicit habitat data and species dispersal data	Utilizes a functional relationship between dispersal distance and a species/ probability of dispersal	Species specific parameterization of dispersal ability typically includes a fixed critical dispersal distance to be established	Allows for comparing connectivity across landscapes by evaluating individual graphs and aids in patch	Cantwell and Forman 1993, keitt et al. 1997, Bunn et al. 2000, Urban and Keitt 2001, Theobald 2006
Cost-Distance	Potential	Provides evaluation of inter-patch matrix and provides routes of movement cost	Patches, spatially explicit habitat data, and cost/permeability surfaces	Relationships between habitat quality and permeability, variations in species vagility and perception influence path	Generally focuses on single Least-Cost Pathway (LCP), expansion of the LCP into a larger landscape unit (e.g., corridor) requires consideration of parameterization	Provides potential routes of movement, can quantify isolation between patches, can be joined with other approaches such as graph theory (e.g., FunConn)	Lindenmayer et al. 1993, Bentley and Catteral 1997, Singleton et al. 2002, Theobald 2006, Beier 1995, 2002 and 2006
Circuit Theory	Potential	Generates a measure of flow through each cell in a landscape	Patches, spatially explicit habitat data, conversion to a resistance/ impedance surface	Similar to those of the cost-distance approach, integrates all possible pathways regardless of	Landscape pinch points are not always priority areas for connectivity and cost distance	Corresponds well with random walk models and depicts graphically pinch points and bottlenecks in the	McRae et al. 2008
Buffer Radius, IFM	Potential	Generates an assessment of potential patch contribution to population viability	Patch occupancy, population size, and dispersal probabilities and distances	Implies connectivity is quantified by metapopulation capacity and persistence	Model performance is sensitive to the chosen buffer radii, these are often arbitrarily selected	Provides a potential quantification of a landscapes ability to maintain a viable metapopulation over time	Hanski 1994, Hanski et al. 1996, Ovaskainen and Hanski 2001, Nieminen 2002
IBM/SEPMs	Actual	Simulate actual paths of individuals, and provide population viability assessments	Highly parameterized and species-specific foraging, life history, and dispersal data, telemetry, and mass capture/release	Parameterization is equal across large heterogeneous landscapes and observed Immigration and colonization rates are adequate for	The data-intensive nature of direct measurement methods generally limits the utilization and spatial scales to which these approaches can be	Provides the best detailed estimates of how well particular patches are connected in the landscape and provides measures of population	Sutherland 1996, Gillis and Krebs 1999, Meegan and Maehr 2002, Carroll 2005, Schumaker 2008
Connectivity Approach	Type of Connectivity (Functional)	Landscape Analysis Provision (Maximum)	Data Inputs (Many, High Detail)	Key Model Assumptions (More: Explicit)	Key Model Limitations (Fewer)	Key Model Utility (Greater)	Examples

The Role of Corridors in Landscape Connectivity

When the matrix fails to facilitate historical patterns of movement and dispersal, threats to species' population viability may ensue. Restoring landscape connectivity through rehabilitating historical landscape connections or newly delineated corridors between isolated patches is one way to counter the negative effects of landscape fragmentation (Williams and Snyder, 2005). Among the most widely utilized definitions of a corridor, the Ninth U.S. Circuit Court of Appeals defined corridors as "avenues along which wide-ranging animals can travel, plants can propagate, genetic interchange can occur, populations can move in response to environmental changes and natural disasters, and threatened species can be replenished from other areas" (Walker and Craighead, 1997).

The inclusion of corridors in fragmented landscapes has been shown to have numerous positive effects (Hilty et al. 2006). Corridors have been documented to serve as habitat (Hess 1994, Machtans et al. 1996, Perault and Lomolino 2000). They have also been shown to facilitate movement among species of otherwise separate populations enabling recolinization after a local extinction (Laurance 1991, Beier and Loe 1992, Brosset et al. 1996). Others have confirmed that the increased connectivity provided by corridors also promoted dispersal. This allowed for an increase in genetic exchange to take place, thus reducing the risk of population decline via inbreeding and increasing resiliency to environmental change (Beier and Loe 1992, Rosenberg et al. 1997, Bennett 1999, Banks et al. 2005). Corridors may also aid dispersing individuals circumvent predation (Noss, 1987) and avoid human-related mortality (Noss 1987, Haddad 1999).

Still however, there remain critics of corridors as they may also facilitate the

spread of disease, exotic invasives, and function as avenues to be exploited by predators (Simberloff and Cox 1987, Hobbs 1992, Simberloff et al. 1992, Dobson et al. 1999). In the face of these criticisms, Beier and Noss (1998) reviewed some 32 published corridor studies and concluded that "evidence from well-designed studies generally supports the utility of corridors as a conservation tool…almost all studies on corridors suggest that they provide benefits to or are used by animals in real landscapes". Additionally they conclude that 10 studies "offer persuasive evidence that corridors provide sufficient connectivity to improve the viability of populations in habitat connected by corridors. No study has yet demonstrated negative impacts from corridors".

Implications of Large Scale Corridors

To date, reserve identification has focused largely on locating irreplaceable sites based on habitat surrogates and species range data (Noss 1987, Scott and Csuti 1997, Noss et al 2002, Cowling et al. 2003, Lombard et al 2003, Higgins et al. 2004, Knight et al. 2006, Knight et al. 2007). While the adoption of this site selection methodology has resulted in numerous successes in biodiversity protection and the delineation of many conservation areas, it has tended to focus on individual species, or a suite of them, in more localized efforts and smaller scale applications. The main issue with such an approach is that it potentially fails to consider areas that are important to connectivity and contain smaller but equally viable populations (Knight et al. 2007). Additionally, such an approach for reserve parameterization may also fall short when incorporating biological and environmental patterns as well as landscape processes and persistence under the protection umbrella of any one reserve. As Knight et al. (2007) point out, this generally

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results in an implicit tradeoff between species representation and the persistence of ecologic functionality as a goal within any one reserve. Ecoregion-scale corridors may provide a useful alternative to dealing with this tradeoff.

Ecoregion-scale corridors may prove useful in helping to achieve "planning for persistence" as outlined by Cowling (1999). Planning for persistence generally includes the mapping of species representation targets and spatial surrogates for incorporating environmental processes at larger scales (Knight et al. 2007). Additionally, it aims to include both representation and persistence of biodiversity (Cowling et al. 1999, Margules and Pressey 2000) and thus may be achievable in ecoregion-scale corridors by virtue of their large land area.

Ecoregion-scale corridors may also prove to be useful mechanisms for capturing environmental processes (Rouget et al. 2006). Species movement (Laurance and Laurance, 1999) and geographic speciation (Cowling and Pressey 2001, Moritz 2002) are both large-scale processes which may be accommodated by large-scale corridors (Rouget et al. 2006). Including additional environmental processes such as source-sink population dynamics, disturbance regimes, and environmental succession also require large tracts of land (Noss et al. 2002, Cowling et al. 2003). It is believed that these and other environmental processes are best captured and incorporated at the landscape scale (Balmford et al. 1998, Terborgh and Soule` 1999, Noss 2003). Again, the relatively large size of ecoregion-scale corridors provides an enticing means by which these aspects of environmental persistence may be incorporated.

Large scale corridors may also prove critical to species persistence in the face of climate change by facilitating movements along gradients as ranges shift (Bennett 1990,

Beier 1995, Harris et al. 1996, Rouget et al. 2003, Hilty et al. 2006). As such, ecoregion-scale corridors may prove beneficial in incorporating planning for persistence, large-scale environmental processes and species resiliency from climate change because they encompass such vast assemblages of land.

Large-scale conservation assessments which either incorporate or evaluate the use of far reaching corridors are becoming more numerous (Jongman, 1995, Soule` and Terborgh 1999, Dinerstein et al. 2000, Carroll et al. 2001, Sanderson et al. 2002, Muruthi 2004, Rouget et al. 2006). Coarse scale conservation approaches such as these may combat fragmentation and promoting biodiversity by connecting smaller patches or reserves into a system that functions more like larger ones. This, in turn, may have positive effects on regional biodiversity by increasing functional island size.

Towards Modeling Corridors

The landscape evaluation and corridor development tool used here (FunConn) employed two of the landscape connectivity metrics that were discussed earlier in this chapter (graph theory and cost-distance in Table 4.1). A more detailed discussion of these components has been provided in the sections that follow.

Introduction to a Graph Theory Approach

Widely utilized and rigorously developed in other disciplines, the graph theoretic approach is being integrated with success in conservation planning. Originally discussed by Harary (1969), Urban and Keitt (2001) have made a meaningful translation of the graph theoretic approach into one applicable in conservation planning. While

terminology abound, an abridged accounting of the vocabulary most essential for understanding the links between graph theory and GIS based conservation planning is provided here (Figure 4.1). A dictionary of additional terms specific to landscape networks and FunConn is provided in Appendices B.

Figure 4.1 – Graph Theory & Landscape Network Terminology
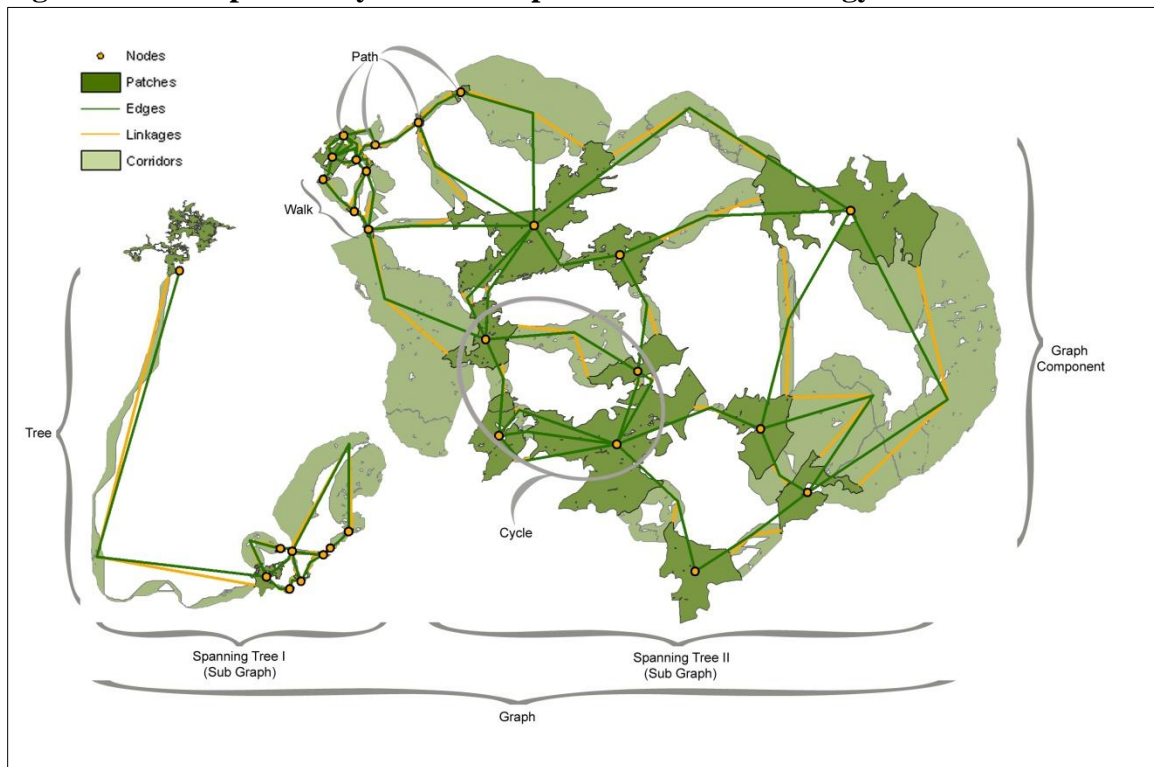
An example of key landscape network terms in a simulated landscape. Nodes represent the weighted center of each patch, they are connected by edges. Linkages originate at patch boundaries and correspond with each edge. Corridors are delineated between patches based on the parameterization of the landscape links Qn value.

Application of the Graph Theoretic Approach in Connectivity Modeling

The application of graph theory in ecoregion-scale conservation planning is particularly useful for a number of reasons. First, graph theory advances the conceptual development of spatial modeling by shifting perspective away from one of categorizing the landscape into discrete patches. It does so by focusing the lens on thinking about a series of environmental gradients that must be traversed in order to achieve functional connectivity (Hobbs & Theobald, 2001).

This thinking lends itself quite well to coarse scale conservation approaches because it aids resource managers in targeting conservation efforts in subregions that play a critical role in maintaining connectivity in the ecoregion as a whole. This is something that may be overlooked in local level connectivity work. Second, graphs can prove to be an elegant means by which landscape connectivity can be analyzed (Theobald 2006). The very nature of the graph theoretic approach is that it helps to evaluate landscape connectivity once potential connections between patches have been established (Fagan & Calabrese 2006). Additionally, various operations such as adding or deleting potential nodes and edges (patches or reserves, and their corresponding corridors) can allow for landscape level assessments to be made that prioritize nodes and edges based on their contributions to overall landscape connectivity (Urban & Keitt 2001). By identifying those patches, reserves, and corridors that play the most significant role in maintaining overall landscape connectivity, the graph theoretic approach may aid resource managers in focusing their conservation efforts on a select set of zones that will have the greatest conservation impact. These represent several reasons why graphs may provide a

substantially more comprehensive perspective than patch-to-patch approaches for examining ecoregion-scale measures of connectivity.

Landscape Networks

Theobald (2006) makes several substantive advances in adapting the graph theoretic approach to model landscape connectivity. They can be categorized into two classes; additions to the LCP methods for modeling effective distance between patches, and the establishment of landscape networks as a construct for better representing the landscape context of graph theory. The first category addresses known issues with LCP analysis already outlined in this chapter, namely the variability introduced when deriving a focal organism's likely path.

Traditionally speaking, the graph theoretic approach within GIS uses the LCP method for establishing edges or linkages between patches; Theobald's contributions here are twofold and focus on the derivation of possible "multiple pathways" between patches. First, in order to address concern over quantifying the probability that an organism can successfully navigate between patches, Theobald proposes providing an output that provides the full distribution of cost-distance values along the allocation boundary formed by two patches. This differs from simply reporting the raster grid cell that demarks the lowest cost-distance along the allocation boundary, as is done in traditional LCP analysis, and is potentially more useful.

Broadening the LCP lowest cost-distance to include the full distribution of values has several benefits. It addresses variability amongst an organism's choice of multiple pathways because there is some possibility that the organism may choose a path other

than that demarked by the lowest cost-distance alone. Reporting all cost-distance values allows for multiple pathways to be identified and delineated. This is an important adaptation in the approach because it aids in addressing an often unrealistic assumption that the single least cost-pathway will be used. Second, the derivation of multiple pathways also can be thought of as a cost-weighted approach for identifying the "Nth-optimal corridor" (Berry, 1993). Thinking of multiple paths in this way, a modeling run will identify the least-cost pathway (most optimal) and additional corridors that correspond to a specified threshold that contains the next most optimal route or routes (Theobald 2006). Ecologically speaking, this modeling improvement also aids in building in functional redundancy in overall landscape connectivity.

Theobald's construct of likening the graph to a landscape network is also potentially useful for evaluating connectivity at the ecoregion-scale. Loosely defined, the landscape network is distinguished by four critical characteristics. First, the landscape network equates to that of the topologically related graph and its graph geometry. This is critically important in conservation planning because metrics such as patch size (associated with the graph nodes) and corridor orientation, length, and width (associated with edge angles and effective distance) are important to understanding how ecological systems function.

Second, nodes are used to represent patches of habitat or reserves. Again, there is utility assigning attributes to these nodes that reflect various spatial metrics of the patch or reserve that they are intending to represent. Adding metrics such as patch shape, area, edge ratio, and habitat quality help to better describe how the patch may function or contribute to connectivity at larger scales.

Third, straight line distances can be appended to include the effective distance along an edge linking two nodes. Aside from providing a more accurate accounting of permeability along the edge and identifying the optimal least cost-path, additional edges can be generated that represent multiple pathways or the next optimal connection/connections between multiple nodes. Finally, the landscape network construct implies a potentially more realistic movement assumption for mobile organisms. The assumption built in to the graph theoretic approach is that organisms move across a landscape in a stepping stone fashion (Theobald 2006). In this view, each patch (represented by a node) serves as a possible stopping point for carrying out life functions prior to potentially moving onward to another patch (via an edge or multiple path).

A Graph Theoretic and Landscape Network Modeling Approach: FunConn

Here an overview is provided intended to illustrate both the application of FunConn at the ecoregion-scale and outline variations of its possible use. This encompasses an exploration of a number of methodological adaptations and attempts to provide possible users with some general insight pertaining to the pros and cons, appropriate uses, and general assumptions that may be useful to consider when embarking on connectivity modeling of your own. For purposes here, it is useful to discuss the major modeling steps and their associated tools in the sequence they would likely be applied, although as you will see, there is room for alteration within each step.

Developed by Theobald et al. (2006), FunConn aims to provide significant advances to traditional least cost path approaches of modeling landscape connectivity. FunConn applies graph theory as a basis for modeling and the evaluation of connectivity

between individual patches. Loosely defined for a user starting from scratch, the workflow for FunConn begins with creating a habitat quality surface, defining functional patches, and building a landscape network. The FunConn modeling toolbox for ArcGIS v9.2 also includes a number of tools for processing existing datasets into landscape networks and the means for analyzing the resulting landscape network through evaluating various connectivity scenarios.

Creating a Habitat Quality Dataset

The first step within the FunConn approach for modeling landscape networks is the development of a habitat quality dataset. While the habitat quality dataset's primary purpose within FunConn is the delineation of patches, it can also be used in refining the permeability cost surface when building the landscape network later in the process. Using the habitat quality dataset in cost surface refinement however assumes that the more suitable the habitat, the less costly it is to traverse, which may not always be the case.

The creation of the habitat quality dataset within FunConn is based on the factors of resource quality, patch structure, and distance from disturbances (Theobald et al. 2006). The resource quality component is intended to reflect the surrogacy between a species' habitat requirements and site specific conditions such as land cover. This dataset is reclassified to represent resource quality scores in which higher values represent more suitable land cover types. The patch structure component attempts to insert measures of spatial contiguity by evaluating the proximity to a patch's edge. This is a measure by which possible edge effects may be integrated into modeling habitat quality. Finally, the distance to disturbance variable attempts to place a measure of potential habitat quality

degradation based on proximity to some negative land use disturbance. For this component, the habitat quality dataset is again reclassified based on proximity to some negative disturbance, essentially diminishing habitat quality within some specified distance. The resulting output of this tool is a habitat quality raster that demarks a range of high (100) to low (0) habitat suitability values.

As discussed in the early portions of Chapters Two and Three, these tools can be data and knowledge intensive. The use of this tool for example requires the user to establish both minimum resource quality thresholds and minimum patch sizes in order to delineate primary habitat areas as precursors to defining functional patches. There is always the possibility that these values may be little known and that variations in these values could ultimately lead to significantly different habitat quality outputs, functional patches, and connectivity schemes. These concerns however are not necessarily specific to this approach and the user must always be mindful of the potential cascading effects that early parameterization may have in the final outputs of any analysis.

Moreover, the Create Habitat Quality Tool being evaluated here is not the only game in town; there exist multiple alternative methods for accomplishing similar results. Perhaps most accessible, is ArcMap's Model Builder. Within Model Builder, a user could easily construct a workflow that encompasses the major components evaluated here through linking tools such as reclassify, euclidean distance, and neighborhood functions. Such an exercise would essentially result in a habitat suitability analysis for the organism in question. Additional environmental parameters could also be integrated thus allowing for a more detailed habitat analysis to result.

Defining Functional Patches

The Define Functional Patches tool within FunConn aims to delineate functional patches based on organism-specific parameters. This method identifies functional patches based on user-defined inputs such as an organism's foraging habits and its ability to move between patches (Girvetz & Greco 2007). This tool requires several user-defined parameters including a resource quality threshold, the minimum patch size, the maximum foraging radius, and the core habitat percentage. Each of these parameters can be thought of as a selection criterion that continually culls all available patches leaving only those that meet all of the required functional characteristics.

The resource quality threshold establishes the minimum habitat quality that will be considered for region-grouping or assembling the first cut of habitat patches. The higher the threshold value (necessary for species that are more restrictive in their habitat requirements) the more restrictive the patch selection process will become. The minimum patch size parameter is also used as a measure for eliminating patches that are not large enough to sustain the focal species. Similarly, the maximum foraging radius parameter attempts to incorporate a measure of how far an animal travels during foraging, to aid in identifying patches that meet minimum size requirements. Finally, the core habitat percentage parameter refines again which patches are functionally suitable by aiming to add a measure of the species interior versus edge habitat requirements. Those species that are negatively affected by edge (edge negative species: lynx) would require a higher value to be entered, while those species that are indifferent to edge (edge neutral: bobcat) and positively affected by edge (edge positive: mountain lion) would require lower values

to be entered as the patches for these species need not be as restrictive (Theobald et al. 2006).

The derivation of functional patches is necessary if a user intends to model connectivity from the ground up when no existing data are present, intends to evaluate how patches outside of already protected areas contribute to landscape connectivity, or are interested in identifying possible candidate sites for additional conservation enrolment.

Building the Landscape Network

The third major component within this process is the generation of a landscape network which represents habitat patch connectivity. The inputs required for constructing the landscape network include a raster dataset of the patches to be used (either those derived from the Functional Patch Tool above or those from a preexisting dataset such as existing protected lands), a raster dataset (such as land cover) that will serve in the generation of a cost surface upon which landscape permeability will be based, and a table that serves as the link for converting the cost surface into landscape permeability.

The first subprocess within the generation of the landscape network tool is the most fundamental to understanding how it works. In this step, a raster surface such as land cover is reclassified according to user-defined permeability values, these values are then inverted to generate a cost surface upon which the LCP process will begin linking patches. Take this example of an edge-sensitive species for instance, land cover between two patches may consist of two types, deciduous forest and row-cropped agriculture. In this case, permeability of the deciduous forest is greater than that of the agricultural land.

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The inverse of this is a cost surface in which the agricultural land is more costly to traverse than the forested land.

Allocation zones are then grown from the source patches across this cost surface until they meet, forming an allocation boundary. Based on a user-defined threshold, certain cost-distance values are retained and extracted, these cells serve as the midpoints for the first set of initial linkages. Within each allocation zone, cells exhibiting values less than the user-defined threshold are removed to form the resulting corridor (Theobald et al., 2006).

Model Error Propagation

It is important to understand how error is potentially propagated at each step of the modeling process. Every modeling approach contains assumptions that are both implicitly hidden and explicitly stated which have the ability to influence the modeled products in potentially negative ways. Take the resource quality threshold parameter discussed earlier for example; if this parameter is set lower than a species actually requires, the resulting functional patch output will include patches that provide no habitat contributions to the species in question. This in turn, can result in the derivation of erroneous patches and linkages. These represent features that while delineated on the computer screen and appear to contribute to the conservation of the species, do little to actually conserve the species.

This is to serve as a word of caution during this and any other modeling procedure. There may be significant disconnects between patches that are structurally identified in a model and those that are functionally used in the real world. Assuming a

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patch is used for the persistence of a species or for contributing to landscape connectivity in a modeled plan, when in the real world it is not, could have potentially damaging conservation outcomes.

Ecoregion-scale Connectivity Modeling Methods

FunConn V1 software (Theobald et al., 2006) was used in conjunction with ArcGIS v9.2 for modeling landscape networks within the Northern Appalachian/Acadian Ecoregion (330,000 km^2). Three landscape connectivity scenarios were developed using a 90m ecoregional human footprint dataset as a generalized resistance layer (Woolmer et al. 2008). The first scenario used C-PAN derived patches from the previous chapter as reserve nodes (N = 225). Under the second scenario, Corridor Design derived patches were used as reserve nodes (N = 209). The third scenario was comprised of FunConn derived habitat patches as the input set of reserve nodes (N = 31). Under each of these scenarios, it is assumed that connectivity is being evaluated for core-dwelling species and those most sensitive to human landscape transformations.

The workflow for FunConn is typical of all habitat modeling approaches in that it involves 1) creating a habitat quality surface and 2) defining functional patches, and diverges by 3) building and evaluating landscape networks. As these modeling scenarios used an existing habitat quality surface (human footprint) and predefined source patches (C-PAN, Corridor Design, FunConn), only the landscape network tool was used for modeling connectivity.

Each run used the human footprint dataset as the permeability raster. Since the human footprint dataset is scaled from 0 (most wild, least influenced by human activity)

to 100 (least wild, most impacted by human activity) a simple conversion was undertaken in order to convert these values into the scale range accepted by the tool (0-1). In this conversion for example, values of 100 for the human footprint data became 0 for the permeability value associated with the cost surface. No aggregation factor (1) was assigned so that the original resolution of the human footprint data (90 x 90 meters) would be maintained in the resulting corridors[23]. Additionally, the default links Qn value (10) was used for corridor parameterization, this was chosen in an effort to not be overly restrictive or liberal in the selection of potential linkages[24].

Upon completion of each landscape network, several resulting corridors were removed in order to better reflect real-world barriers that were not present in the original human footprint dataset. These were corridors that local experts deemed structurally unfeasible due to crossing long distances of ice-free saltwater with significant tidal fluctuations.

Ecoregion-scale Connectivity Modeling Results

The landscape network generated for connecting C-PAN patches (N = 225) consisted of 1,062 linkages and edges and 1,058 corridors spanning across the ecoregion. The landscape network consisted of two graphs, one largely connected graph for the majority of the ecoregion and one smaller more linear graph spanning Nova Scotia. This indicated that while the majority of the study area has the potential for redundant

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[23] The aggregation factor is a modeling parameter which specifies the resolution of the output datasets. This value was set to be as detailed as the input dataset (90 x 90 m).

[24] The links Qn value is a modeling parameter which specifies the selectiveness of the modeled corridors. It represents the threshold value for the cost surface upon which corridors are delineated. Cells with values below the established threshold are used to construct the corridor.

connections, no connections were delineated between this graph and the Nova Scotia. Additionally, the linear nature of the graph located in Nova Scotia has less redundancy and potentially lower connectivity. The minimum spanning tree[25] required to connect each of the C-PAN patches within the ecoregion consisted of 223 corridors. The C-PAN scenario landscape network is depicted in Figure 4.2.

The landscape network generated for connecting Corridor Design patches (N = 209) consisted of 944 linkages, edges, and corridors across the ecoregion. The landscape network consisted of two graphs. The graph generated for the majority of the ecoregion while still largely connected, consisted of fewer redundant connections between the southwest and central portions of the region. Again, no connections were delineated connecting Nova Scotia with the rest of the ecoregion. This indicates that while local connectivity is potentially present in these two separate regions, widespread ecoregional connectivity is less likely. The minimum spanning tree required to connect each of the Corridor Design generated patches consisted of 207 corridors. The Corridor Design scenario landscape network is depicted in Figure 4.3.

The landscape network generated for connecting FunConn patches (N = 31) consisted of 224 linkages and edges and 216 corridors across the ecoregion. The landscape network consisted of two graphs, one large graph for the majority of the ecoregion and one small unconnected graph in southern Nova Scotia. Just as in the other two scenarios, no connections were delineated connecting Nova Scotia with the rest of the ecoregion. Additionally however, no linkages were identified connecting southern Nova Scotia with patches located in the north. This indicates that these locations are

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[25] The minimum spanning tree represents the most efficient set of linkages required to link all nodes in a graph.

potentially isolated from the rest of the ecoregion. The minimum spanning tree for

connecting FunConn patches consisted of 27 corridors. The FunConn scenario landscape

network is depicted in Figure 4.4.
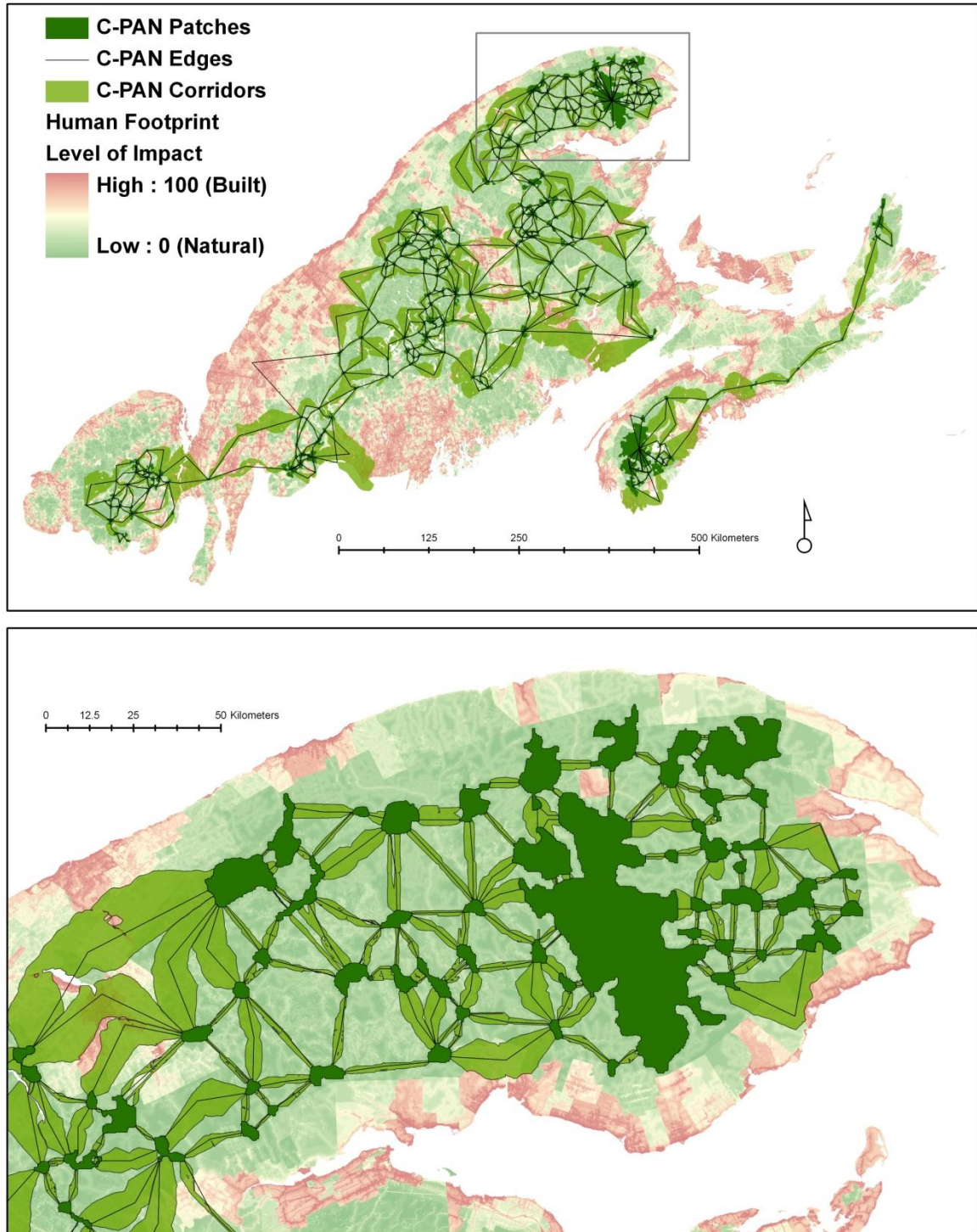
Figure 4.2 – C-PAN Landscape Network

The landscape network generated for connecting C-PAN patches (N = 225) consisted of 1,062 linkages and edges and 1,058 corridors across the ecoregion. The landscape network consisted of two graphs, one largely connected graph for the majority of the ecoregion and one smaller, more linear graph spanning Nova Scotia. The minimum spanning tree for the ecoregion consisted of 223 corridors.

The Corridor Design Landscape Network

Figure 4.3 – Corridor Design Landscape Network

The landscape network generated for connecting Corridor Design patches (N = 225) consisted of 944 linkages, edges, and corridors across the ecoregion. The landscape network consisted of two graphs, one largely connected graph for the majority of the ecoregion and one smaller, more linear graph spanning Nova Scotia. The minimum spanning tree for the ecoregion consisted of 207 corridors.
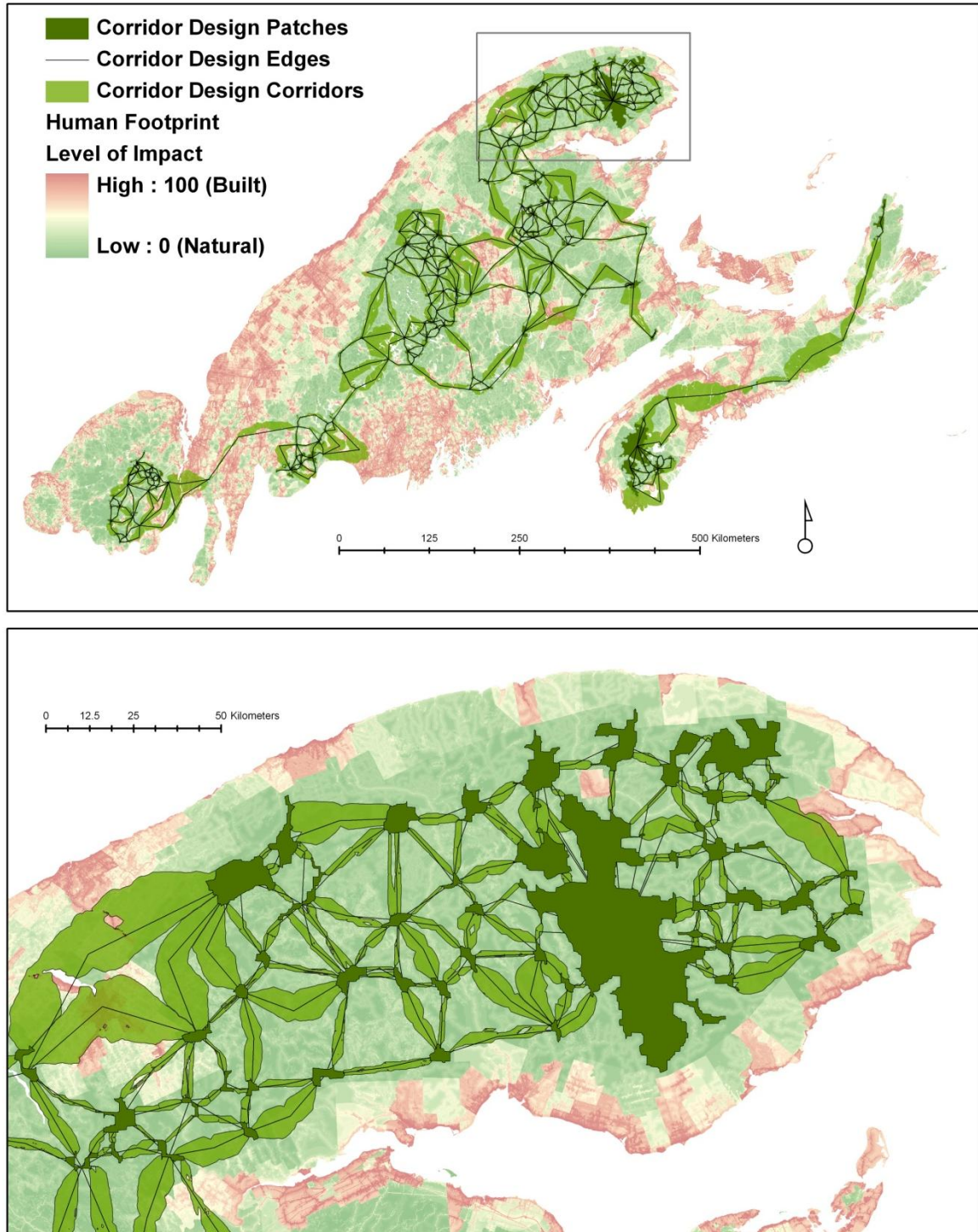
The FunConn Landscape Network

Figure 4.4 – FunConn Landscape Network
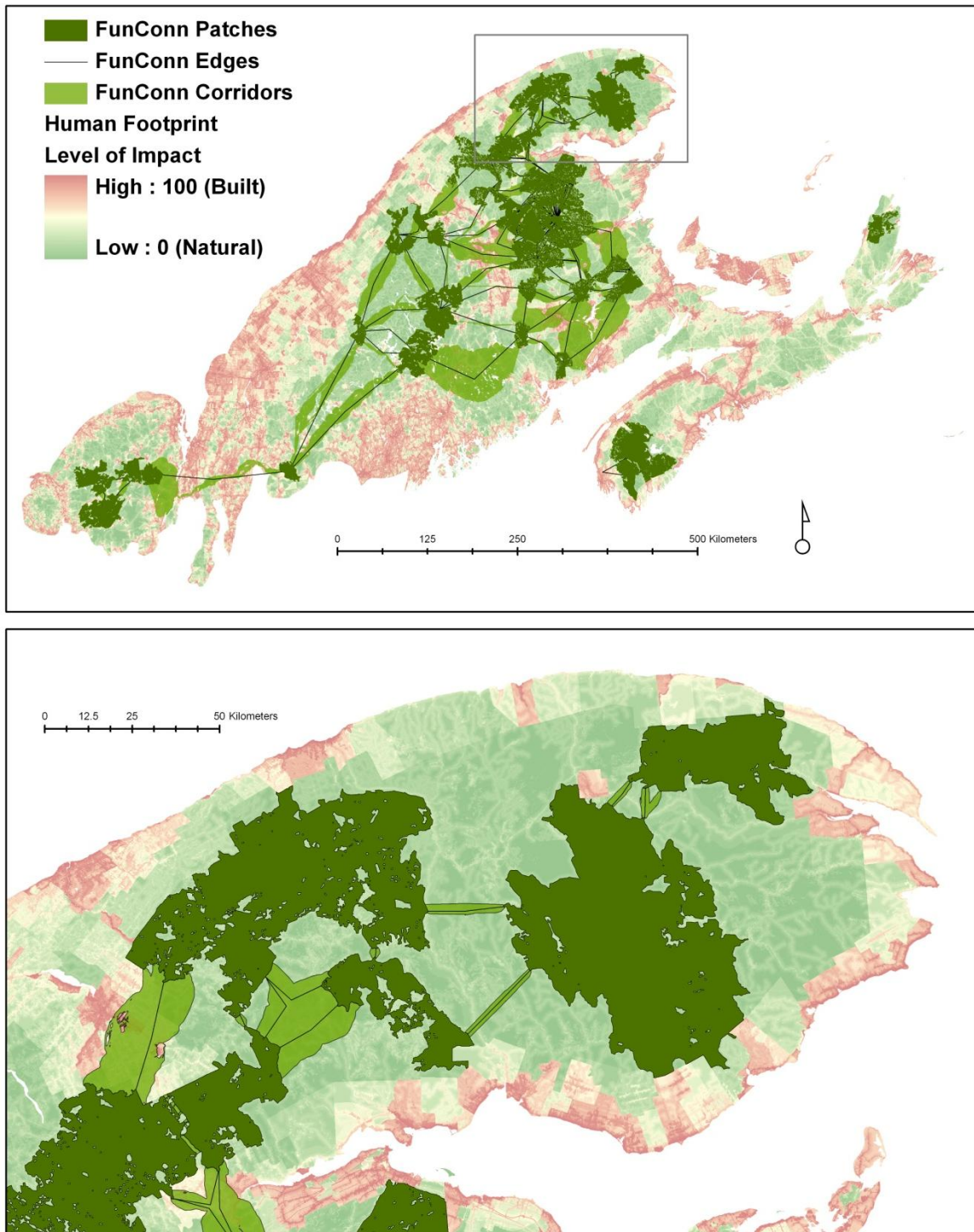
The landscape network generated for connecting FunConn patches (N = 31) consisted of 224 linkages and edges and 216 corridors across the ecoregion. The landscape network consisted of two graphs, one largely connected graph for the majority of the ecoregion and one small unconnected graph in southern Nova Scotia. The minimum spanning tree for the ecoregion consisted of 27 corridors.

Landscape Network Comparisons

The C-PAN landscape network scenario was comprised of the greatest number of habitat patches (nodes). As such, it reported the highest number of potential edges, linkages, and corridors among the three scenarios. This indicates potentially greater redundancy between patch connections. When compared to the other the scenarios, it reported the smallest minimum edge length (distance from adjacent patch center to adjacent patch center) and had intermediate maximum and average lengths for both edges and linkages. The C-PAN landscape network also had intermediate area requirements for measures of corridor area when compared to the others.

The Corridor Design landscape network scenario was comprised of slightly fewer patches (16) than the C-PAN scenario. This translated into 118 fewer edges and linkages when compared to the C-PAN scenario indicating a slightly less connected network with fewer structural and potentially beneficial connections. It reported the shortest distances for maximum and average edge and linkage length. Additionally the corridor area requirements for the Corridor Design landscape network scenario were the smallest among all approaches.

The FunConn landscape network scenario was comprised of the fewest number of patches (N = 31). This resulted in the fewest number of edges and linkages to be delineated among the three scenarios. This resulted in markedly longer min, max, and average edge and linkage lengths as connections were made between fewer far flung patches. As such, the corridor area requirements for this scenario were also significantly higher, over twice that of the average C-PAN corridor and approximately three times that of the average Corridor Design corridor. It is worth noting however because so few

corridors were delineated as part of this scenario, the total corridor area was nearly half

that of the C-PAN network and slightly less than that of the Corridor Design network.

This information is provided in Table 4.2.

**Table 4.2 – Landscape Network Comparisons**

Landscape Network Components	Scenario A: C-PAN Patches	Scenario B: Corridor Design Patches	Scenario C: FunConn Patches
Nodes	225	209	31
Edges	1,062	944	224
Min Edge Length (meters)	4,830	6,123	20,131
Max Edge Length	225,153	155,551	242,137
Average Edge Length	30,356	28,188	82,018
Std Dev	24,102	21,012	36,107
Linkages	1,062	944	224
Min Linkage Length (meters)	464	291	217
Max Linkage Length	217,919	150,581	192,459
Average Linkage Length	20,007	18,359	22,777
Std Dev	24,087	21,066	37,872
Corridors	1,058	944	216
Min Corridor Area (hectares)	29	26	27
Max Corridor Area	481,150	279,109	710,926
Average Corridor Area	14,626	12,306	38,545
Total Corridor Area	15,474,947	11,617,723	8,325,855
Std Dev	34,852	27,993	92,010
Minimum Spanning Tree Edges	223	207	27
Min Edge Length (meters)	4,830	6,123	20,131
Max Edge Length	150,094	150,263	217,237
Average Edge Length	20,745	21,165	72,185
Std Dev	16,827	19,271	44,177
Total Spanning Tree Length	4,626,226	4,381,261	1,949,001

Minimum Spanning Trees

The minimum spanning tree represents the most efficient solution for connecting all nodes within the graph. As such, minimum spanning trees provide a useful metric for comparing landscape connectivity between landscapes or multiple scenarios. They represent the fewest number of edges with the shortest total distance required to connect all nodes in a graph. By design however they do not illustrate redundant connections that may be desired in a real world ecological systems and/or conservation practice.

The C-PAN scenario minimum spanning tree was the largest (4,626 km) as it connected more nodes than in the other two scenarios. The inclusion of these additional nodes however led to reductions in the max, min, and average edge length within the tree. The C-PAN minimum spanning tree exhibited the shortest minimum edge length (4.8 km), maximum edge length (150.1 km) and average edge length (20.7 km) when compared to the other scenarios. The corridor design minimum spanning tree was of intermediate length (apx. 4,381 km) and exhibited only slightly longer minimum, max, and average edge lengths at 6.1, 150.3, and 21.2 km respectively. The minimum spanning tree for the FunConn scenario included approximately 1/8 the number of nodes. This however only translated into a landscape network which was approximately half the total length (1,949 km) of the C-PAN tree. Additionally, the minimum edge length of the FunConn minimum spanning tree was 20.1 km, the maximum edge length was 217.2 km, and the average edge length was 72.2 km; all significantly longer than those metrics reported for either of the other two scenarios. The landscape network graph and the minimum spanning tree for each scenario are depicted in Figure 4.5.

Figure 4.5 – Minimum Spanning Tree Comparison
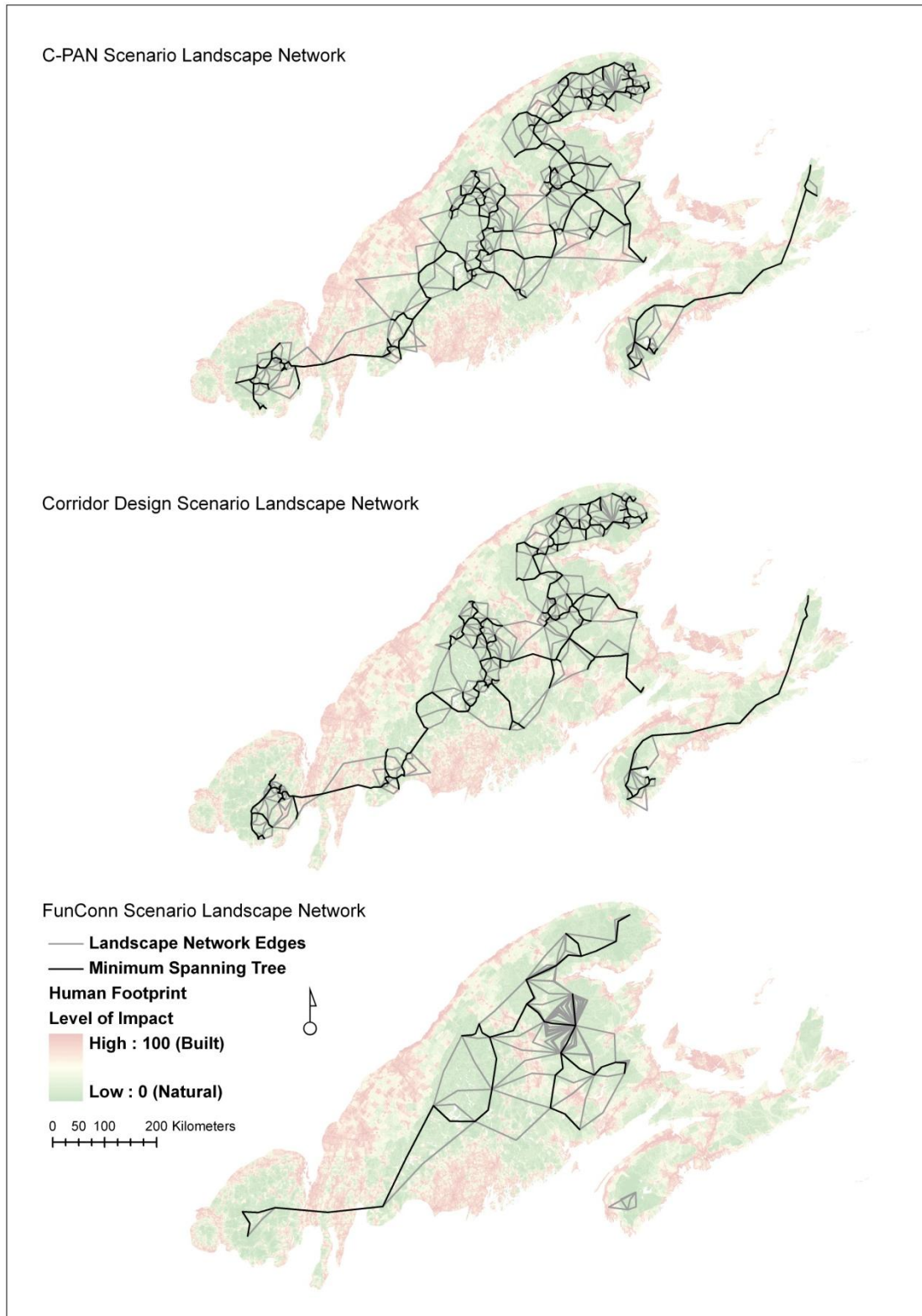
The minimum spanning tree for each scenario is depicted in black and the entire landscape network is depicted in grey. While each scenario depicts isolated graphs for Nova Scotia, the FunConn scenario is among the most potentially isolated.

Patch and Corridor Gap Analysis Modeling Methods

The resulting landscape networks and their source patches were converted to raster datasets and combined to perform a gap analysis evaluating the effective coverage of each scenario. Cells depicting their relative inclusion in 1, 2, or all 3 scenarios were then categorized and quantified in order to identify which areas were unique or held in common when compared across all of the scenarios. These areas were then extracted and classified to locate the conservation gaps in coverage between both the source patches and corridors within each scenario.

Patch and Corridor Gap Analysis Results

The gap analysis conducted here indicated significant deficiencies in conservation coverage when compared to all three scenarios. When evaluating patches within each scenario, 14% of the patch area for all 3 scenarios was spatially coincident, 9% was coincident over 2 scenarios, while the majority of patch area (76%) was non-redundant. This indicates significant gaps in source area coverage between these scenarios. A spatial output of this analysis is provided in Figure 4.6.

Additionally, 5% of the corridor area for all 3 scenarios was spatially coincident, 34% was coincident over 2 scenarios, while the majority of corridor area (59%) was non-redundant; again indicating significant coverage gaps in the corridors between these scenarios. A summary of this information is provided in Table 4.3 and the spatial output is provided in Figure 4.7.

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Table 4.3 – Patch & Corridor Gap Analysis

Gap Analysis Overlaps	Area Coincident (Hectares)	Percent Area Coincident
Patch Overlaps:		
1 Scenario Alone	3,785,404	76.09%
2 Scenarios Overlap	479,339	9.64%
All Scenarios Overlap	710,045	14.27%
Corridor Overlaps:		
1 Scenario Alone	6,966,340	59.75%
2 Scenarios Overlap	4,055,895	34.78%
All Scenarios Overlap	637,788	5.47%

Patch Gap Analysis

Figure 4.6 – Patch Gap Analysis Overlaps
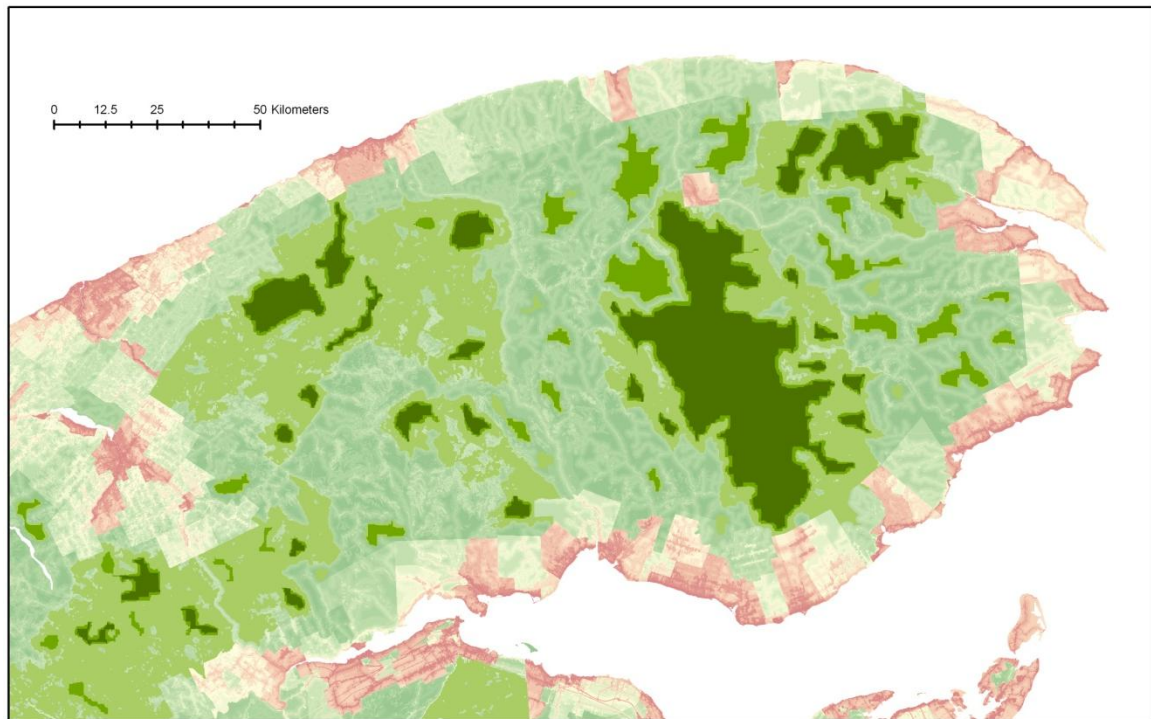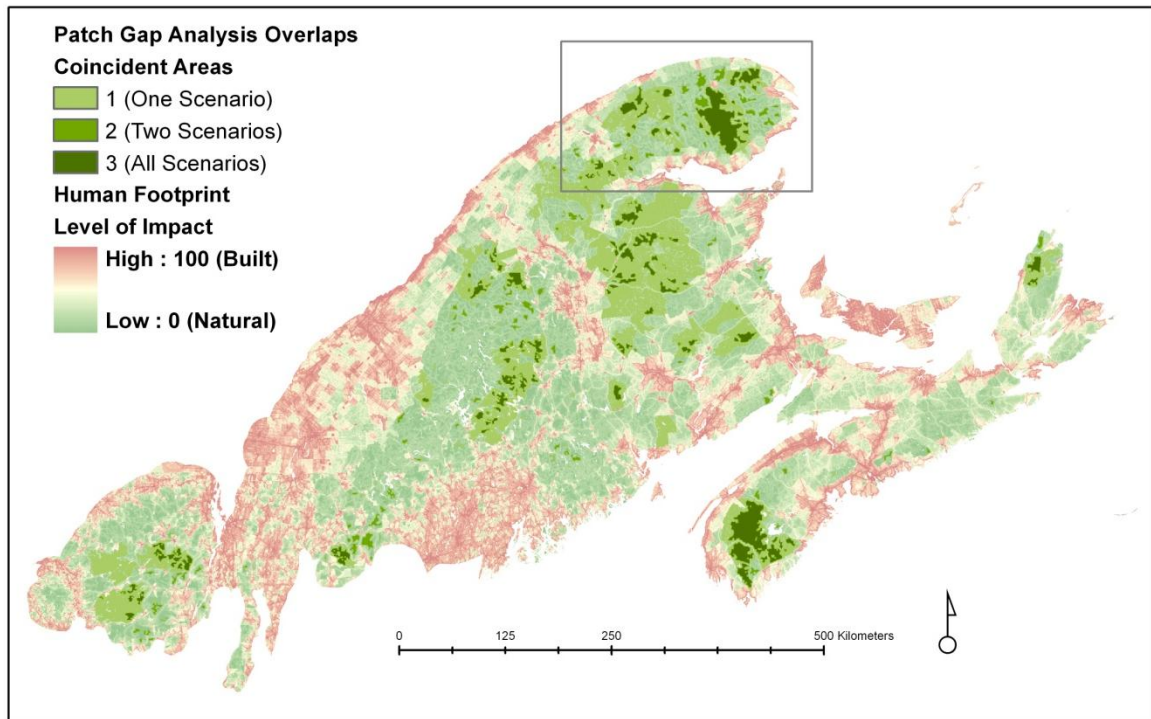
Patch area that is unique to one scenario is depicted in light green (76.1%), patch area that is held in common by two of the scenarios is an intermediate shade of green (9.6%), and areas in dark green represent patch regions that are part of all three scenarios (14.3%).

Corridor Gap Analysis

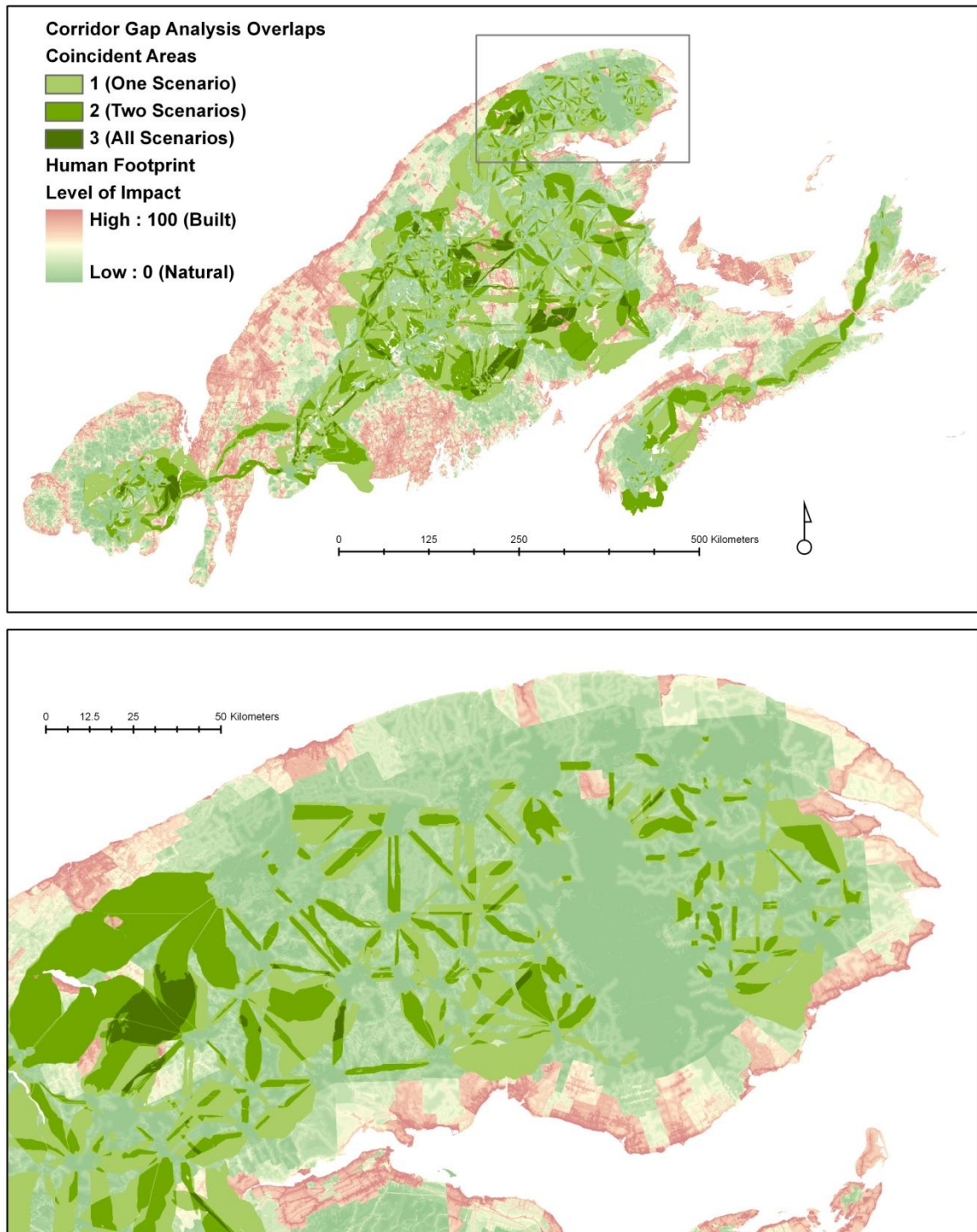**Figure 4.7 – Corridor Gap Analysis Overlaps**

Corridor area that is unique to one scenario is depicted in light green (59.8%), patch area that is held in common by two of the scenarios is an intermediate shade of green (34.8%), and areas in dark green represent patch regions that are part of all three scenarios (5.4%).

Connectivity Modeling Discussion

Ecoregion Connectivity

The three landscape networks modeled here indicated that while local connectivity in portions of the ecoregion is potentially present, widespread connectivity across the ecoregion as a whole is less likely. This was apparent in the C-PAN and Corridor Design patch scenarios, as multiple connections were delineated across the majority of the study area. Even so, no connections were delineated connecting the large central graph with a smaller more linear one spanning Nova Scotia. This is due to the narrow land area that could potentially serve as connection to this region and the relatively high human footprint found in this area. While the FunConn patch scenario landscape network also reported no connectivity to this area, it also depicted a general lack of connectivity spanning Nova Scotia as no linkages were delineated between patches in the north and south of this region. While it is speculative, it is also likely that providing additional stepping stone patches throughout this choke point may improve connectivity between Nova Scotia and the rest of the region.

Landscape Networks

The C-PAN patch network scenario was comprised of the greatest number of patches. This ultimately resulted in the delineation of multiple and potentially beneficial redundancies in the landscape network. Increasing the number of patches also improved distance metrics within the minimum spanning tree for this scenario. More patches served as intermediate stepping stones which resulted in shorter linkage and edge lengths and smaller average corridor requirements. The FunConn patch landscape network however

connected significantly fewer patches. This resulted in the longest linkage and edge
distances and the largest average corridors within the ecoregion. This is an apparent
tradeoff between the number of potentially beneficial redundant connections and total
landscape network corridor area. While more connections may contribute to increased
landscape connectivity and landscape function, the increased area requirement may
dictate that it is also potentially more costly to implement. On the other hand, fewer
connections may be less costly from an implementation standpoint, but may also reduce
landscape connectivity and ecological function.

Gap Analysis

The gap analysis used here resembles the process utilized by others for detecting
unprotected high-conservation value areas (Scott 1993 and Scott et al.. 2002). A
simplifying assumption is often that coarse-scale corridors may provide overlapping or
"umbrella" effects (Perkl and Baldwin, In Prep). This ecoregional patch and corridor gap
analysis provided the means for testing this assumption by evaluating corridor overlap
and coverage gaps between scenarios. To this author's knowledge, this is among the first
the first corridor gap analyses to be conducted at this scale.

The patch gap analysis indicated that the majority of patch area (76%) contributed
to a single scenario, while 9% and 14% of the patch area was held in common among two
and three scenarios respectively. It is important to point out however, that while the
majority of patch area is dissimilar, this is to due to variations in patch delineation among
approaches. The majority of all patches delineated within the ecoregion share common
nodes of origin. This is to say that the patches cover many of the same core areas but vary

in the extent of their individual size. As the modeled landscape networks share common nodes of origin, corridor coverage and gap comparisons can be made across scenarios.

The corridor gap analysis indicated that 5% of the corridor area for all 3 scenarios was spatially coincident, 34% was coincident over 2 scenarios, while the majority of corridor area (59%) was non-redundant. While this indicated significant coverage gaps in the corridors among these scenarios, areas held in common may prove to be no-regret areas for conservation action. These results indicate that selecting "what" to connect at the ecoregion-scale has significant implications for selected corridors. As there was so little modeled corridor area in common among scenarios, there is little reason to believe alternate corridors would be functionally equivalent. This indicates that connecting any one set of habitat nodes would not likely serve as a corridor umbrella for all other scenarios.

Ecoregion-scale Implications and Implementation

Landscape networks derived by FunConn are useful tools for evaluating ecoregion-scale connectivity. It is particularly useful for comparing connectivity across multiple scenarios. While each scenario evaluated here exhibited differences in components of their respective landscape networks, a number of regions of connectivity concern became readily apparent. These areas have been categorized into two distinct categories: regions with few redundant landscape linkages and areas lacking habitat nodes necessary for anchoring linkages. In regions where few linkages are present, connectivity is potentially threatened by poor quality matrix and relatively long and narrow corridors spanning these areas. Additionally, corridors within these regions are

critically important to connectivity of the ecoregion as there are potentially no alternate

or redundant corridors to serve their function. Corridors within these areas are of

potentially the highest priority for protection and mitigation as they are located in highly

fragmented landscapes with a relatively high human footprint. They represent the last

remaining linkages to adjacent natural areas. These areas are delineated in Figure 4.8.

Other areas lacked the nodes necessary for anchoring linkages. When large

portions of the ecoregion were void of habitat nodes, the lack of landscape linkages was

attributable to a heightened and impassable cost distance associated with traversing these

areas. Providing additional stepping stone patches and mitigation of the matrix within

these areas may prove critical to rehabilitating connectivity within and through these

regions. These areas are depicted in Figure 4.8.

Priority Connection Areas and Linkages

       Figure 4.8 depicts areas of conservation priority that have been categorized into two distinct categories, regions with few redundant landscape linkages, and areas lacking habitat nodes necessary for anchoring linkages. Regions 1, 2, and 4 represent areas where few linkages are present and connectivity is potentially threatened by poor quality matrix and relatively long and narrow corridors spanning these areas. Area 3 was highlighted in all three ecoregion connectivity scenarios as lacking any linkages between New Brunswick and Nova Scotia. This was largely attributable to the fact that there is a geographic bottleneck, a high human footprint, and a lack of any modeled habitat patches that may serve as stepping stones. The lack of connectivity in this area potentially isolates Nova Scotia from the rest of the ecoregion.

Figure 4.8 – Priority Connection Areas
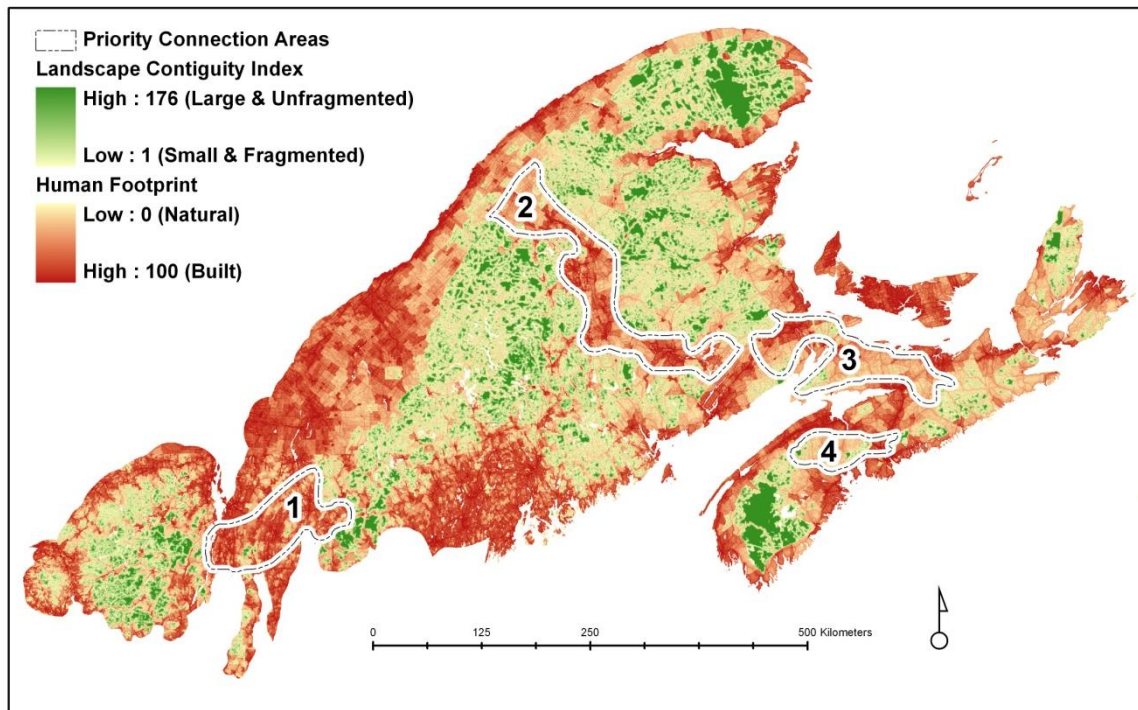
Priority connection areas 1, 2, and 4 represent regions with few modeled linkages. Priority connection area 3 lacks any linkages connecting New Brunswick and Nova Scotia, effectively isolating those regions.

Priority Connection Area 1

Priority connection area 1 (Figure 4.9) is comprised of four linkages, two from the

C-PAN and one each from the Corridor Design and FunConn scenarios. Regions in dark

green represent areas where the corridors for these scenarios overlapped. These regions

may be no-regret areas for conservation action as they are critical to connecting the

Adirondacks in the southwest with the Green-White Mountains to the northeast.

Figure 4.9 – Priority Connection Area 1
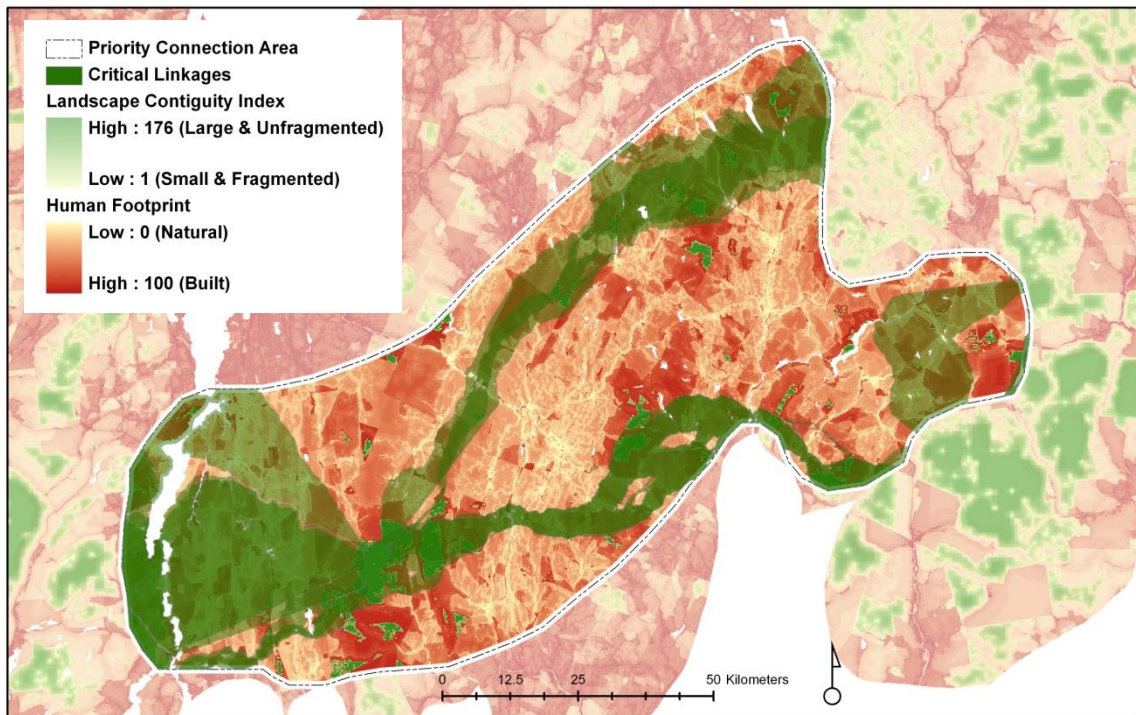
Priority Connection Area 2

Priority area 2 (Figure 4.10) encompasses a thin ribbon of poorly connected matrix which separates the core of the ecoregion located in northern Maine from largely connected portions to the north in Quebec. These relatively short corridors are critical to connecting the largest and most intact natural areas of the ecoregion.

Figure 4.10 – Priority Connection Area 2
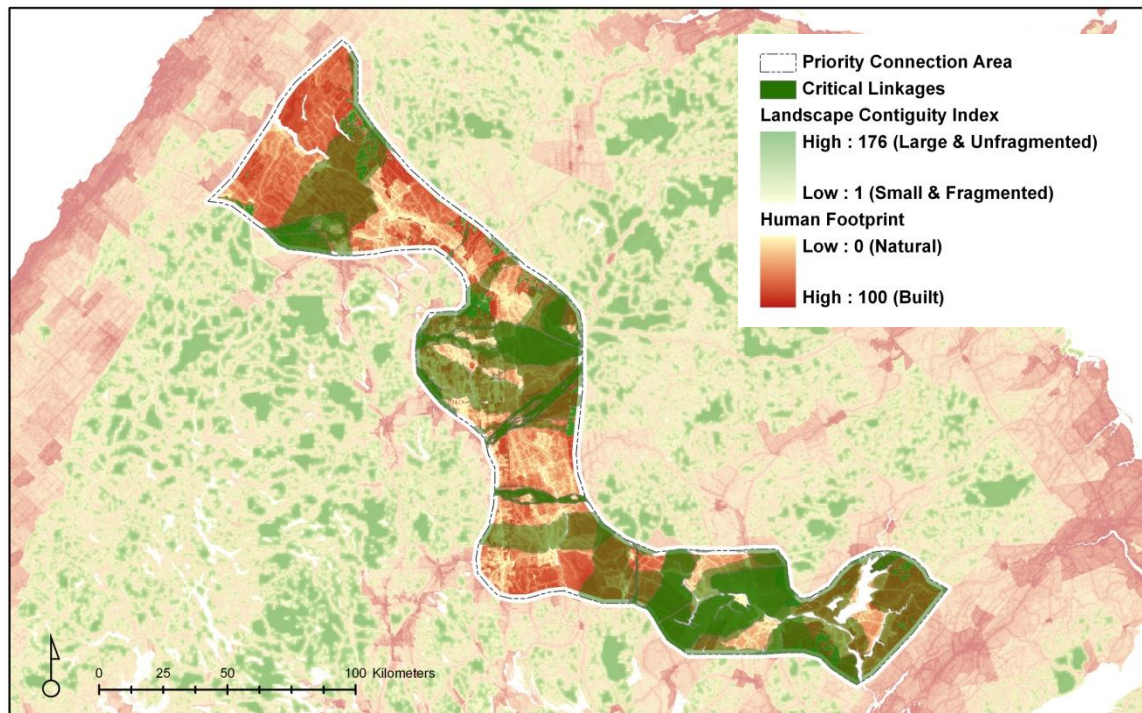
Priority Connection Area 4

Priority area 4 (Figure 4.11) includes a thin strip of land which is critical to maintaining connectivity within Nova Scotia. A single corridor was delineated for both the C-PAN and Corridor Design scenarios within this region. This area is largely important because it serves as the only connection between one of the largest intact blocks of habitat in the south and the rest of the ecoregion.

Figure 4.11 – Priority Connection Area 4
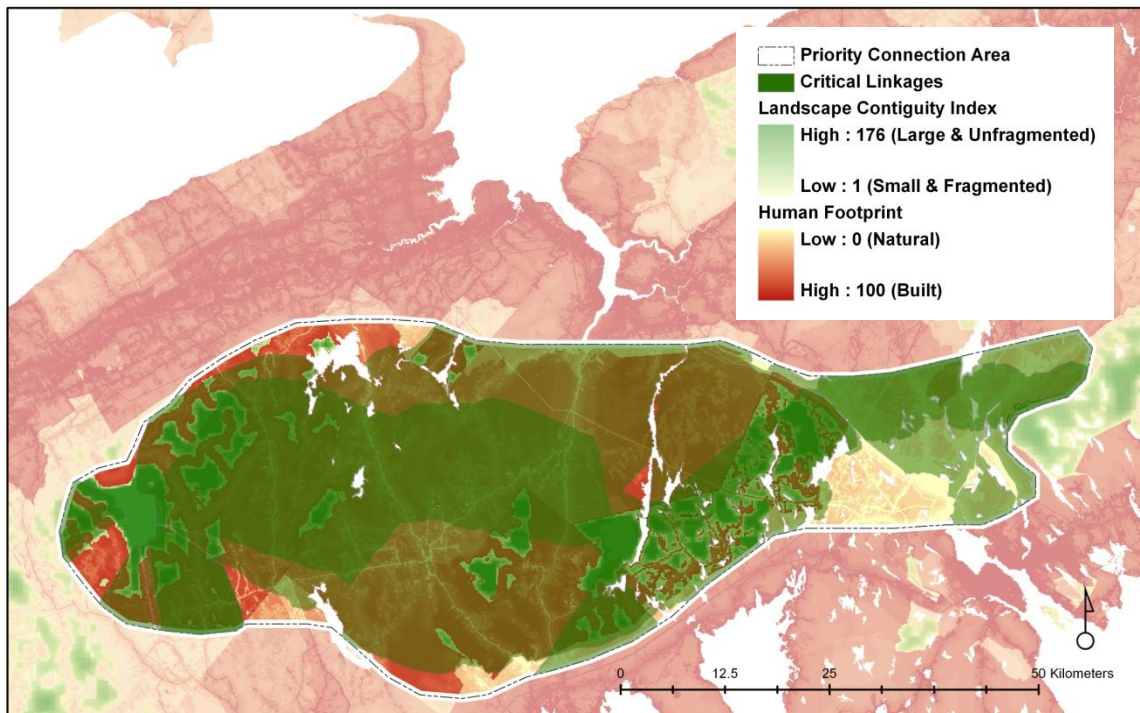
Priority Connection Area 3

Priority connection area 3 represents a region in which no linkages were delineated in any of the connectivity modeling scenarios (Figure 4.12). This is of concern as it results in isolating Nova Scotia from New Brunswick and the rest of the ecoregion. Providing connectivity through this heavily settled geographic bottleneck will likely prove challenging. As it currently stands, protected areas are distantly separated and the matrix between them is costly to traverse. Adding additional protected areas through the acquisition of land, enactment of conservation easements, and buffering existing protected areas within this area are but a few mechanisms by which the provision of connectivity throughout this region could be addressed. Additionally, more detailed and local scale connectivity modeling will be necessary for identifying potential linkages within and throughout this priority connection area.

Figure 4.12 – Priority Connection Area 3
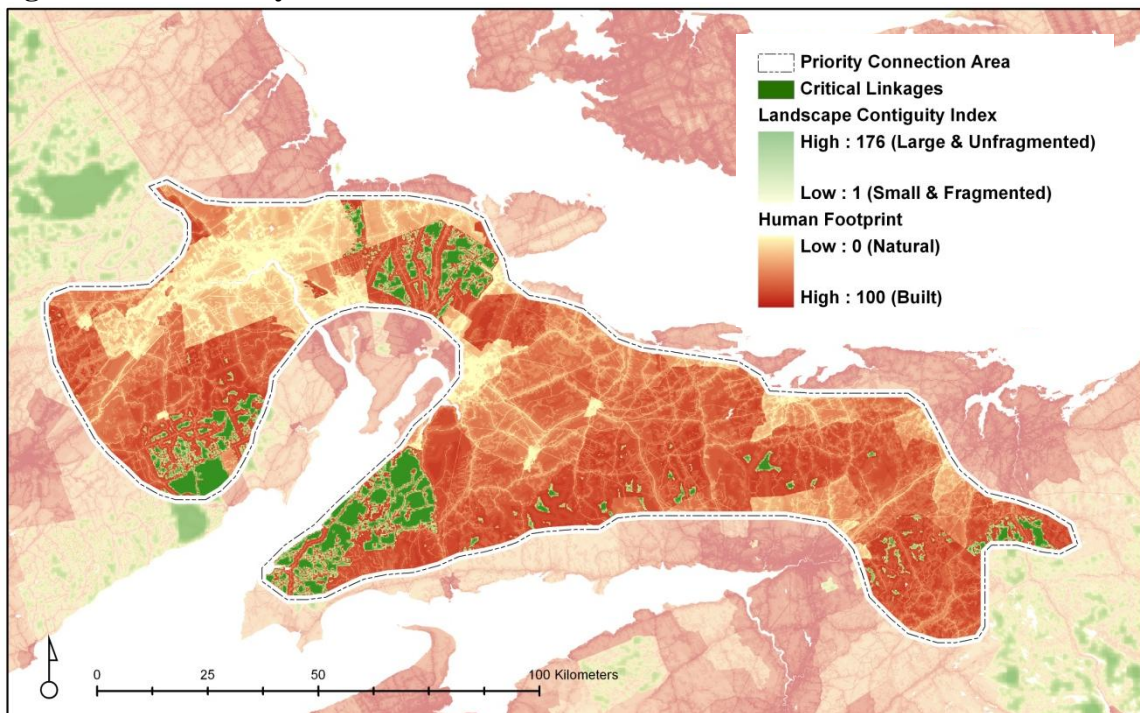
Ecoregion-scale Connectivity Modeling Conclusions

Ecoregion-scale connectivity modeling may prove to be a potential mechanism for better incorporating "planning for persistence" and addressing global climate change as was discussed earlier. The large size and very nature of ecoregion-scale corridors may prove to be the provocative means by which natural disturbance regimes, environmental gradients, and shifting species ranges may be captured in our conservation networks.

The landscape network generated for connecting C-PAN patches (N = 225) consisted of 1,062 linkages and edges and 1,058 corridors spanning across the ecoregion. The landscape network generated for connecting Corridor Design patches (N = 209) consisted of 944 linkages, edges, and corridors across the ecoregion. The landscape network consisted of two graphs. The landscape network generated for connecting FunConn patches (N = 31) consisted of 224 linkages and edges and 216 corridors across the ecoregion. These results taken together with the subgraphs for the region and their respective minimum spanning trees indicated that while local connectivity was potentially present, widespread ecoregional connectivity was less likely.

To this author's knowledge, the gap analysis conducted here is unique in scale and application. The results of the corridor gap analysis indicated that selecting "what" to connect at the ecoregion-scale has significant implications for selected corridors. As there was so little modeled corridor area in common among scenarios, there is little reason to believe alternate corridors would be functionally equivalent. This indicates that connecting any one set of habitat nodes would not likely serve as a corridor umbrella for all other scenarios.

Additionally, this research served in flagging areas for conservation prioritization based on their connectivity role. As such, ecoregion-scale connectivity analyses such as this may prove useful for evaluating connectivity at local scales. Any one of the subgraphs found within these modeled landscape networks could help inform local scale conservation efforts. Similarly, local scale connectivity and conservation actions could be added to the ecoregion-scale landscape network. As with many things, a successful landscape network is made up of the sum of its locally implemented parts.

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Theoretical Rationale: Why Model Large Reserves and Core Habitat?

Habitat loss, fragmentation, and species reduction are all inextricably linked to accelerated rates of human induced land use change. The conversion of natural landscapes to human dominated land uses causes habitat loss in two primary ways (Weber et al., 2005). First, the direct reduction in area of available habitat can drastically reduce or eliminate entirely certain species and their ecosystems (Dramstad et al., 1996). Second, the diffuse pattern of present day urban and suburban expansion effectively fragments the natural landscape creating smaller patches of intact natural areas of reduced quality (Dramstad et al., 1996).

Urban expansion is perhaps the most well-studied and often modeled type of land-use change worldwide. Current accounts have found that within the United States alone, there has been an effective doubling of high density developed areas from 1960 to 1990 (Theobald, 2001). This however pales in comparison to the rate of suburban expansion. Exurban development generally results in the unplanned dispersal of homes on large parcels of land (Hilty et al., 2006). Low density residential development in the United States is now the fastest growing type of land use and the number of suburban residents in many European countries has more than doubled or tripled in the last fifty years (Theobald, 2001).

Numerous studies have shown the negative ecological effects of ecosystem fragmentation on the landscape. Habitat fragmentation is arguably the greatest threat to wildlife and is primarily responsible for species extinction (Sorrell, 1997). In general, less

suitable habitat correlates with lower species richness and fewer specialists (Drapeau et al., 2000). Fragmentation of habitat and increasing edge conditions reduce both the distributions and abundance of North American wildlife species (Weber et al. 2005, Donovan et al. 1995, Robinson et al. 1995, Hansen and Urban 1992, and Yahner 1988). Loosely defined, habitat fragmentation encompasses the conversion of natural landscapes to anthropocentric land uses in a nonsystematic way thus increasing the potential for adverse effects in the remaining habitat. Furthermore, those species that are most vulnerable to the impacts of fragmentation tend to have already small populations, are large in size, have large home ranges, are ecological specialists, have unique habitat requirements, and are those species with variable populations that are dependent on unpredictable resources (Weber et al., 2005).

For these reasons, there is growing support for assembling larger, more cohesive tracts of habitat with substantial core area as opposed to collecting smaller reserves with vulnerable linkages. Increasing patch area may be a better strategy for protecting fragmented populations (Haddad, 1999). Simberloff et al. (1992) state that increasing the size of conservation areas (areas enrolled in some form of protective framework whereas ecosystem sustainability, function, and processes are of primary concern) and habitat patches will improve local population persistence. Larger habitat patches tend to have larger local populations and larger populations of more species while smaller patches may be entirely void of some species altogether (Beier et al., 2002). This is supported further by Falcy et al. (2007) in that populations tended to be greater in larger patches rather than smaller and more fragmented patches with approximately similar area. This was achieved primarily through the provision of high quality interior core habitat

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(Simberloff et al., 1992). In this way, average population size and persistence increase if the patch size required to sustain viable populations is large enough (Falcy et al., 2007). This association is documented in the individual-area relationship (Conner et al., 2000) and the density-area relationship identified by Matter (1997).

Habitat fragmentation and patch size are inherently related to edge-to-area ratios. Peck (1998) states that fragmentation increases "edge" habitat and decreases "interior" habitat. Edge habitat has been shown to vary greatly in terms of conditions and composition from that of the interior. In general, the microclimate associated with edge conditions tends to be more severe than that of the interior (Saunders et al., 1991). Edge areas are also exposed to a greater degree of the impacts from adjacent land uses. Chief amongst these impacts is the introduction of new species to the edge area (Hobbs and Huenneke, 1992). The dispersal of these species tends to alter the makeup of the natural habitat patch even though it remains, in space, unaltered. Generalist species tend to persist in edge environments and over time will often outcompete the more sensitive native inhabitants (Peck, 1998). In this way, the reduced size and fragmented characteristics associated with natural areas changes the ratio of edge to interior or core habitats; as interior habitats decrease, so to do the more sensitive native species (Peck, 1998). Larger contiguous patches however tend to encompass a greater degree of interior habitat thus mitigating edge effects. This is important from a modeling perspective because patches can be identified and selected based on their measures of core interior habitat.

The negative impacts of edge effects on inhabitants are well documented. Paton (1994) has shown that edge effects can reduce avian nesting success rates. In another

study, some birds are found in and throughout patches of all sizes while other birds are only observed in patches of certain sizes, in the interior, or in the edges of others (Beier et al., 2002; Ford et al., 2001; Trzcinski et al., 1999). Additionally, Ewers and Didham (2007) have found that irregularly shaped habitat patches exhibited regularly diminished populations of core-dwelling species by 10-100%, depending on the scale and the relative proportion of edge area to interior area.

In these ways, maintaining relatively large and cohesive patches is tied closely with sustaining viable populations of natural inhabitants. More specifically however, the positive effects of patch size can be diminished if the patch is irregularly shaped and has a relatively low proportion of interior or core habitat to edge conditions. Based on these well supported suppositions, it would appear that the best conservation management solution would be to assemble a vast array of relatively large and cohesive habitat areas.

Patch size matters on a theoretical level as well. There are a number of scientific principals and theories that scientists call upon to better manage and explain landscape functionality (Hilty et al. 2006). Those that are centrally tied to the existence of habitat patches include: optimal foraging theory (MacAurthur and Pianka, 1966), island biogeography (Wilson, 1967), dispersal theory (Fahrig and Merriam, 1985), source-sink dynamics (Pulliam, 1988), hierarchical patch dynamics (Wu and Loucks, 1995), wildlife-habitat relationship modeling (Morison and Hall, 1998), metapopulation dynamics (Hanski, 1999), landscape metrics (Vos et al. 2001, McGarigal et al. 2002), predicting species occurrences (Scott et al., 2002), and metacommunity dynamics (Holyoak et al., 2005) (Girvetz and Greco, 2007).

As many of these theories are directly tied to the function of patch size and cohesion, greater discussion of them is appropriate here, chief among them: island biogeography theory (Wilson, 1967), the intermediate disturbance hypothesis (Connell, 1978), metapopulation theory (Levins, 1969), and metacommunity theory (Wilson, 1992). As stated by Pulliam and Johnson (2001), island biogeography has become one of the fundamental paradigms for conservation reserve design and for understanding the biological consequences of habitat fragmentation, that is, the splitting of contiguous habitat into smaller, isolated fragments. E.O. Wilson (1967) surmised that both the populations and variety of species on islands are influenced by the patterns of immigration and local extinctions in addition to competition between inhabitants for resources. Furthermore, he points out that the patterns of immigration are functions of distance from the mainland and that local extinctions are functions of island size. In general terms, islands with closer proximity exhibit more sustainable patterns of immigration and islands of larger size are more likely to sustain populations with little likelihood of local extinction. In this same way, larger and more cohesive patches of habitat may better sustain local populations.

Habitat size becomes a paramount component of island biogeography theory. Isolated habitat areas are essentially islands in a sea of competing land uses. Small habitat areas are essentially small islands in the same sea thus making their inhabitants particularly susceptible to local extinctions. In these ways, functional size is expected to increase with progressively greater degrees of physical connectivity (Pullman and Johnson, 2001). In other words, the size and connectivity of habitat islands is critical in

assuring sustainable immigration of inhabitants and lessening possible species

extinctions.

Connell (1978) has shown that areas of the greatest biologic diversity are those

that experience intermediate levels of disturbance. A disturbance is defined as any event

in time that disrupts ecosystem or community structure while changing resource

availability or the physical environment (White & Pickett, 1985). Intermediate

disturbances occur at several different levels ranging from frequent to infrequent, short

time since last disturbance to long time since last disturbance, and large to small (Pulliam

& Johnson, 2001). An example of a large disturbance may include the eruption of a

volcano while a small scale disturbance would include an uprooted tree from a

windstorm.

In the absence of intermediate disturbances, competition among species will result

in superior competitors out competing others. Additionally, very few species can tolerate

extremely frequent or intense disturbances. For these reasons, it is imperative that historic

disturbance regimes be maintained. These regimes include considerations characterized

by their type, frequency, intensity, and spatial extent of the disturbances to ensure various

successional trajectories (Pullman & Johnson, 2001). Peck (1998) makes the effective

connection between maintaining natural disturbance regimes and habitat size; under

optimal conditions, habitat areas should be large enough to accommodate disturbance

regimes that are historically characteristic of the region. In essence, as the size of a

cohesive habitat patch increases, so too does the chance that natural disturbance regimes

will remain intact.

Based on this empirical evidence and these theoretical suppositions, the C-PAN spatial modeling approach outlined herein provides a unique and potentially beneficial method for identifying patches comprised of large cohesive tracts of suitable core habitat. Additionally, once identified, these patches and sites can be ranked based on the newly formed patch metrics associated with core area developed by the C-PAN model. The core area metrics of the C-PAN value, rank (a grading of patch cohesion compared to others), and quotient (a measure of comparison between each patch and the patch with the highest cohesion) ultimately aid in further categorizing and ranking individual patches based on the desired spatial aspects of large cohesive patches with heightened core area. This is largely desirable because of the well documented ecologic benefit to biodiversity that is generated by patches exhibiting these characteristics.

Graph Theory & Landscape Network Terminology

Graph: the collection of habitat patches, blocks, or reserves found within the landscape being evaluated; they are represented as nodes.

Node: the vector data point that represents the location of the habitat patch, block, or reserve; nodes are connected in a graph by edges.

Edge: the line that connects each connected node within the graph; it is not to be confused with other usages of the term edge within conservation planning such as when discussing edge effects, corridors, or interior habitat. Here edge is simply demarking the connection between patches, blocks, or reserves.

Path: a sequence of connected nodes that when taken together form a walk. A path encompasses several patches, blocks, or reserves strung together.

Walk: a unique combination of nodes connected by their respective edges. The length of a walk is represented by the sum of each edge. A walk represents a unique combination of a path, a walk could be thought of spatially as a potential greenway.

Cycle: a type of walk that represents a closed loop of nodes, a walk is considered closed if the starting node and the ending node are the same. A cycle indicates a potential greenway that is closed to form a loop.

Tree: a type of walk that does not represent a closed loop of nodes or cycles. This represents a path that is linear in nature similar to the spatial configuration of a stream.

Spanning Tree: a tree that includes every node, patch, block, or reserve found within the graph or landscape. There may be several spanning trees for each graph, each comprised of a unique combination of paths or walks.

Minimum Spanning Tree: the spanning tree that includes the shortest total distance of edge length.

Connected Graph: a graph where there is a path between any two nodes, thus allowing every node within the landscape to be reachable or connected in some sequence.

Subgraph: a graph where some nodes may be unreachable from others because no path exists. This would be likely in highly fragmented landscapes where edge distances are great, effective distances are too high, or barriers persist.

Graph Component: a connected subgraph where there is a path between any two nodes, thus allowing every node within the component to be reachable. A subgraph can be comprised of multiple isolated components. Individual components, while isolated from each other, may still function as important ecological drivers at the ecoregion-scale.